Université de Montréal

Utilisation d’algorithmes d'intelligence artificielle pour guider le traitement chirurgical de la scoliose idiopathique de l'adolescent

The use of artificial intelligence algorithms to guide surgical treatment of adolescent idiopathic scoliosis

par
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Résumé

La scoliose idiopathique de l'adolescent (SIA) est une déformation tri-dimensionelle du rachis. Son traitement comprend l'observation, l'utilisation de corsets pour limiter sa progression ou la chirurgie pour corriger la déformation squelettique et cesser sa progression. Le traitement chirurgical reste controversé au niveau des indications, mais aussi de la chirurgie à entreprendre. Malgré la présence de classifications pour guider le traitement de la SIA, une variabilité dans la stratégie opératoire intra et inter-observateur a été décrite dans la littérature. Cette variabilité s'accentue d'autant plus avec l'évolution des techniques chirurgicales et de l'instrumentation disponible.

L'avancement de la technologie et son intégration dans le milieu médical a mené à l'utilisation d'algorithmes d'intelligence artificielle informatiques pour aider la classification et l'évaluation tridimensionnelle de la scoliose. Certains algorithmes ont démontré être efficace pour diminuer la variabilité dans la classification de la scoliose et pour guider le traitement.

L'objectif général de cette thèse est de développer une application utilisant des outils d'intelligence artificielle pour intégrer les données d'un nouveau patient et les évidences disponibles dans la littérature pour guider le traitement chirurgical de la SIA.

Pour cela une revue de la littérature sur les applications existantes dans l'évaluation de la SIA fut entreprise pour rassembler les éléments qui permettraient la mise en place d'une application efficace et acceptée dans le milieu clinique. Cette revue de la littérature nous a permis de réaliser que l'existence de "black box" dans les applications développées est une limitation pour l'intégration clinique ou la justification basée sur les évidence est essentielle.

Dans une première étude nous avons développé un arbre décisionnel de classification de la scoliose idiopathique basé sur la classification de Lenke qui est la plus communément utilisée de nos jours mais a été critiquée pour sa complexité et la variabilité inter et intra-observateur. Cet arbre décisionnel a démontré qu'il permet d'augmenter la précision de classification proportionnellement au temps passé à classifier et ce indépendamment du niveau de connaissance sur la SIA.

Dans une deuxième étude, un algorithme de stratégies chirurgicales basé sur des règles extraites de la littérature a été développé pour guider les chirurgiens dans la sélection de l'approche et les niveaux de fusion pour la SIA. Lorsque cet algorithme est appliqué à une large base de donnée de 1556 cas de SIA, il est capable de proposer une stratégie opératoire similaire à celle d'un chirurgien expert dans prêt de 70% des cas. Cette étude a confirmé la possibilité d'extraire des stratégies opératoires valides à l'aide d'un arbre décisionnel utilisant des règles extraites de la littérature.

Dans une troisième étude, la classification de 1776 patients avec la SIA à l'aide d'une carte de Kohonen, un type de réseaux de neurone a permis de démontrer qu'il existe des scoliose typiques (scoliose à courbes uniques ou double thoracique) pour lesquelles la variabilité dans le traitement chirurgical varie peu des recommandations par la classification de Lenke tandis que les scolioses a courbes multiples ou tangentielles à deux groupes de courbes typiques étaient celles avec le plus de variation dans la stratégie opératoire.

Finalement, une plateforme logicielle a été développée intégrant chacune des études ci-dessus. Cette interface logicielle permet l'entrée de données radiologiques pour un patient scoliotique, classifie la SIA à l'aide de l'arbre décisionnel de classification et suggère une approche chirurgicale basée sur l'arbre décisionnel de stratégies opératoires. Une analyse de la correction post-opératoire obtenue démontre une tendance, bien que non-statistiquement significative, à une meilleure balance chez les patients opérés suivant la stratégie recommandée par la plateforme logicielle que ceux aillant un traitement différent.

Les études exposées dans cette thèse soulignent que l'utilisation d'algorithmes d'intelligence artificielle dans la classification et l'élaboration de stratégies opératoires de la SIA peuvent être intégrées dans une plateforme logicielle et pourraient assister les chirurgiens dans leur planification préopératoire.

Mots-clés : Scoliose idiopathique de l'adolescent, niveaux de fusion, approche, intelligence artificielle, algorithmes, arbres décisionnels, logiciel.

Abstract

Adolescent idiopathic scoliosis (AIS) is a three-dimensional deformity of the spine. Management of AIS includes conservative treatment with observation, the use of braces to limit its progression or surgery to correct the deformity and cease its progression. Surgical treatment of AIS remains controversial with respect to not only indications but also surgical strategy. Despite the existence of classifications to guide AIS treatment, intra- and inter-observer variability in surgical strategy has been described in the literature.

Technological advances and their integration into the medical field have led to the use of artificial intelligence (AI) algorithms to assist with AIS classification and three-dimensional evaluation. With the evolution of surgical techniques and instrumentation, it is probable that the intra- and inter-observer variability could increase. However, some AI algorithms have shown the potential to lower variability in classification and guide treatment.

The overall objective of this thesis was to develop software using AI tools that has the capacity to integrate AIS patient data and available evidence from the literature to guide AIS surgical treatment.

To do so, a literature review on existing computer applications developed with regards to AIS evaluation and management was undertaken to gather all the elements that would lead to usable software in the clinical setting. This review highlighted the fact that many applications use a non-descript “black box” between input and output, which limits clinical integration where management based on evidence is essential.

In the first study, we developed a decision tree to classify AIS based on the Lenke scheme. The Lenke scheme was popular in the past, but has recently been criticized for its

complexity leading to intra and inter-observer variability. The resultant decision tree demonstrated an ability to increase classification accuracy in proportion to the time spent classifying. Importantly, this increase in accuracy was independently of previous knowledge about AIS.

In the second study, a surgical strategy rule-based algorithm was developed using rules extracted from the literature to guide surgeons in the selection of the approach and levels of fusion for AIS. When this rule-based algorithm was tested against a database of 1,556 AIS cases, it was able to output a surgical strategy similar to the one undertaken by an expert surgeon in 70% of cases. This study confirmed the ability of a rule-based algorithm based on the literature to output valid surgical strategies.

In the third study, classification of 1,776 AIS patients was undertaken using Kohonen Self-Organizing-Maps (SOM), which is a kind of neural network that demonstrates there are typical AIS curve types (i.e: single curves and double thoracic curves) for which there is little variability in surgical treatment when compared to the recommendations from the Lenke scheme. Other curve types (i.e: multiple curves or in transition zones between typical curves) have much greater variability in surgical strategy.

Finally, a software platform integrating all the above studies was developed. The interface of this software platform allows for: 1) the input of AIS patient radiographic measurements; 2) classification of the curve type using the decision tree; 3) output of surgical strategy options based on rules extracted from the literature. A comparison of surgical correction obtained by patients receiving surgical treatment suggested by the software showed a tendency to obtain better balance -though non-statistically significant - than those who were treated differently from the surgical strategies outputted by the software.

Overall, studies from this thesis suggest that the use of AI algorithms in the classification and selection of surgical strategies for AIS can be integrated in a software platform that could assist the surgeon in the planning of appropriate surgical treatment.

Keywords : Adolescent idiopathic scoliosis, levels of fusion, approach, artificial intelligence, algorithms, decision trees, rule-based algorithms.

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List of Abbreviations:

3D: Three-dimensional

AI: Artificial intelligence

AIS: Adolescent idiopathic scoliosis

AVT: Apical Vertebral Translation

AVR: Apical Vertebral Rotation

ASF: Anterior Spinal Fusion

BMU: Best Matching Unit

C7PL: C7 plumb line

CDT: Classification Decision Tree

CSVL: Central Sacral Vertical Line

EV: End Vertebra

GL: Gravity Line

GUI: Graphic User Interface

LIV: Lower Instrumented Vertebra

MT: Main Thoracic

NV: Neutral Vertebra

PSF: Posterior Spinal Fusion

PT: Proximal Thoracic

RSH: Radiographic Shoulder Height

SDSG: Spinal Deformity Study Group

SOM: Kohonen Self-Organizing-Map

SPAASP: Software Platform to Assist AIS Surgical Planning

SSRBA: Surgical Strategy Rule Based Algorithm

SV: Stable Vertebra

TL/L: Thoraco-Lumbar/ Lumbar

UIV: Upper Instrumented Vertebra

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Introduction

Adolescent idiopathic scoliosis (AIS) is a three dimensional deformity of the spine. It affects about 1% to 3% of children between the ages of 10 to 16[6]. As stated by its name the aetiology of AIS is unknown but care must be taken to exclude other known forms of scoliosis, which can be due to syndromic disorders, neuromuscular disorders or secondary to congenital vertebral malformations. Patients are usually screened using the Adam's forward bending test and a scoliometer reading, but definite diagnosis is usually defined as Cobb angle greater than 10 degrees when measured with standing radiograph.

Management of AIS is based on the severity of the curve and the likelihood of progression, which depends on patient skeletal maturity. For curves less than 25 degrees, observation is usually warranted. For greater curves between 25 and 45 degrees bracing is considered in skeletally immature patients while other patients can be followed with serial imaging. For patients with curves greater than 40 degrees, surgical intervention should be considered in order to prevent further progression[7]. The scope of this thesis will be limited to this last group of patients for which surgical decision has been made.

Surgical treatment remains controversial with respect to the choice of approach, levels of fusion and instrumentation. Surgical planning is challenging because of the many factors that must be taken into consideration given the complex deformity of the spine and the variability in assessing those factors[8-10]. In addition, Majdouline et al[11] demonstrated a large variability in scoliosis correction objectives. Ultimately this leads to a treatment variability amongst surgeons that has been repeatedly documented[10, 12-14].

Simple algorithms such as decision tree or rule-based algorithms[5] and more complex ones involving artificial intelligence algorithms based on clustering have demonstrated their benefits in improving AIS classification[15-17]. More recent studies have also demonstrated the benefits of using neural networks in predicting spinal stenosis surgical outcome more accurately than common statistical models such as linear regression[18]. Therefore artificial intelligence tools have proven to be useful in the classification and outcome prediction from surgical treatment of spinal pathologies.

This thesis is divided in eight chapters. Following this introduction, the first chapter will constitute a background and literature review about AIS, its evaluation, its management and particularly its surgical treatment as well as a superficial introduction to artificial intelligence and the algorithms that will be used in this thesis. It will also include a summary of applications that have been developed in the last decade to assist AIS assessment and treatment to highlight the role of artificial intelligence algorithms in AIS management. Chapter 2 will detail the problematic, the hypothesis and the objectives and present the methodology in each of the articles. The primary objective of this thesis being to develop a software based on AI tools to guide surgical treatment of AIS. Chapter 3 presents our first article, which is a critical appraisal of recent literature on computer algorithms used in the management of AIS, findings from this work have guided the way we chose algorithms and integrated them in the software. Chapter 4 presents an article on a decision tree developed to classify AIS according to Lenke classification and its benefits when used in a clinical setting. Chapter 5 presents an article on the surgical strategy rule-based algorithm for AIS which outputs multiple surgical strategies based on rules extracted from the literature. Chapter 6 presents a novel classification for AIS using Kohonen self-organizing-maps (SOM). The first article is a technical paper describing the algorithms used and how the classification is generated and validated. The second article is a clinical paper highlighting how this classification allows assessment of treatment variability when comparing surgical treatment done and treatment suggested by Lenke classification. Chapter 7 presents the software platform that was developed to guide AIS surgical treatment and integrating all the algorithms described above. Chapter 8 will constitute a discussion of the findings in this thesis with recommendations for future research and a conclusion will follow.

Chapter 1. Background and literature review

The objective of this first chapter is to present essential background about AIS and artificial intelligence that will be necessary to the understanding of this thesis.

1.1 AIS epidemiology

Adolescent Idiopathic Scoliosis (AIS) is a complex three-dimensional (3D) deformation of the spine and rib cage with a prevalence of 1-3% in the adolescent population. It is the most common adolescent spine deformity, affecting primarily young adolescent females[6, 19]. AIS patients have pathological spinal curves in the coronal plane, alteration of kyphosis or lordosis in the sagittal plan and rotation of the vertebrae in the axial plane. Of all patients with AIS, 3-9% will require treatment[6, 19]. Of those patients, 90% are treated conservatively in a brace and 10% surgically with fusion of the spine to correct and prevent progressive deformity.

The close follow up and treatment of patients with AIS has been emphasized after studies had shown increased psychological and physical morbidity with deformity progression [20-24]. AIS patients are more susceptible to suffer from back pain [25] , from cardio-pulmonary complications [20, 22, 23, 26] and from psychological disorders [24, 27-30].

1.2 AIS evaluation

1.2.1 AIS clinical evaluation

Patients with AIS often present after truncal asymmetry is noted or following a positive Adams bend test during school screening or physical examination for athletics. During the Adams forward bend test, patient face away from the examiner and touches the toes. If a hump or rotation of the spine is noted, the test is considered positive and referral to a physician ensues[31].

Patients with AIS are usually asymptomatic. Nonetheless, up to 35% of patients may experience have some degree of back pain[32]. Scoliosis can be the first sign of a subjacent pathology and all diagnostics should be excluded before the diagnosis of idiopathic scoliosis is assigned. . For this reason, a thorough neurological exam at presentation is essential to screen for possible anomalies that could increase the suspicion of intra-spinal pathology. Scoliosis could also be a compensatory mechanism for painful pathologies such as osteoid osteoma or could present secondary to Scheuermann's kyphosis, disc herniation, syringomyelia, thethered spinal cord or intraspinal tumor.

An important component of AIS evaluation relates to the assessment of skeletal maturity and the stage of the patient in relation to the adolescent peak height velocity because of the close correlation with the curve acceleration phase. Useful markers in assessing skeletal maturity include menarchal status, bone age from hand radiographs (digital skeletal age [DSA]), Risser triridiate cartilage stage from ossification of the iliac crest on AP radiographs of the pelvis, and Tanner stage [6]. Nault et al.[33] have demonstrated that Risser stage 0 with a closed triradiate cartilage and Risser 1 were the best predictor of the beginning of the curve acceleration phase.

Physical examination of the AIS patient exhibits truncal asymmetry, shown by the trunk leaning toward one side, leaving a gap between the rib cage and arm. Asymmetry can be evaluated using a plumb bob from the cervico-thoracic junction and measuring deviatation from the midline with the patient in the upright position. This also reflects the amount of coronal imbalance that can result from the scoliosis. Shoulder asymmetry should also be noted as it can be corrected with surgery and influence the selection of levels of fusion. As a result from the spinal rotation, elevation of the scapula can result from the rib hump and can be best observed during the Adams forward bend test.

Proper diagnosis of AIS by excluding other etiology for the scoliosis, adequate assessment of skeletal maturity and detailed physical examination are essential to lead to proper management and surgical planning if required.

1.2.2 AIS radiographic evaluation

Most of the radiographic measurements described below were extracted from the SDSG radiographic measurement manual[34], which was used for all radiographic evaluation undertaken in this thesis.

Plain radiographs allow the evaluation of the degrees of deformity, the resulting change in balance (in the sagittal and coronal plane), and the presence of other associated pathologies such as spondylolisthesis or other conditions that could lead to a non idiopathic scoliosis.

The two most common first radiographs used in the evaluation of scoliosis are the standing postero-anterior and lateral x-rays. They should include the lower cervical spine down to and including the pelvis. Those landmarks on the radiographs are important in order to get proper radiographic measurements.

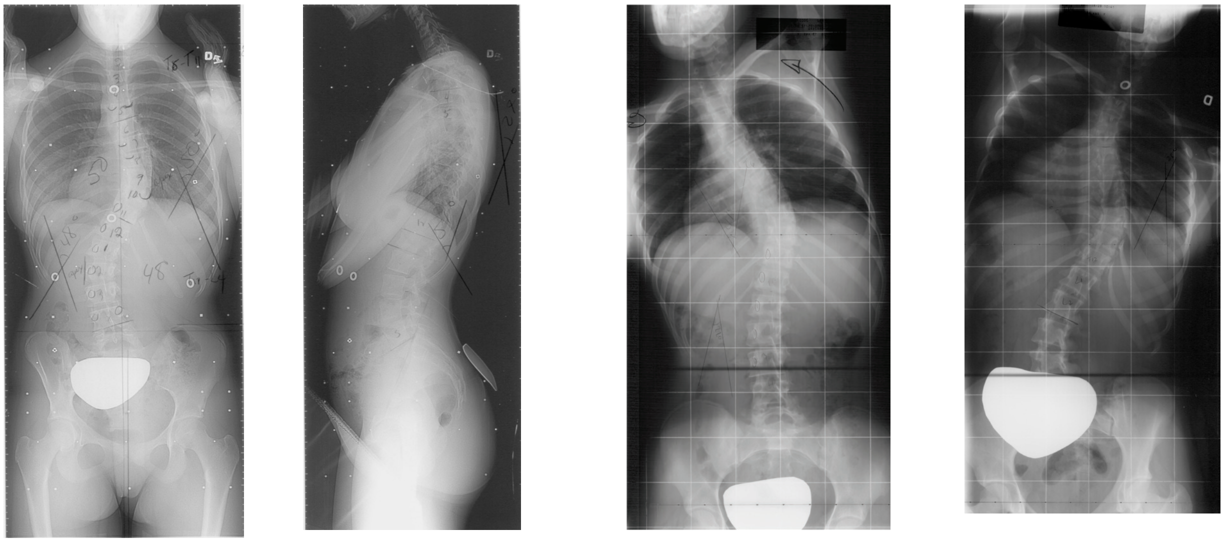


Figure 1: X-rays from left to right: postero-anterior, lateral, left side bending and right side bending.

John Cobb first described the Cobb angle in 1948 in order to measure the magnitude of scoliosis in the frontal plane. Cobb angle is measured between the endplates of the upper and lower end vertebra, which have the most significant tilt. This technique can also be used in the sagittal plane in order to measure kyphosis and lordosis. Cobb angle measurements can be seen in figure 1. Those same measurements can be repeated on the side bending x-rays and comparison of upright and side bending x-rays Cobb angle allow assessment of the flexibility of the spine. This is important when considering how rigid a curve is and whether or not it should be included in the region fused.

Balance assessment is critical and studies have highlighted the influence of balance on spinal deformity patients' quality of life in [1]. Sagittal spinal balance is measured on the lateral radiograph by drawing a vertical line from the center of the C7 vertebral body down to the sacrum. When the spine is unbalanced, the body is able to compensate by mobilisation of the pelvis and the hips. Nonetheless, a positive sagittal balance over 6 cm is correlated with a poor ODI (Oswestry Disability Index) in the adult population [1]. The balance is measured in relation to the postero-superior corner of the S1 vertebra. A positive value representing a plumb line anterior to the corner and a negative value represents a plumb-line posterior to it. Coronal plane balance can be measured by tracing a vertical line through the C7 vertebral body on PA x-rays. The relation of that line to the center of S1 or a line erected from the center of S1, the center sacral vertical line (CSVL, fig. 2), represents the amount of coronal-plane imbalance. Patients remaining within 2 centimeters of the CSVL are considered balanced.

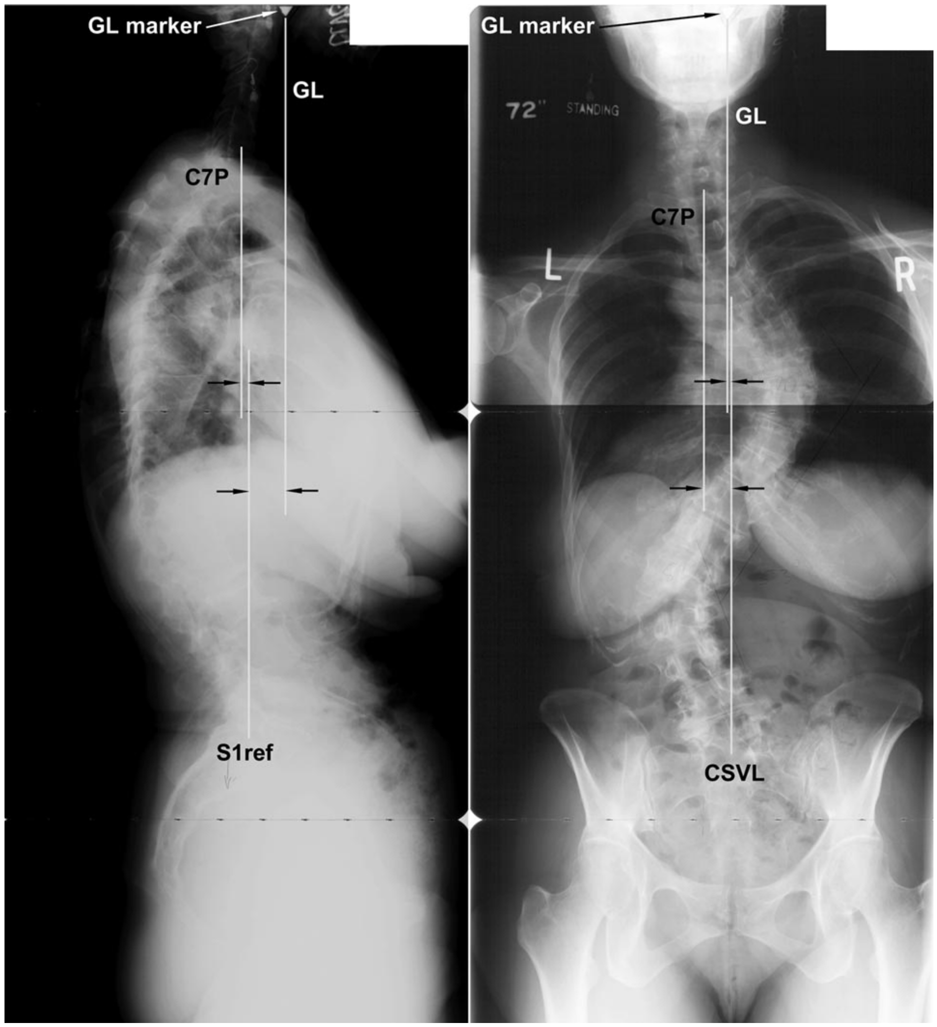


Figure 2 : Balance measurement in sagittal (left) and coronal (right) plane with C7 plumb line

When evaluating AIS, reference vertebrae are required in order to describe the spine and select the levels to be instrumented. Three reference vertebras are widely described and used in the spinal deformity literature. The end vertebra (EV), also commonly referred as the Cobb vertebra is the most tilted vertebra at the cephalad and caudal end of the curve. The neutral vertebra (NV) is the most cephalad vertebra below the apex of the major curve whose pedicles are symmetrically located within the radiographic silhouette of the vertebral body. To identify the stable vertebra (SV), the CSVL is first drawn. The most cephalad vertebra immediately below the end vertebra of the major curve which is the most closely bisected by the CSVL is the SV. Typically, those three reference vertebra are on different segments, but they might however overlap[34]. When studying reliability in identifying those reference vertebrae, Potter et al.[2] found good intraoberserver but poor interobserver agreement unless a one level leeway was given in which case agreement increased significantly.

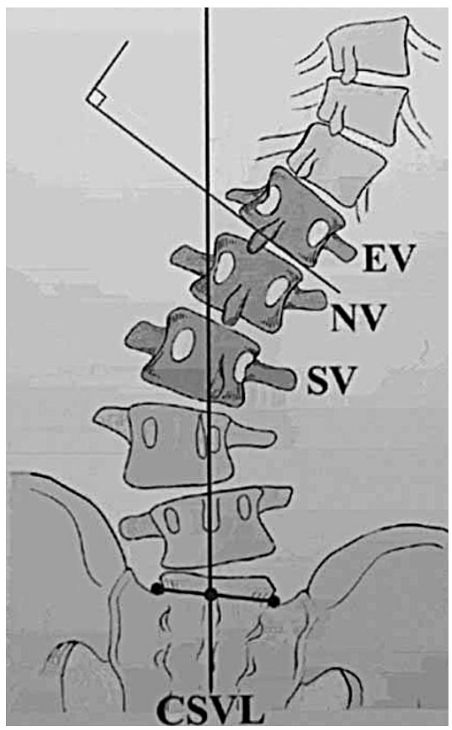


Figure 3: End (EV), Neutral (NV) and Stable Vertebrae (SV)

In order to assess shoulder asymmetry, T1 tilt angle, radiographic shoulder height (RSH) and clavicle angle can be measured.

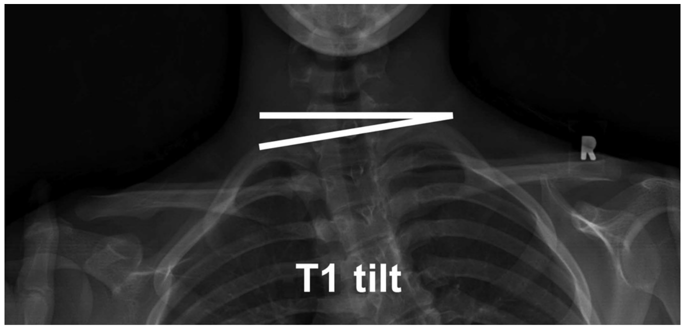


Figure 4 : T1 tilt angle

In order to measure T1 tilt, a first line is drawn along the cephalad endplate of T1 or along the zenith of both first ribs if the T1 endplate is not well visualized. A second line is drawn perpendicular to the vertical edge of the radiograph. T1 tilt is the angle formed by those two lines. When the left edge of the vertebral body is up, the tilt angle is defined as positive and as negative with the right edge is up.

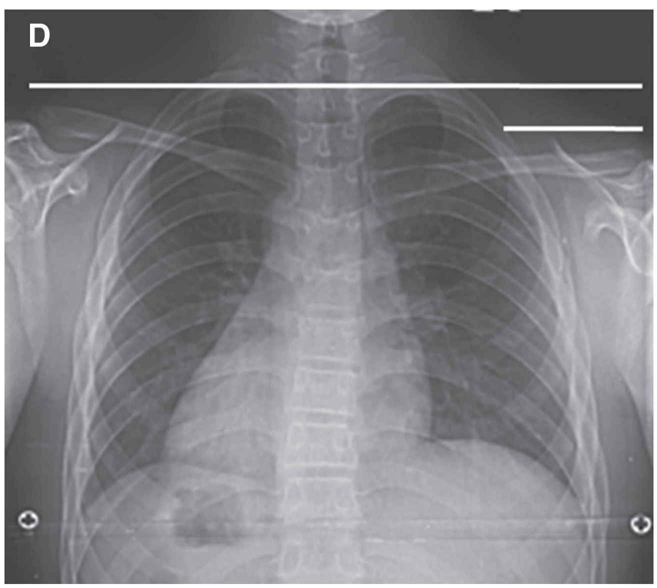


Figure 5: Radiographic shoulder height

Radiographic shoulder height is defined as the linear distance measured in millimeters between the superior horizontal reference line, which passes though the intersection of the soft tissue shadow of the shoulder and a line drown vertically up from the acromio clavicular joint of the cephalad shoulder, and the inferior horizontal reference line constructed in a similar fashion over the caudal acromio clavicular joint. The RSH is the distance between those two lines and is positive if the left shoulder up and negative when the right shoulder is up.

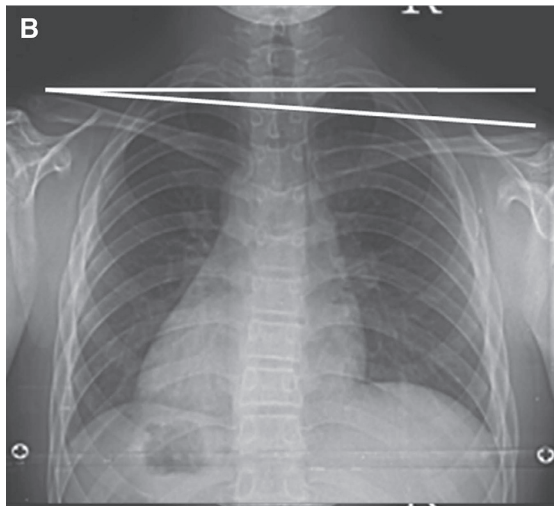


Figure 6: Clavicle angle

The clavicle angle is the angle between the horizontal line and a line which touches both the most cephalad aspect of both the right and left clavicles.

In order to assess vertebral rotation, Nash-Moe rotation/Apical Vertebral Rotation (AVR) is used[35]. This system evaluates the rotation of the vertebra based on the visibility of the pedicles on PA radiographs. When pedicles are symmetric, grade is 0 or neutral. When one of the pedicles is at the edge of the vertebral body, the grade is 1. Grade 2 and 3 correspond to disappearing and disappeared pedicles respectfully. The AVR is the Nash-Moe grade of the vertebra at the apex of a curve.

An additional measure of the curve magnitude is the apical vertebral translation (AVT). It represents the position of the apical vertebra compared to the C7PL for the PT and MT curves and the position of the apical vertebra compared to the CSVL for the TL/L curve.

1.3 AIS Classification

AIS presents with a great variety of spinal conformations, which are great challenges to classify. King [36] and Lenke [37] classifications for AIS are the two most widely used clinical classifications.

1.3.1 King Classification

King classification[36] for AIS has been the gold standard to guide orthopaedic surgeons in their evaluation of AIS. It describes 5 categories of thoracic curves based on the magnitude and flexibility of each of the curves and recommends levels of fusion for each of the curve types. Yet a major limitation of that classification, as stated by Lonstein [38], is that only 80 to 85% of all AIS curve types, are covered in Kings classification. Therefore since its introduction in 2001, The Lenke[37] classification system has been more widely used.

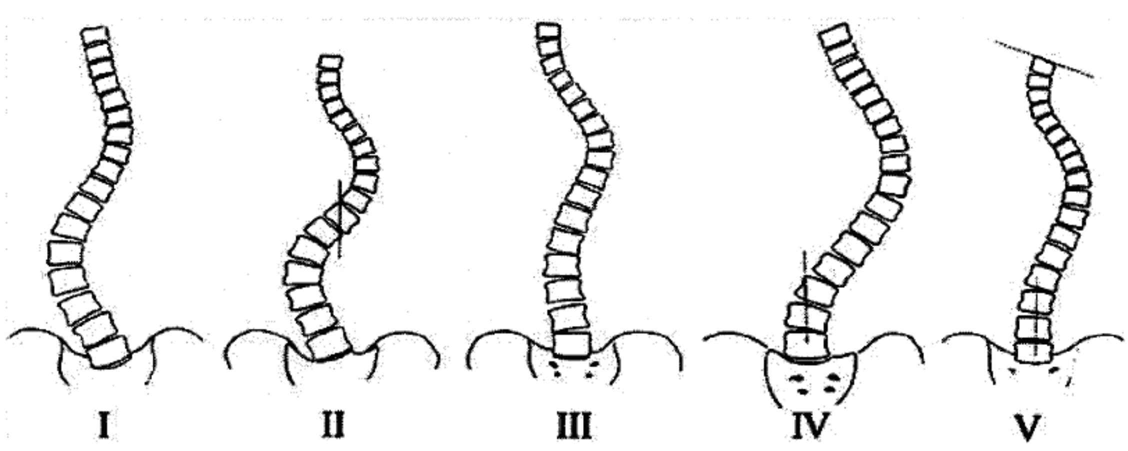


Figure 7: King classification for AIS

1.3.2 Lenke Classification

The Lenke classification system [37] (fig. 8) is widely used by surgeons because it guides surgical treatment according to curve characteristics. It divides the spine into three segments, proximal thoracic (PT), main thoracic (MT) and thoraco-lumbar /lumbar (TL/L) in the coronal plane, organized into 6 basic curve types depending on the structurality and dominance of each of these segments. In addition to curve types, lumbar spine and thoracic sagittal profile modifiers are also part of the Lenke Classification system. Based on this classification any structural curve (major or minor) should be included in the fusion, thoracic and lumbar modifiers could also influence the approach and the extent of the fusion.

Curve Type

Type	Proximal Thoracic	Main Thoracic	Thoracolumbar / Lumbar	Curve Type
1	Non-Structural	Structural (Major*)	Non-Structural	Main Thoracic (MT)
2	Structural	Structural (Major*)	Non-Structural	Double Thoracic (DT)
3	Non-Structural	Structural (Major*)	Structural	Double Major (DM)
4	Structural	Structural (Major*)	Structural	Triple Major (TM)
5	Non-Structural	Non-Structural	Structural (Major*)	Thoracolumbar / Lumbar (TL/L)
6	Non-Structural	Structural	Structural (Major*)	Thoracolumbar / Lumbar - Main Thoracic (TL/L - MT)

*Major = Largest Cobb Measurement, always structural
Minor = all other curves with structural criteria applied

STRUCTURAL CRITERIA
(Minor Curves)

Proximal Thoracic: - Side Bending Cobb ≥ 25°
- T2 - T5 Kyphosis ≥ +20°

Main Thoracic: - Side Bending Cobb ≥ 25°
- T10 - L2 Kyphosis ≥ +20°

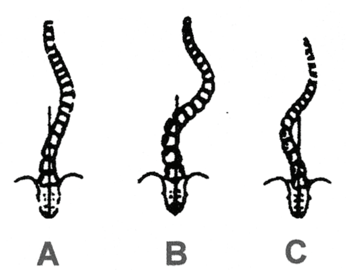
Thoracolumbar / Lumbar: - Side Bending Cobb ≥ 25°
- T10 - L2 Kyphosis ≥ +20°

LOCATION OF APEX
(SRS definition)

CURVE	APEX
THORACIC	T2 - T11-12 DISC
THORACOLUMBAR	T12 - L1
LUMBAR	L1-2 DISC - L4

Modifiers

Lumbar Spine Modifier	CSVL to Lumbar Apex
A	CSVL Between Pedicles
B	CSVL Touches Apical Body(ies)
C	CSVL Completely Medial



Thoracic Sagittal Profile T5 - T12	
- (Hypo)	< 10°
N (Normal)	10°- 40°
+ (Hyper)	> 40°

Curve Type (1-6) + Lumbar Spine Modifier (A, B, or C) + Thoracic Sagittal Modifier (-, N, or +)

Classification (e.g. 1B+):___________

Figure 8: Lenke classification for AIS

1.3.3 Classifications reliability

Most studies have shown good reliability for Lenke and King classification for AIS with pre-measured radiographs [39-43]. Other studies[38, 44] have nonetheless detected only poor to fair intra and inter-observer reliability with non-premeasured radiographs which is closer to the clinical situation. This difference of reliability between those studies can be due to the known variability of Cobb angle measurement, which is known to be between 3 and 11 degrees depending on sources cited [8, 45-49]. The limited reliability of AIS classifications and error in classification could lead to unnecessary fusion or missing necessary fusion. Therefore, computer methods to improve Cobb angles measurement [8, 50] and classification reliability have been described [5, 51, 52].

The introduction of picture imaging and archiving systems (PACS) in the healthcare system and the democratization of computer systems have led to the evaluation of Cobb angle measurements using digital imaging. While Shea et al. [8] compared manual and digital measurements of Cobb angle in AIS with an intra-observer measurement yielding a 95% CI of 3 degrees, the difference between the two methods was statistically significant and digital measurements were recommended in order to lower measurement errors. In addition, decision trees and rule-based algorithms implemented in computer software for the King [5, 52, 53] and Lenke [51] classification have shown to increase those classification reliability.

1.3.4 3D Classifications

Another limitation of the King and Lenke classification is their consideration of two-dimensional features extracted from postero-anterior (PA) and lateral (LAT) X-rays for a pathology that's truly three-dimensional. Several studies have looked into generating three-dimensional classifications from databases of AIS patients with three-dimensional reconstructions of their spines. Poncet et al. [54] introduced the concept of geometric torsion to classify AIS based on that 3D measurement. They extracted three distinct patterns of torsion, which can classify AIS based on compositions of those basic torsion patterns. Sangole et al. [17] performed an unsupervised clustering using 3D reconstructions from 172 patients with Lenke 1 curve type. Cobb angle, axial rotation of the apical vertebra, orientation of the plane of maximum curve of the thoracic curve and kyphosis (T4-T12) were used as indices. They extracted 3 primary sub-groups, one non-surgical and two surgical. Duong et al. [15] developed a 3D classification using an unsupervised learning algorithm, fuzzy K-means clustering, applied to 409 3D spine models. A five and a twelve classes classification with relevant clinical features (Cobb angle and plane of maximum curvature) and true 3D components were generated. While all those former studies showed the potential of unsupervised algorithms to generate three-dimensional classifications, they did not lead to a clinically useable classification. In an effort to develop such a 3D classification, Duong et. Al [16] studied several 3D clinical parameters (plane of maximum curvature (PMC), best fit plane (BFP) and geometric torsion) that could be integrated in the Lenke classification. Performing cluster analysis to evaluate the statistical distribution of those parameters, they showed specific 3D deformation patterns within Lenke 1 type curves using best-fit plane and geometric torsion patterns but not using the plane of maximum curve. They concluded that with the advances in computer vision and the introduction of 3D reconstructions such indices could be of much use in the development of future 3D classifications. Stokes et al. [55] performed cluster analysis of 245 AIS curves from 110 patients using Cobb angle, apex level, apex vertebra rotation and rotation of PMC as the input factors. 4 clusters were extracted but of 56 patients followed longitudinally only 25 were consistently grouped in the same cluster at all clinic visits. They concluded that based on those inputs factors, the clusters were susceptible to change with repeated observations and could not be used alone to determine treatment strategies.

While there is need for a true 3D classification of AIS, no study have yet proposed a clinically usable classification. Much of the current research has focused on 3D measurements that could be integrated or could be the basis of a 3D classification. Yet the measurements to be used are still debated. Most of the studies have relied on 3D reconstructions of AIS spines, which are not readily available in clinical settings and therefore cannot be used at this time. Implantation of additional 3D measurements to define AIS could lead us to a better understanding of that pathology, yet they need to be fully understood and accepted by clinicians before being usable in a classification. A classification, which is based on known measurements such as Cobb angles, which can overcome measurement variability, cut-off values between classes and which addresses the three-dimensional characteristics of AIS needs to be developed.

1.4 AIS treatment

1.4.1 Conservative treatment of AIS

Conservative management of AIS includes observation and bracing. Depending on the stage of skeletal maturity, management is adjusted based on the severity of the curve. In the skeletally immature patient, close follow up will be required for curves less than 25° while bracing should be considered for patients with curves between 25°- 45° degrees. If the curve greater than 40°, a surgical treatment should be considered[7].

Until a recent randomized control trial, much controversy remained about the benefits of bracing. The goal of bracing of moderate scoliosis is to limit further progression of the curve with the hope of avoiding surgery. Nonetheless this treatment can be quite demanding for the patient and her family. It requires continued maintenance for brace fitting to optimize curve correction and to maintain compliance. Weinstein et al.[56] published a prospective multi-centric randomized controlled and preference cohort for AIS patients in their peak velocity curve growth (Risser 0, 1 and 2) with moderate curves between 20 and 40 degrees. Based on sample size calculation, 342 patients were supposed to be enrolled in the study. After enrolment of 242 patients the study was stopped due to evident efficacy of bracing over observation. The study demonstrated that bracing significantly decreased the progression of high-risk curves to the threshold for surgery and that benefits from bracing increased with longer hours of brace wear.

Several challenges remain in the conservative management of AIS, much of which relate to the follow-up of small curves and prediction of their progression. In order to assist clinicians with those challenges, several applications have been developed.

When AIS is first detected with small curves, it can be monitored. Yet, there are no clear measurements or criteria to determine which individuals are at risk of progression and much research is undertaken in that area. A study from Villemure et al. [57] longitudinally followed 28 patients between 2 follow-up visits and analyzed how spinal curvatures and vertebral deformities changed during scoliosis progression. They challenged the existence of any typical scoliotic evolution pattern and suggested that scoliosis evolution might be quite variable and patient dependant.

In order to answer that question, Wu et al. [58] used an hybrid learning technique combination of fuzzy c-means clustering and artificial neural networks (ANN) to predict Cobb angles and lateral deviation. 72 data sets of 4 sequential values of Cobb angle and lateral deviations from 11 subjects were used. 10 progression patterns in Cobb angles and 8 progression patterns in lateral deviations where identified using a fuzzy c-means clustering algorithm. A trained ANN was able to predict Cobb angle within 4.40° (±1.86). Wu et Al. [59] also developed a similar application using Generalized Cross-Validation (GCV) extrapolation instead of ANN to predict Cobb angle. The GCV method was able to predict angle with a precision within 3.6° with a 95% confidence interval which is comparable to clinical measurements variability. Clinically, such prediction could be useful in the determination of the need for follow-up and its frequency. To evaluate the need for such follow-ups, Ajemba et al. [60] used sequential radiological measurements and included clinical parameters assessing developmental status such as Risser sign and chronological age to predict risk of progression. They used several models of Support Vector Classifier (SVC) to predict the risk of progression of AIS. 44 patients with moderate AIS were assigned to have progression of scoliosis if the Cobb angle between two visits had increased by more than 5°and to non-progression if the increase was lower than 5°.. The accuracy of assignment to one of those two categories by the SVC was estimated to be between 65% and 80%, which is better than former models based on statistical methods of regression. Those applications have tried to answer the enigma of curve progression in AIS, but their clinical usability has yet to be demonstrated.

In the mean time, follow-up is based on the judgment and experience of the surgeon and spinal deformity reassessed at each visit using new radiographic studies. Unfortunately, that method requires radiation exposure, which can increase the risk of cancer in a paediatric population [61]. Therefore applications [62-65], based on surface topography and artificial intelligence methods to assess AIS severity were developed. Jaremko et al. [63] used 360° torso surface models and ANN. They were able to predict Cobb angles within 6° of clinical Cobb angle. Such applications could be used for screening and follow-up purposes.

Applications have also been developed to optimize AIS bracing. Biomechanical models[66-69] and computer simulations[70-75] have been studied for their abilities to optimize bracing adjustment and to improve treatment effect. Labelle et al. [74] have randomly assigned 48 AIS patients treated with bracing to brace design using the conventional manner (control group) or using a computer assisted tool (test group) combining surface topography, surface pressure measurement and 3D reconstruction of the trunk. They found that better 3D correction of scoliotic curves was obtained in the test group.

In summery, many applications have been developed to optimize conservative treatment of AIS. ANN were were successfully used to recognize patterns in AIS patients. Yet clinical applicability has been limited and only few applications have proven to be beneficial and implementable. Similar applications based on artificial neural network need to be developed to guide and optimize surgical treatment.

1.4.2 AIS surgical treatment

When AIS curves have reached severe magnitude (>45°) and there is important curve progression surgical treatment is often necessary. Primary objectives of surgical treatment with instrumentation have traditionally been to arrest progression, achieve maximum permanent correction of the deformity in all three dimension, improve appearance by balancing the trunk and limit short and long-term complications [6]. Nonetheless, there is a large variability in scoliosis correction objectives. Madjouline et al. [11] have surveyed 25 spine surgeons from the Spinal Deformity Study Group (SDSG) and asked them to rank 20 parameters of scoliosis correction for each of the AIS Lenke curve types. They also asked them to provide weights for correction in the coronal, sagittal and transverse planes and for mobility according to their importance for 3D correction. They found large variability in scoliosis correction objectives that were both surgeon and curve type dependant. Only achievement of sagittal and coronal balance seemed to be constant objectives.

In order to attain those objectives, surgical treatment of AIS has evolved with the available instrumentation. Historically treated with Harrington instrumentation [76], posterior fusion of the spine is now achieved using modern third-generation instrumentation evolved from the Cotrel-Dubousset system in the 1980's. This modern instrumentation allows multiplanar (coronal, sagittal and transverse plane) correction, stable fixation, reduced levels of fusion and avoidance of post-operative immobilization in cast or brace [6]. Many surgical strategies are available and surgeons need to select surgical approach, extent of the fusion, derotation manoeuver and need for an osteotomy amongst other things. In fact, intra and inter-observer variability [12-14, 77] of preoperative planning for surgical correction has been documented. Robitaille et al. [77] presented pre-op x-rays of 5 AIS patients to 32 scoliosis surgeons which were asked to provide their preferred posterior instrumentation planning. Variability was noticed for the number and type of implants, the lower instrumented vertebrae (LIV), the upper-instrumented vertebrae (UIV), which varied up to 6 levels and the constructs attachment sequence. There are many reasons for such treatment discrepancies which include variation in surgeon training, expertise, and experience, variation in scoliosis correction objectives, and also unclear directives defined in the literature.

For posterior fusion of the spine, several implants are available. These implants include the use of pedicle screws, pedicle hooks, transverse hooks and wires permit fixation on posterior spinal element (pedicle, transverse processes and lamina). All those implants allow reduction of the spinal curve to the contoured rod. Suk et al. [78-80] [81] have pioneered the extended use of many segmental pedicle screws in the thoracic spine. Cuartas et al. [82]

described that the use of all-pedicle-screw construct could lead to better pull-out strength [83], improved correction [84], shorter fusion and lower morbidity based on biomechanical studies and case studies. Those studies showed better correction and maintenance of it when all-pedicle-screw constructs are compared to hooks/hybrid constructs [78, 80, 85, 86] or anterior approaches [87]. While several studies [80, 82, 85, 86, 88-93] have confirmed the superiority of pedicle screws over hooks or hybrid implants, the steep learning curve, increased cost, safety concerns and the difficulties related to its placement in dysplastic pedicles have limited its ubiquitous use. Furthermore, debates amongst spinal deformity surgeons remain about the better implants to use; in two updates on spine surgery published in the JBJS in 2006 and 2009, questions concerning hybrid constructs versus all-pedicle screws in the treatment of thoracic curves remained a disputed area [94, 95].

While posterior instrumentation of AIS is the mainstay of treatment, evolution of anterior instrumentation to dual-rod multiple vertebral screw systems, has permitted good rigid fixation, improved correction in the sagittal plane and minimized the need for postoperative protection [96-98]. Its applicability has been limited to single curve AIS in the thoracic or thoraco-lumbar/lumbar levels. The main advantages are improved sagittal plane correction, reduced number of levels fused and prevention of crankshafting in the immature patient [97, 99]. Disadvantages are related to the organs approached to access the spine, thoracotomy with unfavorable effect on the lungs, implant breakage, pseudoarthrosis and surgical scars. In order to lower surgical scars, thoracoscopic anterior approaches have been developed, but their very steep learning curves, the complications related to lesions to the nearby vital structures and the anaesthesia in one lung have limited their use to some specialized centers [100-103].

Selection of approach and levels to be fused remains the principal challenge in surgical treatment planning. The Lenke classification for AIS separates the spine in three curves; proximal thoracic, main thoracic and thoraco-lumbar/lumbar. Each curve is considered structural or not based on the criteria defined in Figure 8. According to the Lenke classification, a structural curve should be fused. Selective fusion consists of fusing structural curves only and allows non-structural curves to reduce thereafter. Structural curves that are not fused are at risk to progress if not included in the fusion. Fusion of non-structural curves would lead to unnecessary loss of motion [104]. The definition of curve structurality is only based on Cobb angles in Lenke classification and there are actually limited studies [104-111] about the behaviour of unfused curves on the long run to validate the principle of selective fusion and which exact criteria to use to ensure compensatory curve reduction.

To illustrate the complexity involved with decision of fusion extent, we will first discuss the case of proximal thoracic curves. Cil et al. [112] confirmed the validity of Cobb angle of the proximal thoracic curve, like it is used in Lenke classification, as a valid criterion for proximal curve inclusion in fusion. Yet Kuklo et al. [113] studied that clavicle angle and not T1 tilt nor Cobb angle provided the best prediction of post-operative outcome. For inclusion of lumbar spine in the fusion, Lenke classification evaluates spine flexibility using bending radiographs and determine the lower instrumented vertebra (LIV) based on the upright PA X-ray, yet Keith et al. [114] advocate the use of fulcrum bending to determine the LIV. Therefore criteria to select extent of fusion are still debated. Furthermore with the evolution of instrumentation and the use of all-pedicle constructs, those parameters might change and the fusion length shorten [86, 99]. Many other studies [14, 36, 37, 39, 40, 81, 104, 108, 115-121] have evaluated or recommended parameters to decide of levels of fusion, but no clear guidelines are available.

Complications related to lungs damage, implants, dural tears, hematologic disorders, neurologic lesions and infections can be caused by surgery. The choice of approaches has often been influenced by the fact that anterior approaches were thought to be more at risk because of vital organs surrounding the approach. Nonetheless, Coe et al. [122], in a report of 58197 cases for the SRS morbidity and mortality committee, found that they were no statistical difference in complications in anterior (5.2%) vs. posterior (5.1%) instrumentation fusion, but that there was a statistical difference when both approaches were combined (10.2%) and compared to a single approach. Long-term complications such as corrosion and late infection [122] or junctional kyphosis were also described [123, 124].

With the advent of all-pedicle screws, increase in implant cost compared to hybrid constructs has been discussed because its added benefit is debated [95]. Kim et al [86] described that average implant cost with screws with an average number of fixation points of 17.1 was $14.200 which is significantly higher than hooks constructs which average 11.8 point fixation for an average cost of $9228. Therefore, implant cost in cases where the added benefit of all pedicle screws are debated could be a factor to take into consideration in surgical strategies.

Given the many challenges presented above in the surgical planning of AIS, computer applications have been developed to assist clinicians. Using Fuzzy Logic, Nault et al[125-127] developed two models to decide on the need for thoracic and lumbar curve fusion. While the model showed good agreement with clinicians, the lack of justification for a given output in cases of total contradiction with clinicians highlights the limitations from using such systems based on approximate rather than precise reasoning. Another area of research is surgical simulation, given the biomechanical properties of the spine and the forces and stresses applied to correct scoliosis, fine element analysis [128, 129] and flexible multi-body approach models have been developed to simulate surgical manoeuvres with good agreement between simulation results and post-operative results from imaging measurements. Simulations were also able to highlight construct area of high stresses at risk of screw pull-out and to test multiple configurations therefore showing the possibility to guide and optimize surgical treatment.

1.5 Artificial intelligence (AI)

In computer science, AI is "the study of the modeling of human functions by computer programs". A major advantage of AI algorithms is that they can handle large amount of data that human could not. In the current work we are attempting to develop an application that will gather a large amount of knowledge from the literature on AIS surgical treatment and a large amount of data from a multicenter database of AIS patients to guide surgeons in their surgical strategy. The use of AI tools to process all those data in an intelligent way seems most appropriate as demonstrated by the many applications introduced above.

In this chapter we will concisely introduce three algorithms used in this thesis.

1.5.1 Rule-based systems

Rule-based systems are also called expert systems. They represent a very simple technique, which uses a knowledge base of simple rules. Three components are required to create a rule based system [130, 131]:

1- A database (or short-term-memory), it contains a set of facts that represents the initial working memory.

2- A knowledge base (or long-term-memory), which is a set of rules that should encompass any actions that should be taken within the scope of a problem.

3- A rule interpreter which control the problem solving process and determinates that one or many solutions have been found

Rule-based systems start with a knowledge base encoded into "if-then" rules. Knowledge can be tested on the database and the knowledge based can be altered if necessary (learning process). The rule interpreter decides about which and the order in which the rules are activated. When the set of rules is simple, the rule interpreter can be represented as a simple rule-based algorithm as it has successfully done for AIS classification in the past[5].

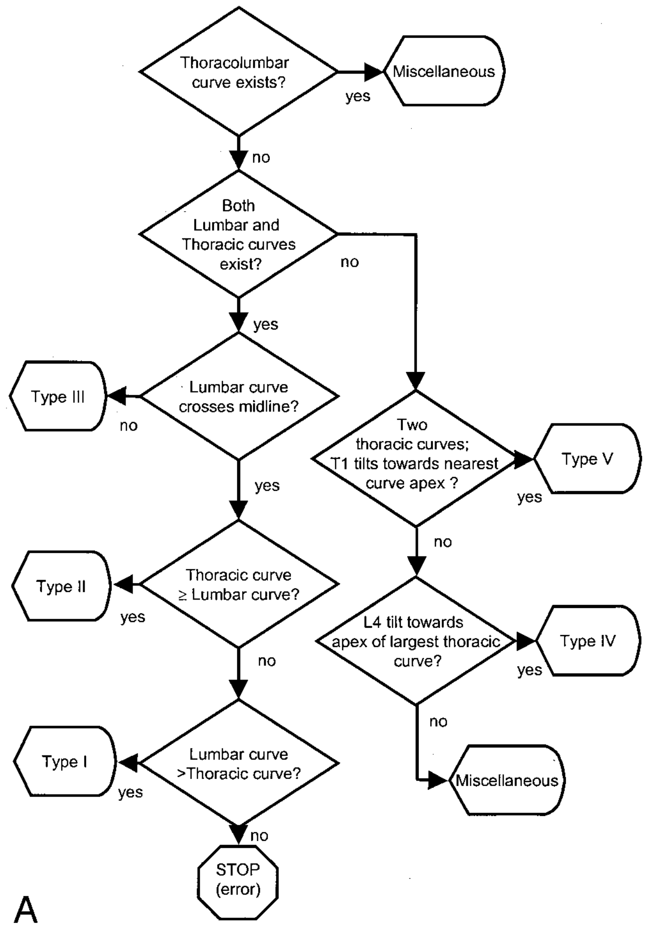


Figure 9 : Flowchart of a rule-based algorithm to classify AIS patients according to King's classification from a postero-anterior radiograph.

1.5.2 Decision trees

A decision tree is a predictive model which can be used to represent a classifier model in which case it is also often called a classification tree[132]. Decision trees classify instances by sorting them down the tree from the root node to some leaf node. At each node, the tree tests some attributes of the instance. Between each node lies a branch corresponding to one of the possible values for this attribute or a condition leading from one node down to the other. The final nodes at the end of the tree represent one of the possible classes.

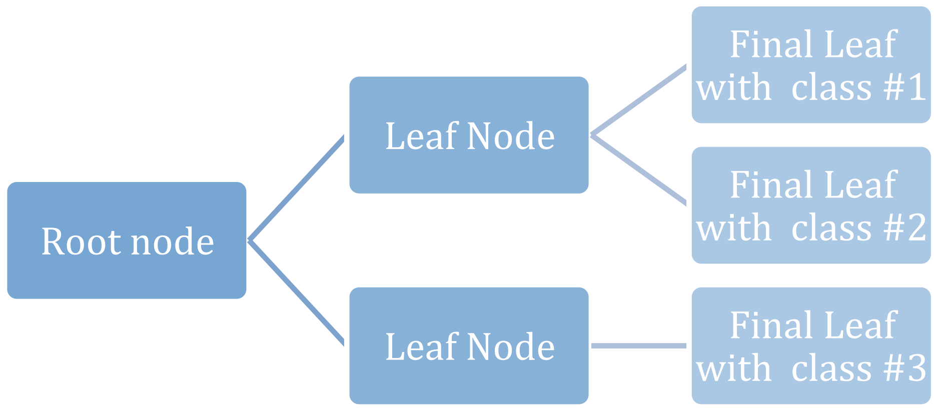


Figure 10: Basic representation of a classifier tree.

The classifier tree described above represents the most basic decision tree and will be used in this project in order to classify AIS according to the Lenke Scheme. As we can see in Figure.11, The root node evaluates the major curve, the first branch leads to the first leaf node based on which curve is structural and subsequent branching depends on Cobb angle measurements.

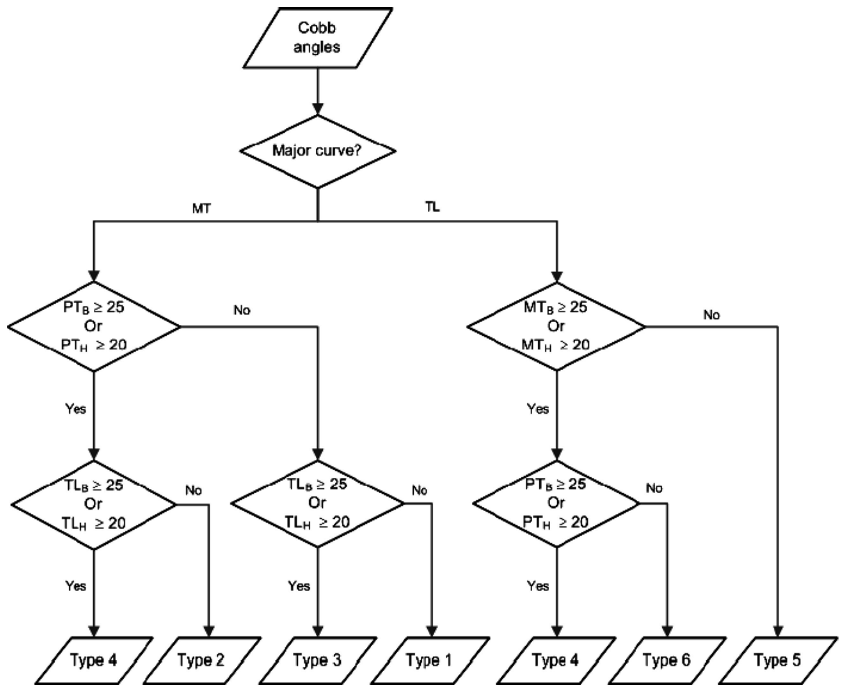


Figure 11: Classifier tree for Lenke classification for AIS

Decision trees can be much more complex when branches contain weighs and are able to learn based on a dataset. Optimization of classification is then obtained by adjusting those weighs to obtain proper classification at the final leaf. Those learning decision trees will not be used in this thesis.

1.5.3 Neural Networks

A neural network is an interconnected assembly of simple processing elements, called units or nodes, whose functionality is loosely based on animal neuron. The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns[133].

The Kohonen neural network [134], also called the Kohonen associative memory and self-organizing-map (SOM), has been the focus of an impressive number of studies in a variety of fields such as optimization, pattern recognition, image processing, and robotics. The bibliography of Oja et al.[135] for instance, gives an addendum of 2,096 references to a previous compilation of 5,384 scientific papers where the Kohonen network is used.

The Kohonen neural network implements a clustering algorithm similar to K-means [136, 137]. It is also a vector quantizer because it represents a given large collection of data patterns by a small set of representative patterns of the same dimension [138]. In coding theory these representative elements are often called “code words” and form “the code book”. The nodes in a Kohonen network are organized in a one- or two-dimensional array as shown in figure 12 . The network can be viewed as an associative memory that encodes input patterns in the form of weight vectors stored at its nodes. The weight vectors are of the same dimension and nature as the input patterns. A characteristic of the Kohonen associative memory is its self-organizing topological ordering: neighbouring nodes encode neighbouring weight values, creating a spatial ordering among nodes.

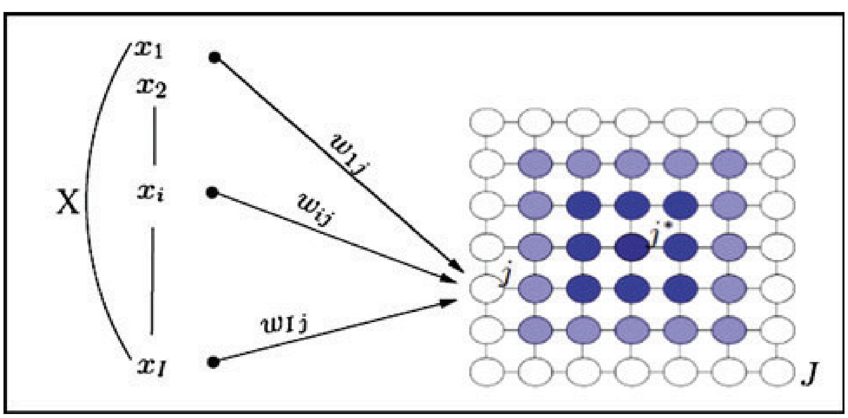


Figure 12: A two-dimensional Kohonen memory of J nodes. X =(x_1,x_2,….,x_I) is an input data vector of dimension I and W_j = (w_{1j}, …, w_{Ij}), the output of the training, are the weight vectors

stored at nodes j = 1, …, J. j^* , the winner node, contains the weight vector closest to the current input X.

The Kohonen SOM training algorithm is as follow:

Let X =(x1, x2, . . . , xI) be an input data vector of dimension I . The Kohonen training algorithm is based on competitive learning [137]. The weight vectors $W_j = (w_{1j},...,w_{Ij})$ stored at nodes $j = 1,..., J$ are the output of the training. The nodes are organized in a two-dimensional $[N_l \times N_c]$ matrix. After the weights are initialized to small random values, the training process iterates two steps until convergence, one to find the node, j^*, that contains the weight vector closest to the current input X , and the other to update the weight vectors at each node j of the memory according to:

Eq. 1 $$w_{ij}(n+1) = w_{ij}(n) + \epsilon(n)h(n)^{j,j^*}(x_i(n) - w_{ij}(n))$$

where n is the iteration number and,

Eq. 2 $$h^{j,j^*}(n) = \exp - \frac{||j - j^*||^2}{2\sigma(n)^2}$$

Eq. 3 $$\epsilon(n) = \epsilon_1 \left(\frac{\epsilon_2}{\epsilon_1}\right)^{\frac{n}{n_{\max}}} , \quad \sigma(n) = \sigma_1 \left(\frac{\sigma_2}{\sigma_1}\right)^{\frac{n}{n_{\max}}}$$

We used the Euclidian distance to measure weight vectors proximity.

Eq. 4 $$d(X, W_j)^2 = \sum_{i=1}^{I}(x_i - w_{ij})^2$$

Function h^{j,j^*}, called the *neighborhood function*, acts as a smoothing kernel and defines the influence of node j^* on node j during update at j. It decreases with increasing grid distance between nodes j^* and j. It depends on a parameter $\sigma(n)$ which decreases with the number of iterations between values σ_1 (initial value) and σ_2 (final value) (Eq. 3). The $\varepsilon(n)$ parameter modulates the update amount of the weights; it varies with the number of iterations from ε_1 (initial value) to ε_2 (final value) (Eq. 3). σ_1, σ_2 and ε_1, ε_2 affect both the initial conditions and the duration of the update iterations. Therefore, they affect the algorithm convergence and topological ordering. They must be chosen appropriately, and this is done empirically.

Once the training is performed, the map nodes are labeled using the training data. The training data are projected on the Kohonen map and a node is labeled according to the most frequently projected class, a procedure known as majority voting [139].

Once the classification and the map are generated it is important to evaluate their quality. A useful indicator is the topographic error, which measures the proportion of all data vectors for which the first and second best-matching units (BMU) are not adjacent vectors [140], i.e, the proportion of all data vectors for which the first and second nearest neighbor nodes are not adjacent nodes in the Kohonen map. The topographic error is calculated according to the following equation:

Eq. 5 $$T\_\text{error} = \frac{1}{N}\sum_{i=1}^{N} u(X_i)$$

Where the function $u(X_i)$ is equal to 1 if X_i data vector's first and second BMU are adjacent, and 0 otherwise.

1.6 Multicentric database

1.6.1 The Spinal Deformity Study Group (SDSG) database

The spinal deformity study group was a group of spinal deformity surgeons (32 of which participated in the database used in the current project) who conducted prospective studies on various spinal deformities amongst which AIS. Those surgeons came from across the world with a majority from North America and contributed cases into the SDSG database. The database contains cases from 30 hospitals worldwide with 63 surgeons contributing cases between 2002 and 2008. That database offered the unique property to gather the expertise of surgeons with different approach in an area with known variability and consistent data from patients that were recruited prospectively. The large amount of cases and the quality of the data gathered offered a unique opportunity to study AIS using this database.

1.6.2 Data available

The data collected included pre-operative, immediate post-op, follow-up radiographic and clinical data. Surgical technique details were also collected and included approach, instrumentation used, levels of fusion, osteotomy, releases, estimated blood loss and duration of surgery. Collection of data was done through a web interface while the x-rays were uploaded into an image repertory system. All spinal deformity radiographic measurements were done using validated software by a third party company, PhDx[50]. The radiographic measurements collected and used in the work of this thesis are presented in the radiographic evaluation of AIS above and summarized in the following table 1.

Lenke curve type with lumbar and thoracic modifier
Coronal (CB) and sagittal balance (SB) pre-op, post-op, first and at one year follow-up
Cobb angle for Proximal Thoracic (PT), Main Thoracic (MT), and Thoraco-Lumbar (TL) pre-op, post-op, first and at one year follow-up
Upper and Lower instrumented vertebra on post-op x-rays
Radiographic shoulder height, T1 tilt and clavicle angle on pre-op, post-op, first and at one year follow-up
Nash-Moe rotation index, AVT and AVR for the MT and TL curves pre-op, post-op, first and at one year follow-up

Table 1: List of data extracted from the SDSG database used in this project.

1.6.3 Cases extracted from the database

Participation of those centres and many surgeons to contribute in this database has allowed the collection of over 2500 AIS cases. In the studies presented in this thesis, that database was thoroughly screened for data missing for our experiments. We have therefore used 1776 AIS cases from that database that had complete radiological data and post-operative levels of fusion and approach in order to create the classification using kohonen Self-Organizing-Maps (Chapter 6). For testing of the surgical strategy rule-based algorithm (chapter 5) and the software (chapter 7) further post-operative data were required and 1556 AIS cases were extracted from the database in order to complete the statistical analysis desired.

1.6.4 Limitations

All the work in this thesis was made from numerical data, which were measurement made by PhDx as opposed to using the radiographic imaging to which we did not have access with the exception of patients from our institution. Nonetheless, none of our experiments required direct access to the radiographs and the dataset available was sufficient.

Experiments in this thesis were started with a database at the beginning of its prospective recruitment phase in 2006. Unfortunately, due to discontinuation of funding, the study group was brought to a stop in 2010 and updated data were not available thereafter. While the software programming was started with longer follow up in mind for statistical analysis, much of our data is only available until the first year follow-up.

Chapter 2. Problematic, objectives and hypothesis

2.1 Problematic:

Adolescent Idiopathic Scoliosis (AIS) is a complex three-dimensional deformation of the spine and rib cage for which much research is undertaken to understand its etiology, natural history and to optimize its treatment whether conservative or surgical. Software have been used to better evaluate it with improved imaging modalities using three-dimensional reconstructions of x-rays[141-146], to better follow and predict its progression [60, 62, 65, 147, 148] and to optimize its treatment[149-152]. In medicine, large multi-centric database of patients are being created and have permitted retrospective and prospective studies to assess and compare treatments and their outcomes. Some software have used such databases to optimize medical treatment based on patients specific characteristics. Adjuvant! [153] is a successful example of an application that helps oncologists and cancer patients decide on the added value of adjuvant and chemotherapeutic treatments based on prognosis of former similar patients. It uses databases from published RCT's to predict a patients' prognosis. Such software are particularly relevant for pathologies requiring multiple parameters to be taken into account and for which large amount of data that only computers can process are being used. AIS evaluation is complex due to the uniqueness of each patient and the several parameters to take into account for their management (e.g: age, stage of development, geometry and advancement of the spinal deformity, perception of the appearance, pain). This has led to a documented variability in its surgical treatment [12, 13, 77]. As stated by Lenke et al [14], "best surgical treatment" for each AIS patient will require " a classification and grading system of AIS that allows similar curves to be grouped together to critically and objectively evaluate the variable treatments used for each particular curve patterns". Software with artificial intelligence algorithms have been written to predict AIS progression, to assess its geometry and to better classify it in three-dimensions. Yet, no integrated software has been developed to guide AIS treatment based on large multi-centric databases using artificial intelligence algorithms to group similar curve together and compare the various treatment options.

The object of this thesis is based on the following observations:

1- The known variability in surgical treatment of AIS patients leading to likely varying outcomes and the necessity to guide surgeons in their surgical planning.
2- The lack of guidelines for AIS treatment due to the complex nature of the pathology and the challenges involved with its classification.
3- The emergence of software based on Artificial Intelligence algorithms such as Neural Networks having shown the ability to compute large amounts of data to recognize AIS progression patterns and classify AIS .
4- The collaboration of multiple-centers has permitted the unique access to a large multi-centric database with detailed pre and post-operative AIS cases information (x-ray, radiographic measurements, outcome measurements).
5- The possibility to integrate advanced algorithms in a software which could be used in the clinical environment to guide surgical management.

2.2 Primary objective:

The primary objective of this thesis is to develop artificial intelligence tools and integrate them in a software platform to guide the surgical treatment of AIS patients.

Given the lack of clear guidelines for the treatment of AIS, a treatment algorithm based on available evidence in the literature for surgical treatment will output surgical strategy alternatives. Given the accessibility to a large AIS surgical database (SDSG AIS database), those treatment alternatives will be compared by using an AI algorithm to extract similar patients and perform treatment comparisons based on outcome measurements.

Properly implemented in a software platform, those tools could guide surgeons in selecting their surgical strategy based on comparison of formerly treated patients with similar characteristics.

2.3 Hypothesis:

The main hypotheses for the current thesis are the following:

Hypothesis 1 (H1): AI tools can improve evaluation and treatment by clinicians caring for AIS patients, but there are limitations leading to their non-integration in the clinical setting.

Hypothesis 2 (H2): Simple algorithms such as decision trees and rule-based algorithms can assist clinicians in the classification and the surgical management of AIS.

Hypothesis 3 (H3): Based on a large multi-centric database, extraction of similar AIS cases and evaluation of treatment patterns can be done using neural networks algorithms.

Hypothesis 4 (H4): AI tools can be integrated in a comprehensive software platform to output surgical strategy alternatives for a given case and allow the comparison of similar cases extracted from large databases. It could allow optimization of surgical treatment.

2.4 Objectives:

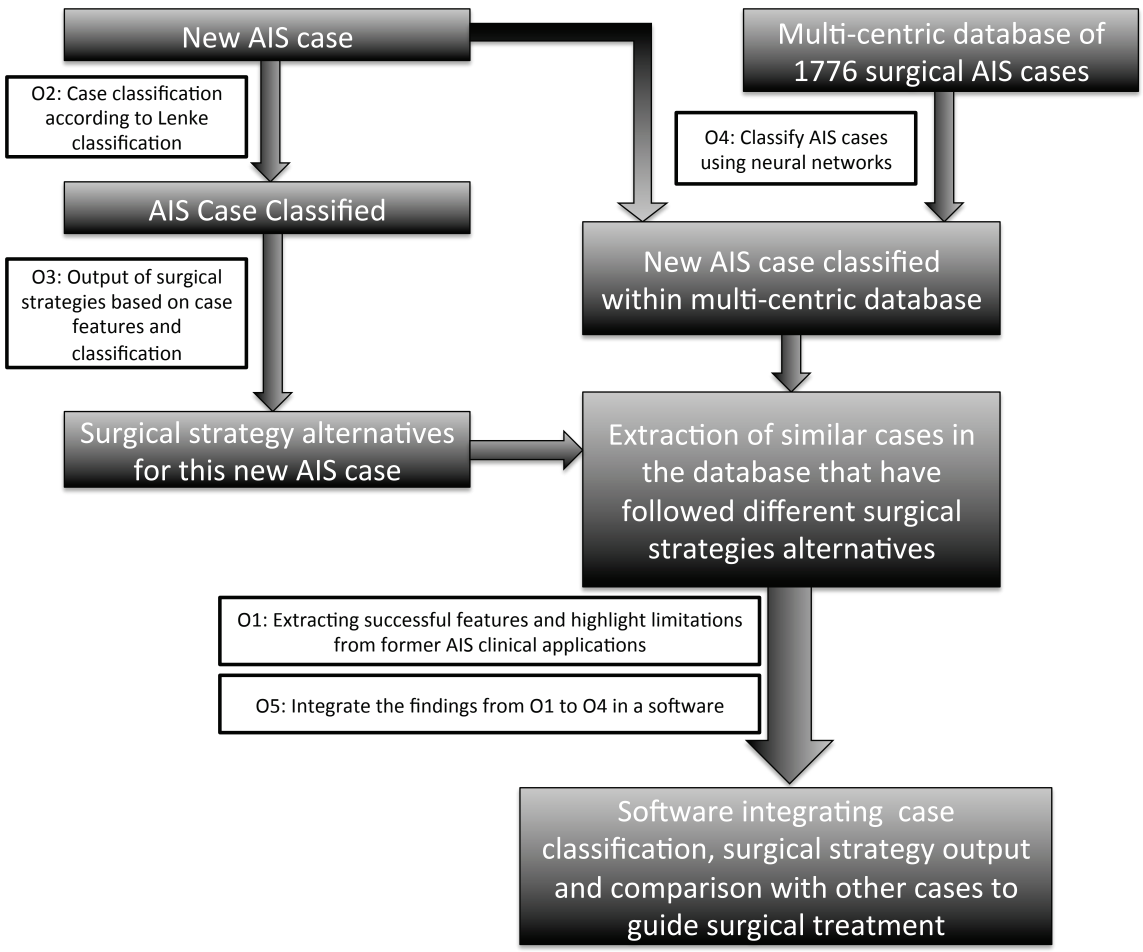


Figure 13: Summary diagram of objectives of this thesis.

The following paragraphs will describe the first 4 objectives, which will verify the first 3 hypotheses in work published or submitted for publication. The last objective will verify our last hypothesis and will be presented under the form of a chapter.

Objective 1 (O1): To review the literature for existing computer applications based on AI algorithms to improve AIS evaluation and treatment. To extract features that will lead to a successful clinical application while avoiding limitations of former applications.

With the development of computing technology in the last 20 years, transition of those technologies to the clinical setting is an area in which much research is undertaken. Yet daily use of technological tools in the clinical assessment and treatment of AIS patients is limited. This objective is to review the recent technologies developed to assist AIS management. Particularly, it will be important to highlight the reasons those applications fail to be incorporated into the clinical environment and which features lead to successful applications. Findings from this objective will be used in the approach and the development of our software platform and verify hypothesis 1.

Objective 2 (O2): To develop a classification decision tree (CDT) to classify AIS according to Lenke classification and test its accuracy when used by clinicians.

Decision trees are basic AI algorithmic structure. Often used in computer programming to represent multiple pathways for a given input, they can have a graphic representation that's easy to follow and understand. Simple tools such as checklists have proven to improve clinical safety and outcomes[154]. We will investigate how a CDT for Lenke classification can improve its reliability, which has been repeatedly questioned.

This CDT will verify the first part of hypothesis 2, which stipulates that decision trees could assist clinicians in classifying AIS. Several clinicians with various degree of experience will be asked to classify AIS cases with and without the decision tree. Statistical analysis using paired Wilcoxon ranking tests to evaluate differences in classification accuracy and speed with and without the CDT will be calculated with an alpha value set at 0.05 for statistical significance.

Objective 3 (O3): To develop a surgical strategy rule-based algorithm (SSRBA) based on the literature to output alternate strategies for approach and levels of fusion in the surgical treatment of AIS and evaluate its ability to match surgical strategies used by surgeons on patients from a large multi-centric database.

A systematic review of the literature and rule extraction from peer-reviewed articles will be undertaken. A SSRBA will be designed to display alternatives in the selection of approach and levels of fusion for the surgical treatment of AIS. Weight assignment for the rules extracted from the literature will be based on the level of evidence in the literature and by recursive testing against cases present in a large database. This objective will verify the second part of hypothesis 2, which stipulates that SSRBA, could assist clinicians in the surgical management of AIS. In this case, we wish to verify that the rule-based algorithms can output valid surgical treatment alternatives. All surgical cases from the database will be run through the SSRBA. Descriptive statistics will be used to evaluate the proportion of cases for which surgery undertaken by the surgeon corresponded to a strategy output from the SSRBA. Given the high variability in the selection of spinal instrumentation for AIS[12] and the lack of gold standard it is difficult to put a statistical goal. To verify this objective, we want to see whether the SSRBA can output strategies that can correspond to an expert deformity surgeon opinion for a given AIS. All outputs from the SSDT will follow rules published in the literature. According to Clement et al.[155], there is deviation from the Lenke classification recommendation up to 30% of the time when evaluating structural curve left unfused and non-structural curve fused in a study group influenced by that classification. Having a strategy output match with the surgical management from the database in 70% of cases with respect to approach and level of fusion with a one level leeway will be considered to verify our hypothesis.

Objective 4 (O4): To classify AIS using neural networks and to analyse surgeon treatment pattern based on that classification.

Multiple classifications for AIS have been developed using neural networks. Yet no classification use the most common radiographic measurements gathered for Lenke classification, which is the standard classification used clinically nowadays for AIS. Using a multicentric database of AIS cases treated surgically, we will compare the classification outputted by the neural network with the Lenke classification. The main advantage of neural networks and particularly Kohonen Self-Organizing Maps (SOM) is that classification is based on gradients of values rather than strict cut-off values, as it is the case in the Lenke classification. SOM can be graphically represented on a two-dimensional matrix, which allows the superposition of treatment on the classification map and analyse treatment patterns. This objective will verify hypothesis 3, which stipulates that based on a large multi-centric database, extraction of similar AIS cases and evaluation of treatment patterns can be done using neural networks algorithms. To verify the quality of the map and classification, topographic error will be calculated. To analyse surgeon treatment pattern, kappa analysis for agreement between fusion realized and fusion recommended by Lenke classification at each node on the SOM will be calculated.

Objective 5 (O5): To integrate the AI tools developed in O2 through O4 in a software platform while taking lessons learned form former applications in consideration (findings from O1). To test the platform by comparing radiographic outcome from patients in the multi-centric database. This objective will attempt to verify hypothesis 4.

Using a Matlab graphic user interface (GUI), software will include the following components:

- GUI with definition of software interface for parameters input, output components, database query fields, patient information display.
- Classification according to the Lenke classification. The CDT developed in objective 2 will be integrated taking input details about the new case.
- Output of surgical strategies by the SSRBA. Surgical strategies will include: surgical approach, levels of fusion (with UIV and LIV) and level of evidence for strategy output using a scoring system for approach alternatives
- Extraction of neighbouring cases from the database based on the SOM
- Comparison of various surgical strategies applied on neighbours in the SOM.
- Statistical analysis of outcome measurements including: balance, curve correction, SRS-30 post-operatively. Mann-Whitney-U and chi-square with statistical significance set to alpha = 0.05 is adjusted with Bonferonni correction to alpha = 0.005 since we test multiple variables each time.

In order to test the efficacy of the software to output proper surgical strategies, statistical analysis comparing the outcome from surgeries following the strategy most recommended by the software and the outcome from surgeries that did not will be undertaken. The outcome measured will be the magnitude of the curves, the correction achieved for each of the curves and the patient balance.

2.5 Chapter and articles presentation:

Chapter 3 will include a review article of the literature with a critical appraisal of the recent literature on computer algorithms and applications developed for the evaluation and treatment of AIS. Conclusion from this paper will guide the development of the software in order to avoid limitations encountered by former applications and emphasize successful features. This will cover our first objectives and hypothesis.

Chapter 4 will include an article presenting the CDT developed to classify AIS according to Lenke classification. It will cover our second objective (O2) and verify a first part of our second hypothesis (H2) in confirming whether decision trees, can effectively classify AIS; in particular, it will evaluate the value in using CDT for AIS with respect to classification accuracy and speed.

Chapter 5 will include an article presenting the SSRBA developed to output surgical strategies using rules extracted from a systematic review of the literature. This will cover our 3rd objective and verify the second part of our 2nd hypothesis, investigating how SSRBA can assist clinicians in the surgical management of AIS.

Chapter 6 will include two articles presenting the use of a SOM in order to classify AIS and its ability to highlight treatment patterns. The first article is a technical paper providing in depth explanation of the algorithm used and the classification validation. The second paper focuses on the clinical application of this classification and its ability to evaluate treatment patterns. A description with cases studies will demonstrate the utility of this tool in the clinical setting. That second paper was published in a shortened version as requested by the journal editor. The full paper is therefore integrated in this chapter followed by the shortened published version. Those articles will cover our fourth objective and verify our third hypothesis

Chapter 7 will present the software developed and integrating the knowledge extracted from objective 1 through 4 to achieve the fifth objective. It will also integrate a statistical analysis of radiographic outcomes in order to verify our 4th hypothesis and the ability of such software to guide and optimize surgical treatment.

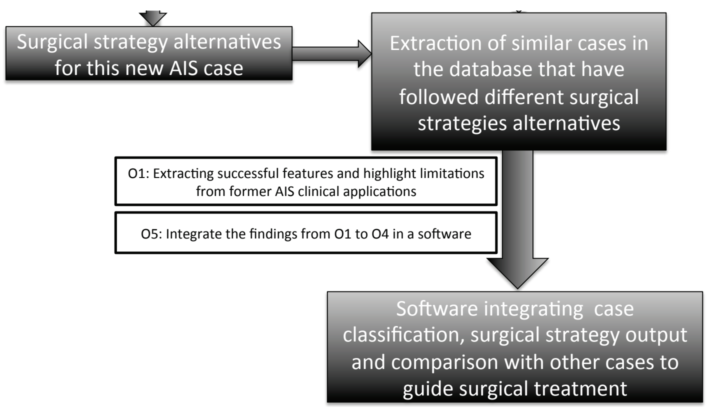
Chapter 3. Critical appraisal of recent literature on computer algorithms and applications used in the evaluation and treatment of AIS

This chapter includes the first paper of this thesis published in the European Spine Journal.

Phan P, Mezghani N, Aubin C-E, de Guise JA, Labelle H.

Computer algorithms and applications used to assist the evaluation and treatment of adolescent idiopathic scoliosis: a review of published articles 2000-2009. Eur Spine J. 2011 Jan 30.

This article presents a critical appraisal of recent applications developed to assist AIS assessment and treatment and answers objective 1.



Authors' contribution:

Phan P: Literature review and selection of articles retained for inclusion, manuscript writing and submission

Mezghani N: Correction of article and input on engineering aspect of article

Aubin C-E: Input on methodology, manuscript editing.

de Guise JA: Revision of article, project funding.

Labelle H: Revision of article, project funding.

Eur Spine J
DOI 10.1007/s00586-011-1699-4

REVIEW ARTICLE

Computer algorithms and applications used to assist the evaluation and treatment of adolescent idiopathic scoliosis: a review of published articles 2000–2009

Philippe Phan · Neila Mezghani · Carl-Éric Aubin · Jacques A. de Guise · Hubert Labelle

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Abstract Adolescent idiopathic scoliosis (AIS) is a complex spinal deformity whose assessment and treatment present many challenges. Computer applications have been developed to assist clinicians. A literature review on computer applications used in AIS evaluation and treatment has been undertaken. The algorithms used, their accuracy and clinical usability were analyzed. Computer applications have been used to create new classifications for AIS based on 2D and 3D features, assess scoliosis severity or risk of progression and assist bracing and surgical treatment. It was found that classification accuracy could be improved using computer algorithms that AIS patient follow-up and screening could be done using surface topography thereby limiting radiation and that bracing and surgical treatment could be optimized using simulations. Yet few computer applications are routinely used in clinics. With the development of 3D imaging and databases, huge amounts of clinical and geometrical data need to be taken into consideration when researching and managing AIS. Computer applications based on advanced algorithms will be able to handle tasks that could otherwise not be done which can possibly improve AIS patients' management. Clinically oriented applications and evidence that they can improve current care will be required for their integration in the clinical setting.

[redacted]

Keywords Adolescent idiopathic scoliosis · Algorithms · Classification · Progression prediction · Surgical treatment planning

Introduction

Adolescent idiopathic scoliosis (AIS) is a complex three-dimensional (3D) deformation of the spine. Screening, diagnosis and follow-up of AIS are challenging because the evolution of scoliotic spines does not follow determined patterns [1–4]. The patients require regular evaluation by physicians and imaging to detect any curve progression which has been defined as an increase in Cobb angle >10° between two clinical visits [5]. Yet Cobb angle reliability was shown to be limited. Its inter-observer and intra-observer variability has been estimated to vary up to 9° and 5°, respectively [6–8]. King et al. [9] and Lenke et al. [10] classifications for AIS are the two most widely used classifications but some studies have demonstrated only poor to fair intra- and inter-observer reliability [11, 12]. This lack of reliability in the assessment of AIS may lead to variability in its treatment. In fact, large intra- and inter-observer variability of instrumentation strategy in AIS was documented [13, 14]. With the wide availability of computers used in the clinical setting, researchers are developing applications to improve AIS assessment and treatment. Our working hypothesis is that algorithms and computer applications can improve AIS care by solving AIS enigmas such as variability in evaluation and treatment; unknown progression pattern and classification. The objectives of this review paper are to summarize the applications developed to improve AIS care, evaluate their clinical usability and suggest necessary developments to increase their clinical integration.

Materials and methods

Searching strategy

A literature search of articles published between January 2000 and July 2009 was performed in three major electronic databases Medline, Google Scholar, and Ovid using combinations of the following keywords: "adolescent idiopathic scoliosis" alternatively with "algorithms" or "computer" or "artificial intelligence". All returned abstracts were evaluated.

Inclusion and exclusion criteria

Applications based on algorithms using AIS data and which can have a potential impact on clinical practice have been included in this review. Therefore, articles discussing imaging modalities and reconstruction techniques were not included in this review. All selected articles were thoroughly analyzed in their full content to evaluate the AIS problems solved by the algorithm, the clinical applicability of the applications developed and the elements lacking for their integration into the clinical setting.

Searching results

One hundred and eighty abstracts were retrieved using the selected keywords and screened for computer applications using algorithms aiming at improving AIS assessment and treatment. The main author (PP) analyzed the full content of 73 articles returned by the query in which the abstracts seemed to correspond to this review article interest. Based on the inclusion and exclusion criteria, 47 papers were retained for presentation in this article; 9 studies on applications evaluating scoliosis severity and progression, 12 studies on classification, 7 studies on bracing treatment, and 19 studies on surgical treatment were selected for presentation and discussion in this paper. Summary tables were generated to facilitate the understanding of the methodology and output.

AIS screening and follow-up

Applications have been developed to screen for AIS by automatically detecting its presence and severity on chest X-rays or surface topography. Other applications aim at improving AIS follow-up by limiting patient exposure to irradiation or detecting changes in scoliosis severity with surface topography. Other applications predict changes in AIS severity with artificial intelligence algorithms. All application algorithms and study methodologies are presented in Table 1.

AIS screening method

Tang et al. [15] proposed a computer system to detect scoliosis from chest X-ray by automatically computing the scoliosis classification index (SCI), a measurement of the deviation of each vertebral segment from the vertical spinal line, proposed by Greenspan et al. [16]. There was poor correlation between SCI and Cobb angle for scoliotic curves below 10° but strong correlation was found for curves above 10°. This was attributed to the difficult measurements of Cobb angle from end-vertebrae in small curves highlighting the limitations of the measurements currently used. As opposed to Cobb angle, SCI computation did not show any variability between two measurements. This application shows the potential of automated screening of scoliotic curves from regular chest X-rays but its use is limited because no cut-off values for SCI could be determined to distinguish clinically significant scoliosis with Cobb angles above 10° from those with lesser curves. Therefore, effective screening would require better correlation for lesser curves but it shows the potential to reduce scoliosis measurements variability using automated systems.

Methods to evaluate scoliosis severity using surface topography

Jaremko et al. [17–19] compared Cobb angles measured manually and Cobb angles calculated from 3D reconstruction of the spine using two X-rays with those estimated from 360° torso surface models acquired using four laser scanners. Asymmetry indices were extracted using genetic algorithms on cross-section of the topographic coordinates from the torso surface models. Together with other clinical indices (age, sex, BMI, and treatment status), those asymmetry indices were used as inputs into an artificial neural network (ANN) designed to predict the clinical Cobb angle (Fig. 1). An ANN is a computational model that simulates biological neural networks. It uses interconnected nodes (artificial neurons) that are interconnected by weighted links (analogous to synaptic connections). This network is usually adaptive and learns from training sets [20]. ANN estimation proved to be of comparable precision to computer and clinical measurements. This technique could be of much use in a scoliosis screening clinic, but the costly set-up required to obtain 360° images of the torso limits its use at the moment [21]. Therefore, methods assessing AIS severity with back shape surface

Table 1 Summary of algorithms applied to screen or follow-up AIS

Article	Input/imaging modality	Methods and algorithm used	Output	Results/comments
Tang et al. [15]	60 digitalized chest X-rays with presence of scoliosis with Cobb angle ranging from 5° to 30°	1. Vectorization of spine's central point → intelligent hybrid approach switching between correlation method and fuzzy estimator 2. Computation of cost function → quantify the deviations of estimated spine locations from fitted straight line	Scoliosis Classification Index (SCI)	Poor correlation ($r = 0.42$) between SCI and Cobb angle for scoliosis <10° of Cobb angle but good correlation above 10° ($r = 0.92$) No definition of a critical SCI No consideration for TL-L curve Good reproducibility
Jaremko et al. [17–19]	46 patients 1. 153 scans of 360° torso surface models from four laser scanners 2. Clinical indices (age, sex, BMI, treatment status)	Comparison of Cobb angle between clinical measurements, 3D reconstruction measurements and prediction by artificial neural network (ANN)	Cobb angle	Accuracy of prediction within 0.1°±6.0° when compared to computer Cobb angle 0.8°±5.9° when compared to clinical Cobb angle
Ramirez et al. [21]	111 AIS patients 1. 3D back shape from one single laser scanner 2. clinical parameters (trunk twist, cosmetic score, scoliometer)	Comparison of X-ray Cobb angle with Output from three types of classifiers 1. SVM (Support Vector Machine) 2. DT (Decision Tree) 3. LDA (Linear Discriminant Analysis)	Binary: 1 Mild (<30°) 2 Non-mild (≥30°)	Highest classification accuracy achieved with the SVM (85%)
Wu et al. [3]	72 data sets of 4 successive values of Cobb angles and lateral deviation taken at 6 and 12 month intervals from 11 subjects	Fuzzy c-means clustering and trained ANN (artificial neural network) Number of progression patterns defined: 1. 10 for Cobb angle 2. 8 for lateral deviation	Prediction of Cobb angle and lateral deviation at the next follow-up visit	Cobb angle prediction within 4.4° (±1.86°) Lateral deviation prediction within 3.57 mm (±2.8 mm)
Ajemba et al. [2]	44 patients with moderate AIS (radiological measurements and clinical parameters assessing developmental status) Two groups depending on Cobb angle increase between two visits * Progression (>5°) * Non-progression (<5°)	Several models of Support Vector Classifier (SVC) each of them using different sets of clinical and radiological parameters to predict the risk of progression of AIS	Binary: 1. Progression 2. Non-progression	Accuracy of assignment of the SVC between 65 and 80%

topography rather than 360° torso surface models have been proposed to lower equipment cost.

Ramirez et al. [21] combined information from back surface topography and clinical data using a support vector machine classifier to assess scoliotic spines severity accurately while limiting irradiation. Patients were classified into two classes defined as mild and non-mild for Cobb angles <30° and above 30°, respectively. Three types of classifiers SVM (support vector machine), DT (decision tree) and LDA (linear discriminant analysis) were then compared. SVMs are supervised learning methods used for classification or regression. Given a set of points in a multiple dimensional plane, the SVM creates one or several hyperplanes to separate data points from different classes [22]. Decision trees are algorithms represented with trees like graphs where nodes containing conditions split into branches leading to a decision. LDA is a classification method where a discriminant score based on a linear combination of features is computed for each class. A new case is then classified into the class for which it has the highest discriminant score. Of the three types of classifiers, SVM achieved the highest classification accuracy of 85%.

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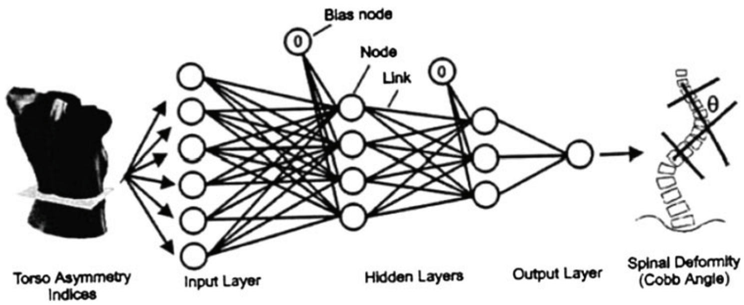

Fig. 1 ANN to estimate the Cobb angle (*right*) from indices to torso asymmetry (*left*). Each node in the hidden layer takes a weighted sum of inputs and produces an output if the sum is greater than a threshold. The ANN "memory" is distributed through the link weights, which are modified to minimize the difference between actual and estimated output by repeated presentation of input–output pairs in training set. Thus, the network "learns" through experience much as humans do. (From Jaremko et al. [17])

Threshold of 30° rather than 10° as defined above as the clinical significant cut-off and the lack of accuracy where up to 15% of patients could be improperly screened are clear limitations of this application.

Methods to evaluate scoliosis progression using artificial intelligence methods

Based on the hypothesis that scoliosis follows progression patterns, Wu et al. [3] used a hybrid learning technique combination of fuzzy c-means clustering and ANN to predict Cobb angles and lateral deviation at follow-up. Fuzzy c-means clustering is a learning method that can be used to classify a data set without supervision. An optimal set of clusters (or classes) is obtained through fuzzy partitioning; which implies iteratively moving the cluster centers and minimizing intra-cluster variance in a given data set. Wu et al. applied those techniques to 72 radiological data sets acquired at successive follow-up clinics from 11 patients and were able to predict Cobb angle at follow-up with accuracy comparable to clinical measurements.

Ajemba et al. [2] have used sequential radiological measurements and included clinical parameters assessing developmental status such as Risser sign and chronological age to predict risk of progression using several models of SVM each of them based on different sets of clinical and radiological parameters. SVM ability to distinguish progressing from non-progressing AIS, was estimated to be between 65 and 80% which is better than former models based on statistical methods of regression.

AIS screening and follow-up rely heavily on the evaluation of the Cobb angle. The applications described above could lower radiation exposure by using surface topography and by optimizing follow-up frequencies. Their use in the clinical setting is limited by their accuracy and the complex setting required for their implementation.

AIS classification

Two major classifications from King et al. [9] and Lenke et al. [23] are used in AIS. Their limited reliability has been described [11, 24, 25], and applications using rule-based algorithms have been developed [26–28].

Stokes and Aronsson [26–28] have developed a rule-based automated algorithm to increase King's classification reliability. In writing that algorithm, ambiguities and absence of precise definitions in the King et al. classification scheme [9] had to be resolved and permitted the identification and resolution of ambiguities in the definition of curve types. Phan et al. [29] have developed a decision tree to increase curve type classification accuracy using Lenke classification (Fig. 2). Similar findings to Stokes et al. work were found; classification accuracy was increased and the use of those tools has shown potential to increase classification reliability independently of user training. Classification accuracy was proportional to the time spent classifying and did not require more time using the decision tree with Lenke classification.

A limitation of the King and Lenke classifications is their consideration of two-dimensional features extracted from postero-anterior (PA) and lateral (LAT) X-rays for a pathology that is truly three-dimensional. Therefore, several studies have generated classifications using databases with three-dimensional reconstructions of AIS patients.

Using Kohonen self-organizing map, a kind of ANN which can display nodes on a two-dimensional matrix, Mezghani et al. [30] were able to automatically classify 3D reconstructions of AIS spines into three classes based on the severity of the deformation. This self-ordering algorithm showed its ability to generalize three-dimensional features to describe the overall severity of the deformity.

Geometric torsion represents the rate of rotation of the plane formed by the tangent and the normal along the

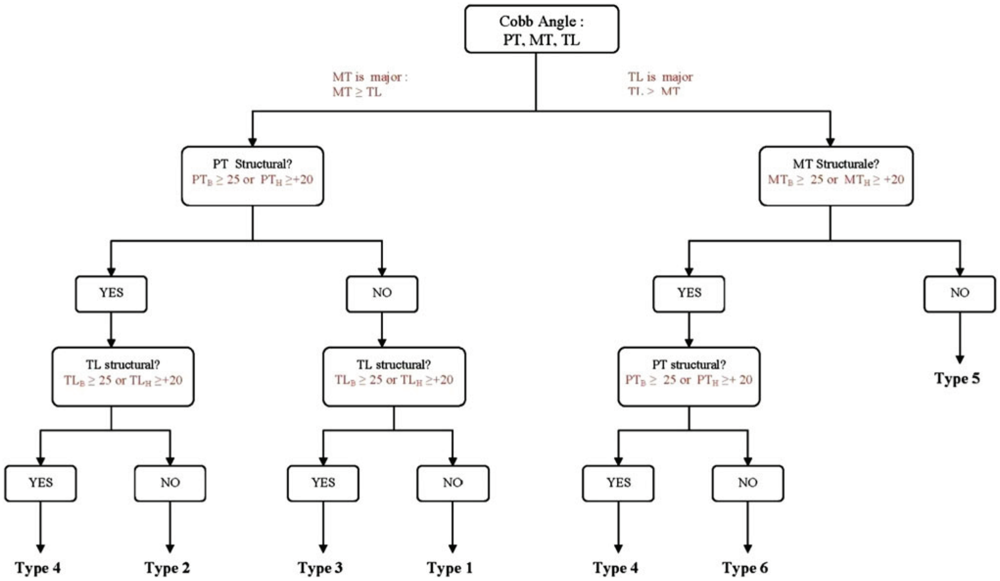

Fig. 2 Decision tree developed to improve classification accuracy of AIS according to the Lenke scheme. *MT* main thoracic, *TL* thoracolumbar/lumbar, *PT* proximal thoracic indices, X_B Cobb angle for segment X on bending PA X-ray, X_H Cobb angle for segment X on sagittal X-ray. From Phan et al. [29]

curved spine. Poncet et al. [31] extracted three distinct patterns of torsion, which can classify AIS based on compositions of those three basic torsion patterns. Integration of torsion into spinal classification could add valuable information about points of high geometric torsion correlating with spine stability and therefore influence surgical treatment.

Sangole et al. [32] have performed an unsupervised clustering using 3D reconstruction from patients with Lenke 1 curve type. They extracted three primary subgroups (two surgical and one non-surgical), and were able to determine variations within Lenke curve type 1 that were not evident on plain X-rays, showing that all curve type 1 were not always hypokyphotic and that the orientation of the plane of maximum curvature (a 3D index) was a discriminating factor. This study was limited to a very specific group of curve types; but it demonstrated the possible benefit that cluster analysis can highlight geometrical features, which could influence treatment.

Stokes et al. [33] have performed cluster analysis on 245 X-rays from 110 patients. Four clusters were extracted but of 56 patients followed longitudinally only 25 were consistently grouped at all clinic visits. Therefore, patterns were susceptible to change with repeated observations and cannot be reliably used alone to determine classifications determining treatment strategies.

Duong et al. [34] have developed a 3D classification using an unsupervised learning algorithm, fuzzy K-means clustering, applied to 409 3D AIS spine models. Two classifications with 5 and 12 classes with relevant clinical features and true 3D components were generated. Duong et al. [35] studied several 3D clinical parameters [plane of maximum curvature (PMC), best-fit plane (BFP) and geometric torsion] that could be integrated in the Lenke classification. Performing cluster analysis to evaluate the statistical distribution of those parameters, they showed specific 3D deformation patterns within Lenke 1 type curves using best-fit plane and geometric torsion patterns.

The accuracy of currently used classifications from King and Lenke can be improved with simple algorithms. More advanced algorithms have permitted the development of complex classifications based on large data sets and taking 3D parameters into consideration. While those classifications have focused on geometrical properties, their clinical use is limited because they do not integrate clinical features nor guide surgical decision-making which current classifications actually do. New classifications will need to

Table 2 Summary of recent 3D classifications developed for AIS

Article	Database	Algorithm	Classification/output	Comments
Mezghani et al. [30]	174 spine models (3D reconstruction from bi-planar X-rays) classified into three categories based on their severity	Kohonen Self-Organizing-Maps classify the spine models using their 3D coordinates	Classification by the automated algorithm into one of the three severity grade with 97% accuracy	Ability to classify based on severity but further developments required for clinical application
Poncet et al. [31]	62 spines, 94 curves where extracted from single and double major scoliotic curves	Applied geometric torsion to describe patterns of curve torsion in AIS scoliotic spines	Three distinct curve patterns of curve torsion were obtained based on their apex orientation and localization	Curve limits were subjected to high geometric torsion as compared to the apices and suggested that natural stability of the spine originates from the limits
Sangole et al. [32]	172 patients with right thoracic adolescent idiopathic scoliosis	Classical unsupervised clustering method (ISOData) on four thoracic segment indices derived from 3D reconstructions [Cobb angle, axial rotation of the apical vertebra, orientation of the plane of maximum curve of the thoracic curve and kyphosis (T4–T12)]	Three main groups defined Two surgical (major curves) One non-surgical (minor curves)	Subgroups within Lenke curve type 1 with 3D features not evident on plain X-rays are highlighted Two surgical subgroups of Lenke type 1 showed that thoracic curves were not always hypokyphotic and that the orientation of the plane of maximum curvature (a 3D index) was a discriminating factor
Stokes et al. [33]	110 AIS patients amongst which 56 studied longitudinally 245 clinical visits with stereo technique X-rays	Cluster analysis of each curve, at each visit using 3D reconstruction and quantified with Cobb angle, apex level, apex vertebra rotation and rotation of PMC as the input factors	4 clusters determined	56 patients followed longitudinally only 25 were consistently grouped at all clinic visits
Duong et al. [34]	409 spine models of patient with AIS	Standard clustering technique (fuzzy k-means) was used to find the optimal regrouping of samples with similar features	Two classifications with five and twelve classes with consistency rated to 100 and 92% respectively when tested on 20 successive running trials	Samples of 3D models in the center of each of the 5 and 12 classes cluster analysis had common patterns with the widely used King and Lenke classifications

integrate accepted clinical parameters and focus on guiding treatment to be used by physicians (Table 2).

Methods developed to assist bracing treatment

For patients with moderate AIS curves that are progressing or are between 20° and 40° Cobb angle with remaining growth, orthotic treatment has been advocated [36]. Computer-assisted design (CAD) and computer-aided manufacturing (CAM) have been tested in the fabrication of orthotics and revealed similar improved efficacy in curve correction when compared to traditional manual methods [37–39] while showing potential to save time in adjustments of the casts [40].

A biomechanical study by Perie et al. [41] has evaluated the effectiveness of the Boston brace using finite element model and experimental measurements. It highlighted the contribution of bracing pads to curve reduction but also suggested that other mechanisms participated in orthotic correction. Adaptation of such finite element models was personalized for patients' specific curve patterns [42]. Bracing simulation with those personalized biomechanical models showed similar results to real in-brace geometry and revealed the potential to optimize bracing treatment of AIS through personalized evaluation and design improvement. A recently developed patient-specific brace simulator was developed based on refinements of the finite element models [43], and allowed to test and assess the efficiency of hundreds of different virtual braces for a given patient, thus optimizing the design of each brace [44]. Labelle et al. [38] undertook a randomized control trial comparing brace design using computer-assisted tool combining surface topography, surface pressure measurement with 3D reconstruction of the trunk (test group) with the conventional manner (control group). At initial visit, the test group had greater diminution of curve deformity in the coronal plane but it also had 3D correction as showed by correction of the plane of maximum deformity, which the control group did not manage to achieve.

A major limitation in orthotic treatment efficacy is patient compliance with timing and tightness when wearing the braces. Recent studies from Katz et al. [45] and Rahman et al. [46] have demonstrated a correlation between patient compliances to bracing treatment and outcome. Lou et al. [47] developed a battery-powered microcomputer system to monitor and guide patient in properly wearing their braces with the prescribed tightness using a feedback module. A limited clinical trial with five patients testing the device on 4 weeks demonstrated improvement in proper wearing of the brace.

These computer applications developed to improve bracing treatment have shown their potential to improve patient care, but cost, time consumption and the lack of clinically integrated systems have limited their use.

Methods developed to assist surgical treatment planning

Despite extensive literature on the surgical treatment of AIS, there is no clear consensus on the optimal treatment, which varies greatly from a patient to another [13, 14]. With the intention to optimize surgical treatment, several computer applications were developed to assist surgeons with their surgical planning.

Fusion levels determination using fuzzy logic

One of the major challenges in AIS treatment planning is to determine whether a curve needs to be fused. In order to assist surgeons in solving this enigma, Nault et al. [48, 49] have developed two fuzzy logic models, one for proximal thoracic curve fusion and another one for lumbar curve fusion. Fuzzy logic is a problem solving methodology based on approximate rather than precise reasoning, it is advantageous in complex systems from which precise mathematical equations cannot be applied which is often the case in medicine [50]. The models developed by Nault et al. output a score of certainty concerning needs for fusion based on rules extracted from the literature. When tested to guide levels of fusion, there was good agreement between those fuzzy logic models and clinicians. Yet the lack of clear justifications for a given output and total contradiction between the model and common agreement between five expert surgeons in spinal deformity for specific examples highlights the limitations of this system.

Surgery simulation

Biomechanical computer modeling offers the possibility to analyze multiple surgical strategies, to assist in decision-making and to compute reaction forces or stresses at different sites in the spine. Due to the complexity of the intervention and the patient characteristics, there are many unknown inputs for the biomechanical analyses. Therefore, appropriate simplifications need to be done.

Finite element analysis

Finite element analyses were commonly used to estimate stresses in internal fixation devices and to analyze the consequences of surgical variables such as the orientation of pedicle screws on the rigidity of the construct. The biomechanics of Harrington instrumentation was analyzed using a wireframe finite element model of the spine [51]. The biomechanics of CD instrumentation also was studied with the same model on an idealized geometry [52] and on 15 surgical cases [53] using patient-specific 3D geometry, built from preoperative stereo X-rays, and intra-operative maneuvers. The simulations of surgical maneuvers showed good agreement with measured effects of surgery in the frontal plane.

Flexible multi-body approach

Aubin et al. [54–58] have developed kinematic model including flexible elements to represent each motion segment, implant-vertebra connections, kinematic joints and sets to model surgical instrumentation of the spine. The spine model is personalized to a specific patient using calibrated radiographs [59]. Recent studies [56, 58] established the validity of this model by simulating the surgical procedures of 10 scoliotic patients who underwent a posterior and anterior instrumentation surgery. Simulation agreed well with documented postoperative results. In comparing simulations of various instrumentations for a same patient, low and high vertebra-implant reaction forces were highlighted. In some cases, those forces were exceeding the experimentally measured pullout values; information that could be valuable in surgical planning. Majdouline et al. [60] simulated 702 different surgical strategies on a computer simulator and demonstrated that strategies with various levels of instrumentation could lead to the same overall correction; such tools could be considered to optimize surgical strategies (Fig. 3).

Discussion

To better evaluate AIS, classification reliability can be improved using rule-based algorithms [26–29]. Much of

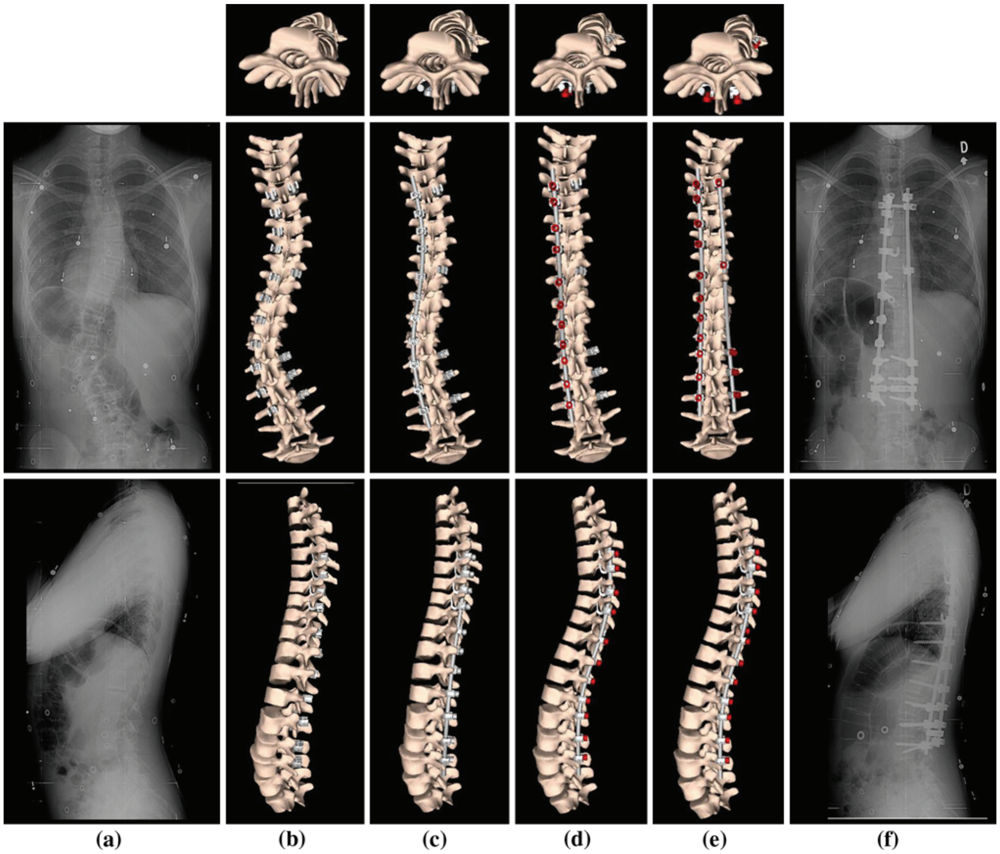

Fig. 3 Representation of a patient with double major AIS spine and instrumentation during a simulation. **a** Preoperative radiographs, **b** initial geometry after the installation of the implants, **c** after the attachment of the first rod on the concave side of the spine deformity, **d** after the rod rotation maneuver, **e** final configuration after the installation of the second rod and nut lock up, **f** postop radiographs

the studies presented have focused on novel 3D measurements parameters such as SCI, PMC or geometric torsion that could be integrated in a classification. Implantation of such measurements to define AIS could lead us to a better understanding of that pathology and its treatment. The measurements to be used are still debated and rely on 3D reconstructions of AIS spines, which are not available in most clinical settings. With the advances in imaging and 3D reconstructions, a classification based on clinically accepted measurements addressing the 3D characteristics of AIS and aimed at guiding its treatment remains to be developed.

Screening and follow-up of AIS patients can impose unnecessary radiation to pediatric patients. Optimization of imaging and its frequency can be achieved. Non-radiation investigations from surface topography using laser scanners can accurately predict Cobb angle [17] and screen for patients requiring further investigation [21]. For screening or longitudinal follow-ups purposes, those radiation free techniques offer attractive alternatives to longitudinal X-ray imaging. Due to the idiopathic nature of the pathology, clinical research has not yet permitted appropriate prediction of its evolution; therefore, applications based on probabilistic or simulative modeling should be developed to guide patient management, in line with the experiments by Ajemba et al. [2] and Wu et al. [3].

Artificial intelligence algorithms were able to take into consideration geometric properties as well as clinical information to predict curve progression [2, 3, 61]. Those applications based on AI algorithms to screen for AIS, evaluate its severity or predict its progression could guide for the need and frequency of follow-up. Being developed in the research setting, their implantation in the clinical setting lacks studies proving their efficacy over current practice. In addition, cost, time consumption and set-up complexity of those systems remain clear limitations.

An application based on fuzzy logic was able to gather and average recommendations from the literature to match a consensus from a panel of experts with adequate accuracy [48, 49]. Such algorithms are able to output solutions around an area of indecision such as AIS surgical planning. Up to now, prediction of surgical outcome during its planning was mainly based on surgeon's experience learned from past cases. Computer simulations permit an objective prediction of surgical outcome, allowing the clinician to test various options of instrumentation. It gives a quantification of forces resulting from instrumentation, with the calculation of vertebra-implant reaction forces; critical information to predict the risk of screw breakage or pullout. Surgical strategies leading to unstable constructs and under-correction could be avoided and those resulting in proper correction with minimum stress on the spine and materials could be proposed to guide surgical treatment. Yet no applications have demonstrated their ability to guide physicians for surgical indications and optimal surgical strategy Approach and surgical levels of fusion are critical decisions in AIS patient management but remain with high variability amongst surgeons [13].

To our knowledge, none of the applications reviewed are actually implemented in the clinical setting outside research institutions. Common obstacles to clinical use have been noticed. Most of those applications are experimental and lack clinical applicability. Consideration and better understanding of clinician's need will be required to optimize those applications clinical usability. For example time efficiency when using those applications is a prime requirement. In addition, acceptance of results from computer application by clinicians will require strong evidence about improved gain in patient assessment and treatment over current methods; in our current review, only Labelle et al. passed this critical step by comparing computer-assisted brace design with conventional method. Finally, despite research efforts and proven improved patient care in some cases, the lack of knowledge transfer of such technologies from laboratory to industrial production, limited budgets, and slow adaptation of physicians to health information technologies remain major obstacles to clinical implementation of those applications.

Applications based on past cases should also be used in assisting surgical planning. Despite the development of patient databases [62], a comprehensive application gathering past cases, outputting an optimal instrumentation using AI methods, simulation or statistical analysis with sufficient accuracy and justification to get acceptance from clinicians remains to be developed.

Conclusion

Due to the complexity of AIS geometry, clinical evaluation and treatment, several computer applications have been developed to improve its management. Fuzzy clustering and support vector classifiers can regroup AIS spines having similar curve and curve progression. Applications based on ANN and surface topography algorithms have been able to compute actual and predicted Cobb angle with good accuracy while limiting irradiation. Rule-based algorithms can increase classification reliability. Fuzzy logic can average multiple rules extracted from the literature and output a degree of certainty in domains where no clear consensuses exist such as AIS levels of fusion. The critical question of optimal surgical strategy in selection of approach and levels of fusion remains unanswered and treatment is subject to personal experience and high variability. Applications need to be developed to permit optimization of surgical treatment by improving classification; by developing models based on literature evidence to provide treatment guidelines adapted to each patient and predict outcome based on past cases or simulation.

All those applications have shown potential to improve AIS care, but incomplete consideration of all AIS curve types, unproven benefit over current management, increased cost and time consumption in the clinical setting are clear limitations. Further studies proving their added value to current methods of management of AIS are needed. With proper development for clinical integration, those computer applications could improve the way AIS is currently assessed and treated.

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Chapter 4. A Decision Tree Can Increase Accuracy When Assessing Curve Types According to Lenke Classification of Adolescent Idiopathic Scoliosis

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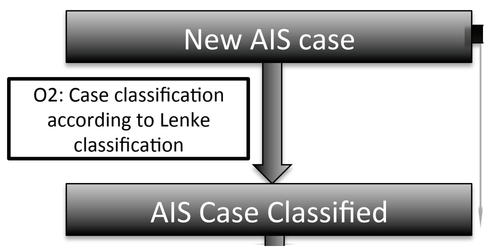
A decision tree can increase accuracy when assessing curve types according to Lenke classification of adolescent idiopathic scoliosis. Spine. 2010 May 1;35(10):1054–9.

This article presents a classification decision tree for AIS according to the Lenke classification and answers objective 2.



Authors' contribution:

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Mezghani N: Preparation of the algorithm, adaptation of algorithm to clinical setting, correction of article

Nault M-L: Input on statistical analysis, revision of manuscript

Aubin C-E: Input on methodology, revision of manuscript

de Guise JA: Proposal of project, revision of manuscript, project funding

Labelle H: Input on methodology, revision of manuscript, project funding

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A Decision Tree Can Increase Accuracy When Assessing Curve Types According to Lenke Classification of Adolescent Idiopathic Scoliosis

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Study Design. The assignment of adolescent idiopathic scoliosis (AIS) curves into curve types (1–6), as described by Lenke et al, was evaluated by 12 independent observers using the original description *versus* a decisional tree algorithm.

Objective. To determine whether a decision tree algorithm can improve classification accuracy using the Lenke classification for AIS.

Summary of Background Data. Curve type classification in AIS relies on several parameters to consider, and its relative complexity has lead to conflicting studies that reported fair-to-excellent interobserver reliability. King's classification reliability was shown to be improved using a rule-based automated algorithm. No similar algorithm for Lenke's classification currently exists.

Methods. A clinical diagram derived from a decision tree was developed to help clinicians classify AIS curves. Twelve clinicians and research assistants were asked to classify AIS curves using 2 methods: the original Lenke chart alone and the decision tree diagram in addition to the Lenke Chart. Wilcoxon ranking tests were used to evaluate any difference in classification accuracy and speed for both methods. Mann-Whitney tests were used to compare experts and nonexperts results. Pearson correlation was calculated to evaluate the relationship between accuracy and time taken to classify.

Results. Use of the decision tree for curve type determination improved classification accuracy from 77.2% to 92.9% ($P = 0.005$) without requiring more time to classify. This improvement was statistically significant ($P < 0.05$). A statistically significant correlation between accuracy and time spent classifying when the decision tree is used was also observed ($R = 0.62$, $P = 0.032$).

Conclusion. Transfer of a computer algorithm, a decision tree, to a clinical diagram improved both accuracy of AIS classification. Algorithmic diagrams could prove beneficial to increase classification reliability due to their systematic approach.

Key words: decision tree, Lenke classification for AIS, classification accuracy, scoliosis. **Spine 2010;35:1054–1059**

[redacted]

Proper curve type classification for adolescent idiopathic scoliosis (AIS) is valuable because it helps guiding surgical treatment according to curve characteristics.[1–3] The Lenke classification[2] (Figure 1) is widely used by surgeons for this purpose. It divides the spine into 3 segments, proximal thoracic (PT), main thoracic (MT), and thoracolumbar/lumbar (TL/L) in the coronal plane, organized into 6 basic curve types depending on the structurality and dominance of each of these segments. In addition to curve types, lumbar spine and thoracic sagittal profile modifiers are part of the Lenke Classification system.

This classification's reliability was studied repeatedly due to its complexity and was found to vary between fair-to-excellent in different reports.[2,4–6] Lenke *et al* reported good-to-excellent interobserver ($\kappa = 0.74$) and intraobserver ($\kappa = 0.893$) reliability from premeasured radiographs,[2] according to the reliability criteria defined by Svanholm *et al*.[7] In contrast, Richards *et al* found only fair interobserver ($\kappa = 0.50$) and intraobserver ($\kappa = 0.60$) reliability from nonpremeasured radiographs,[5] suggesting that part of the lack of reliability arises from radiologic measurement of the many Cobb angles to consider. Niemeyer *et al* compared King and Lenke classification reliability from clinicians with various degrees of training using premeasured and nonpremeasured radiographs.[4] They concluded that both classifications had good reliability and that professional training had an influence only on the outcome of nonpremeasured radiographs.

To improve classification reliability, Stokes and Aronsson[8,9] used a rule-based automated algorithm to classify AIS according to King's classification.[10] It was also found that time spent marking the films rather than professional experience was the major determinant of accuracy and reliability when using that computer algorithm.

A similar algorithm for the Lenke classification has yet to be described. Therefore, the purpose of this work was to develop a clinical diagram based on a decision tree algorithm. Our working hypothesis was that this clinical diagram used in conjunction with the original descrip-

CURVE TYPE

Type	Proximal Thoracic	Main Thoracic	Thoracolumbar/Lumbar	Description
1	Non-Structural	Structural (Major)*	Non-Structural	Main Thoracic (MT)
2	Structural	Structural (Major)*	Non-Structural	Double Thoracic (DT)
3	Non-Structural	Structural (Major)*	Structural	Double Major (DM)
4	Structural	Structural (Major)*	Structural (Major)*	Triple Major (TM)§
5	Non-Structural	Non-Structural	Structural (Major)*	Thoracolumbar/Lumbar (TL/L)
6	Non-Structural	Structural	Structural (Major)*	Thoracolumbar/Lumbar-Main Thoracic (TL/L-MT)

STRUCTURAL CRITERIA
(Minor Curves)

Proximal Thoracic - Side Bending Cobb ≥ 25°
- T2-T5 Kyphosis ≥ +20°

Main Thoracic - Side Bending Cobb ≥ 25°
- T10-L2 Kyphosis ≥ +20°

Thoracolumbar/Lumbar - Side Bending Cobb ≥ 25°
- T10-L2 Kyphosis ≥ +20°

*Major = Largest Cobb measurement, always structural
Minor = All other curves with structural criteria applied
§Type 4 - MT or TL/L can be major curve

LOCATION OF APEX
(SRS Definition)

CURVE	APEX
Thoracic	T2-T11/12 Disc
Thoracolumbar	T12-L1
Thoracolumbar/Lumbar	L1/2 Disc-L4

Figure 1. Lenke chart for curve type definition according to Lenke classification for AIS.

tion could improve classification accuracy. We also wanted to evaluate the influence of experience and time spent classifying on accuracy.

■ Materials and Methods

A decision tree (Figure 2) was developed by our team and included a software that automatically classifies curve types of AIS cases according to the Lenke classification system, based on radiographic measurements of Cobb angles.[11] For this study, a clinical diagram adapted from this decision tree to the clinical setting was designed (Figure 3). Ease of use and clinical reasoning leading to proper curve type determination where emphasized. This diagram focuses on Lenke curve type classification because a total of 8 angles (Cobb angle at the PT, MT, and TL/L levels in standing and bending positions on posteroanterior [PA] radiographs and Cobb angle between T2–T5 and T10–L2 on sagittal radiographs) and up to 5 angle comparisons need to be taken into consideration to determine proper curve type (Figure 1). Modifiers in Lenke classification were not included in the diagram because they do not require consideration of that many parameters. The decision tree uses a systematic approach to determine curve type. At each step, it determines whether each curve of the spine is structural or not with 2 comparisons at most. At most 3 of those steps and 5 comparisons are followed to decide of the proper curve type (Figure 3).

Seventy-two AIS cases were extracted from the Spinal Deformity Study Group multicentric database containing 603 subjects who have undergone posterior fusion. Those 72 cases were selected to have a complete array of AIS cases with all curves types and modifiers according to Lenke classification scheme (Table 1). The database is maintained under the supervision of the pediatric deformity section of the posteroanterior, including the main author of the Lenke classification, and contains preoperative radiographs of AIS surgical cases that are digitally submitted in JPEG format. A software (DrPro, PhDx, Albuquerque, NM)[12] is then used to measure Cobb angles from standing and side benders PA radiographs and assigns a curve type on these measurements and curve location. Proper assignment of curve type for each case taken from this database was double-checked by one of the authors (P.P.) and checked again when there was nonaccordance in classification by participants. For each case, the curve type assigned and double-

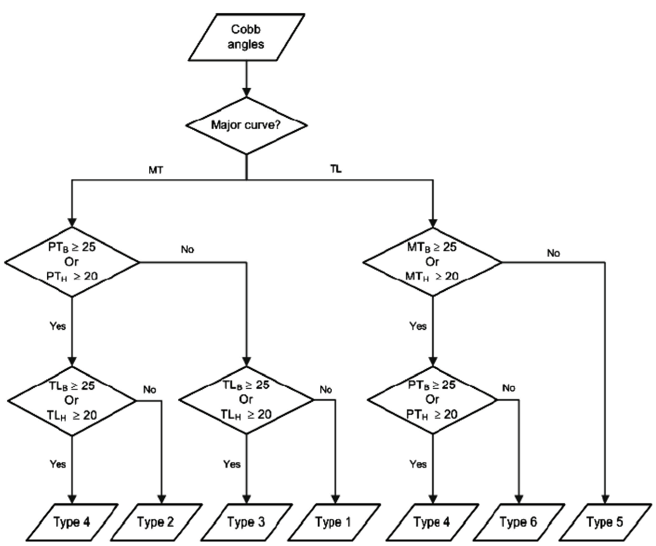

Figure 2. Decision tree of the automated AIS classifier according to the Lenke scheme of classification. MT indicates main thoracic; TL, thoracolumbar/lumbar; PT, proximal thoracic; Indices: X_B: Cobb angle of the curve X on bending PA x-ray; X_H: Cobb angle of the curve X on sagittal x-ray.

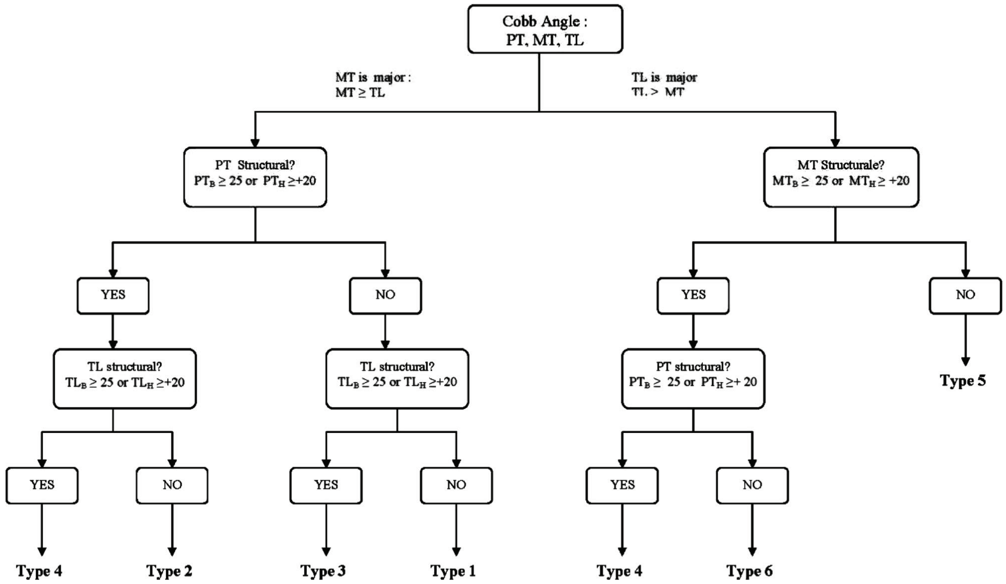

Figure 3. Decision tree diagram adapted for use in a clinical setting. Technical annotations were removed. Clinical reasoning is included to facilitate understanding and use of the algorithm. Legend and indices remain the same as the one described in Figure 2.

checked in the database, which did not contain any misclassification, was set as the gold standard. Three orthopedic surgeons, experts in spinal deformity, 7 orthopedic residents, a research nurse with more than 10 years experience in scoliosis clinics, and a research engineer participated in this study. Two spreadsheets of 36 cases each were generated and contained the 8 Cobb angle measurements for curve type determination. The participants were asked to define the Lenke curve types, 1 to 6, for each case. They were asked to classify each of these sets using the original Lenke chart alone and using the decision tree diagram in addition to the Lenke Chart. For this study, radiologic measurements from each case were presented on a spreadsheet instead of radiographs to focus on the benefit of using the decisional tree on curve type definition and avoid variability from radiograph measurements.[13,14]

Classification accuracy was the primary variable tested in this study. It was calculated by dividing the number of cases properly classified by the participants, using the defined curve type in the database, by the total number of cases classified.

To ensure that time taken to classify would not be a cofounding variable, it was recorded for each set of classified 36 AIS cases. The total time was reported in minutes and the average time per case calculated. This value was used for statistical analysis to evaluate time taken to classify depending on the method used and its relationship with classification accuracy.

Several measures were taken to control for the learning effect described by Niemeyer *et al* in a former reliability study.[4] To avoid repeated classification of the same case, 2 different subsets of 36 cases were generated. To evaluate the learning effect from starting with one method or another, half of the participants were asked to start with the Lenke chart alone (group A) whereas the other half was asked to start with the decision tree in addition to the Lenke chart (group B). Finally, participants were also asked to wait for a week before filling the second spreadsheet; 5 of the 12 participants were unable to fulfill this requirement because of time constraints.

To evaluate the influence of professional training in AIS on classification accuracy, participants were separated into 2 groups depending on their exposure to AIS; expert group (3 surgeons, 2 residents undergoing graduate studies on AIS related topics, and a research nurse performing research in AIS) and nonexpert group (5 residents and a research engineer).

Table 1. Distribution of Curve Types

Curve Type	1 Main Thoracic	2 Double Thoracic	3 Double Major	4 Triple Major	5 Thoracolumbar/ Lumbar	6 Thoracolumbar/ Lumbar-Main Thoracic
72 cases n = 72	27.8% n = 20	22.2% n = 16	22.2% n = 16	13.9% n = 10	6.9% n = 5	6.9% n = 5
Set 1 of 36 cases n = 36	25.00% n = 8	31.25% n = 10	25.00% n = 8	15.63% n = 5	6.25% n = 2	9.38% n = 3
Set 2 of 36 cases n = 36	38% n = 12	19% n = 6	25% n = 8	16% n = 5	9% n = 3	6% n = 2

Table 2. Summary of Classification Accuracy

	Average Classification Accuracy Without Decision Tree	Average Classification Accuracy With Decision Tree	Wilcoxon Ranking Test (*P*)
All	77.1%	92.9%	0.005
Experts	86.3%	93.1%	0.043
Nonexperts	68.0%	92.8%	0.043
Mann-Whitney experts *vs.* nonexperts (*P*)	0.423	0.332	

Table 4. Summary of Classification Speed

	Without Decisional Tree (in Second per Case)	With Decisional Tree (in Second per Case)	Wilcoxon Ranking Test (*P*)
All	36.1	28.0	0.031
Experts	36.1	28.1	0.116
Nonexperts	36.1	27.9	0.14
Mann-Whitney experts *vs.* nonexperts (*P*)	0.745	0.936	

Statistical Analysis

Statistical analysis was performed using SPSS software, version 15.0 (SPSS, Chicago, IL). Paired Wilcoxon ranking tests were used to evaluate statistical differences in classification accuracy and speed depending on the method used. It was applied for all the participants and for expert and nonexpert groups. This test was chosen for its ability to assess any statistical differences for small-paired samples (n = 12 and n = 6 in this case) without normality assumption. Pearson correlation coefficient between classification accuracy and time spent per case was computed for each of the methods to evaluate the influence of time on classification accuracy. Mann-Whitney test was used to evaluate classification accuracy differences between expert and nonexpert groups. Mann-Whitney test was also used to evaluate any difference between group A and B to evaluate a possible learning effect from either method.

Results

Curve type distribution for each set of cases is represented in Table 1. All curve types were present with acceptable variability in distribution (<15%) between the 2 sets for each curve type. Therefore, it was assumed that the 2 sets were equivalent to test curve type classification.

Classification Accuracy

Classification accuracy improvement using the decision tree was statistically significant for experts ($P = 0.043$) as well as for nonexperts ($P = 0.043$) (Table 2). When using the decision tree, classification accuracy increased from 77.2% to 92.9% (Table 3) on average for all participants, a difference statistically significant ($P = 0.005$). Despite achieving only fair classification accuracy without the decision tree (68.6%), nonexperts were able to reach excellent classification accuracy (92.8%) similar to the results obtained by experts (93.1%) using the decision tree. Classification accuracy difference between experts (86.4%) and nonexperts (68.6%) was nonetheless not statistically different without the decision tree ($P = 0.423$).

Time Spent Classifying and Correlation With Accuracy

Average time spent classifying for all participants was 36 seconds per case without the decision tree and 28 seconds per case with it (Table 4). This difference was statistically significant ($P = 0.031$). Mann-Whitney analysis did not show any differences between the expert and nonexpert group. Classification of AIS using the Lenke chart alone did not reveal any correlation between the amount of time spent classifying and accuracy (R = 0.033, $P = 0.919$) (Figure 4). The use of the decision tree revealed strong correlation between accuracy and time spent classifying (R = 0.62, $P = 0.032$). Therefore, the

Table 3. Summary of Classification Results

	Participant	Classification Accuracy With LC	Classification Accuracy With LC + DT	Overall Accuracy	Seconds per Cases LC	Seconds per Cases With LC + DT	Seconds per Cases Overall	First Method Used	More Than a Week Apart Between Classifications
Nonexperts	Eng 1	0.444	0.958	0.787	50.0	40.8	43.9	LC + DT	Yes
	Res 1	0.667	0.778	0.722	20.0	11.7	15.8	LC	No
	Res 2	0.222	0.917	0.569	33.3	16.7	25.0	LC	Yes
	Res 3	0.972	1.000	0.986	31.6	40.0	35.8	LC + DT	Yes
	Res 4	0.972	0.972	0.972	50.0	25.0	37.5	LC + DT	No
	Res 5	0.806	0.944	0.875	31.7	33.3	32.5	LC	Yes
Average nonexperts		68.0% (±30%)	92.8% (±7.8%)	81.8% (±5.6%)	36.1 s (±11.7)	27.9 s (±12.1)	31.7 s (±9.96)		
Experts	R.N 1	0.736	0.875	0.806	31.7	14.2	22.92	LC + DT	Yes
	Res 6	0.833	0.944	0.889	23.3	26.7	25.0	LC + DT	No
	Res 7	0.889	0.958	0.924	26.7	21.7	24.2	LC + DT	Yes
	Surg 1	0.944	0.944	0.944	26.7	28.3	27.5	LC	No
	Surg 2	0.917	0.944	0.931	50.0	33.3	41.7	LC	No
	Surg 3	0.861	0.917	0.889	58.3	45.0	51.7	LC	Yes
Average experts		86.34% (±4.7%)	93.1% (±4.8%)	88.7% (±5.7%)	36.1 s (±12.7)	29.1 s (±4.8)	32.1 s (±8.18)		

LC indicates Lenke chart; LC + DT, Lenke chart and decision tree; res, resident; eng, engineer; surg, surgeon.

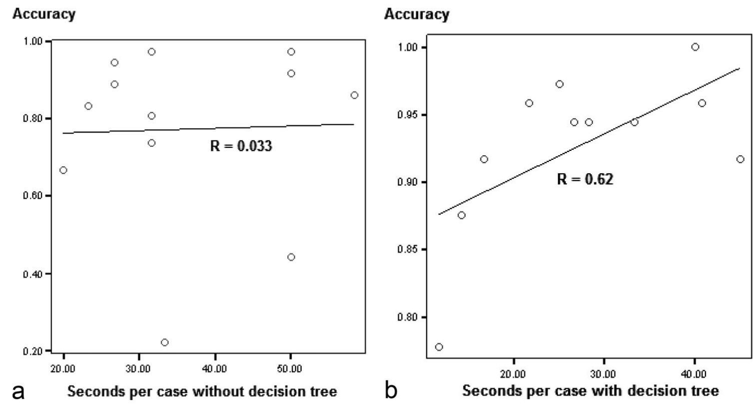

Figure 4. Pearson correlation between classification speed and accuracy depending on the method used. **a,** Without a decision tree, there is no linear correlation. **b,** With a decision tree, there is a strong linear correlation (R = 0.62) between accuracy and classification speed.

more time was spent classifying using the decision tree, the higher classification accuracy was.

Learning Effect

To control for any learning effect, some measures were taken such as having 2 different groups starting with each of the 2 methods. Mann-Whitney analysis for accuracy and time spent classifying with and without decision tree did not reveal any statistically significant differences (Table 5).

■ Discussion

These results have confirmed our hypothesis that a clinical diagram derived from a decision tree can improve classification accuracy. The improvement in classification accuracy was confirmed to be beneficial for the expert and nonexpert group.

Performances in classification from this study are comparable to the ones published in former studies. For instance, in the study by Lenke *et al*[1] 28 scoliosis surgeons classified 7 cases from premeasured radiographs with 84% of accuracy in curve type classification, which is similar to the accuracy achieved by our group of experts without a decision tree (86.3%). The lower performance in our nonexpert group without decision tree (68% accuracy) was highly influenced by resident number 2 (22%) and engineer number 1 (44%) who had little knowledge of AIS. The classification accuracy of both groups (expert and nonexpert) improved to 92.9% average with the decision tree, which is a statistically significant improvement for both groups. In the study of Lenke *et al*,[2] interobserver reliability was measured to curve type classification by the developers of the classification at 93%. Therefore AIS classification with the Lenke classification remains a challenge with a 7% classification error in our study despite the use of a decision tree and a 7% nonagreement between 2 developers of the classification.

Decision trees offer a systematic approach that ensures proper output if each step is followed thoroughly. They avoid omissions leading to classification errors. At most 3 steps and 2 comparisons per steps are taken to determine the curve type using the decision tree diagram. In addition, an examination of the misclassifications without the decision tree has highlighted that sagittal components were occasionally forgotten. Those misclassifications were in some cases corrected using the clinical diagram. Decision trees also avoid unnecessary computation steps. In the case of a structural TL/L curve and a nonstructural MT curve, the proximal-thoracic curve is systematically not considered using the decision tree algorithm.

There was no correlation between the time spent classifying and the accuracy when using the Lenke Chart alone (R = 0.033, $P = 0.919$), whereas there was a statistically significant correlation when using the decision tree (R = 0.62, $P = 0.032$). Therefore, classification accuracy is increased as more time is spent classifying using the decision tree. Nonetheless its use did not require more time to achieve higher accuracy when compared to the Lenke chart alone. Similar findings were described by Stokes and Aronsson when classifying AIS according to King's classification using rule-based algorithms.[9] They found that time spent in selecting radiographs landmark was a significant factor to individual observer's reliabil-

Table 5. Mann-Whitney *U* Analysis Between Groups Starting With Different Methods

	Accuracy LC	Accuracy LC + DT	Accuracy Overall	Speed LC	Speed LC + DT	Speed Overall
Group starting with LC	73.6%	90.7%	82.1%	36.7 s	28 s	32.3 s
Group starting with LC + DT	80.7%	95.8%	89.4%	35.5 s	28.1 s	31.5 s
P-value	0.59	0.065	0.394	0.937	0.394	0.818

ity independently from professional training. The authors propose that such clinical diagram based on algorithms could improve classification reliability because accuracy improvement would only require spending more time classifying when the decision tree is used.

Clinical diagrams could be beneficial for professionals independently of their level of training and exposure to spine pathology. It has been noticed that orthopedic residents had greatly gained in their understanding of the Lenke Classification once they used the decision tree. The resident numbers 3 and 4 in the nonexpert groups who achieved best accuracies admitted to have improved their understanding of the classification by starting with the decisional tree in the first set of classification. In fact, classification accuracy from the nonexpert group was as good as the expert group using the decision tree. Such clinical diagram could therefore be used as educational tools. Our study also confirms the findings from Niemeyer *et al* who did not find any correlation between professional training and interobserver agreement.

Possible limitations from this study include the use of radiologic measurements on spreadsheets rather than radiographs and incomplete control of learning effect (some participants did not wait for a week in between the 2 sets). Data presented to the participants, Cobb angle computationally measured and presented on a spreadsheet, were equivalent to premeasured radiographs used in the studies of Lenke *et al*[1,2] and Niemeyer *et al*.[4] Clinicians were asked to classify 36 cases in a row, which is unlikely to happen in a real clinical setting where more attention will be taken for each case. Therefore, curve type definition from measurements rather than radiographs and evaluation of 36 cases in a row are limiting factors to conclude on the entire reproducibility of our results in the clinical setting.

Additional classifications for AIS including 3-dimensional features[15,16] are being developed and take more criteria into consideration. As more computer applications are developed in the assessment of spinal deformities, transfer of algorithms used in those applications to the clinical setting could benefit clinicians as shown with this study.

■ Conclusion

The transfer of a simple algorithm, a decision tree, from software to the clinical setting was successful in this study. This decision tree can improve classification accuracy without increasing time spent classifying and it can be beneficial to clinicians independently of their knowledge of AIS classification. Its systematic approach to classification has shown a statistically significant correlation between classification accuracy and time spent classifying. Using this decision tree, accuracy of curve type classification could simply be improved by spending more time classifying. Ultimately, clinically adapted algorithms could improve reliability of classifications.

■ Key Points

- A clinical diagram derived from a decision tree for classification of curve types according to Lenke Classification of AIS was successfully developed.
- This clinical diagram can increase classification accuracy, proportionally to time spent classifying, when used by clinicians independently of their knowledge of AIS.
- Such clinical diagrams derived from algorithms could be of much use in complex 3-dimensional AIS classification.

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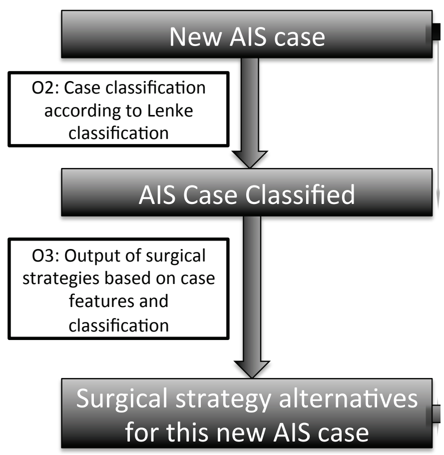
Chapter 5. A rule-based algorithm can efficiently output surgical strategy alternatives in the treatment of AIS.

This chapter includes the third paper of this thesis and was submitted to the European Spine Journal.

Phan P, Ouellet J, Mezghani N, de Guise JA, Labelle H.

A surgical strategy rule-based algorithm based on the literature can efficiently output surgical strategy alternatives in the treatment of AIS. Submitted to Eur Spine J. on April, 19th, 2014.

This articles presents a surgical strategy rule-based algorithm to ouput surgical treatment alternatives and answers objective 3.



Authors' contribution:

Phan P: Literature review, algorithm synthesis, statistical analysis, manuscript writing, submission and revision

Ouellet J: Literature review, manuscript editing

Mezghani N: Programing of algorithm for testing, revision of manuscript

de Guise JA: Revision of manuscript, project funding

Labelle H: Input on methodology, revision of manuscript, project funding

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A rule-based algorithm can efficiently output surgical strategy alternatives in the treatment of AIS

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Abstract:	Background: Variability in surgical strategies for the treatment of adolescent idiopathic scoliosis (AIS) has been demonstrated despite the existence of classifications to guide selection of AIS curves to include in fusion. Decision trees and rule-based algorithms have demonstrated their potential to improve reliability of AIS classification because of their systematic approach and they have also been proposed in algorithms for selection of instrumentation levels in scoliosis. Our working hypothesis is that a rule-based algorithm with a knowledge base extracted from the literature can efficiently output surgical strategies alternatives for a given AIS case. Our objective is to develop a rule-based algorithm based on peer reviewed literature to output alternatives surgical strategies for approach and level of fusion. Methods: A literature search of all English Manuscripts published between 2000 and December 2009 with Pubmed and Google scholar electronic search using the following keywords: "adolescent idiopathic scoliosis" and "surgery" alternatively with "levels of fusion" or "approach". All returned abstracts were screened for contents that could contain rules to include in the knowledge base. A dataset of 1556 AIS cases treated surgically was used to test the surgical strategy rule-based algorithm (SSRBA) and evaluate how many surgical treatments are covered by the algorithm. The SSRBA was programmed using Matlab. Descriptive statistic was used to evaluate the ability of the rule based algorithm to cover all treatment alternatives. Results: A SSRBA was successfully developed following Lenke classification's concept that the spine is divided into three curves segments (proximal thoracic (PT), main thoracic (MT) and thoraco-lumbar/lumbar (TL)). Each of the 1556 AIS patient in the dataset was ran

	through the SSRBA. It proposed an average of 3.78 (+/- 2.06) surgical strategies per case. Overall the SSRBA is able to match the treatment offered by the surgeon in approach and level of fusion 70% of the time (with one vertebral level leeway). Conclusion: This study is to the author's knowledge the first attempt at proposing an algorithm to output all surgical alternatives for a given AIS case. It uses a rule-based algorithm with a knowledge base extracted from peer-reviewed literature in an area with great variability. When tested against a database of AIS patients treated surgically, the SSRBA developed has the ability to propose a surgical plan with respect to approach and levels of fusion that matches the surgeon plan in a great majority of cases. Since this SSRBA seems to output multiple valid surgical strategies, it could allow the comparisons of various strategies for a given case and guide surgical treatment.

A rule-based algorithm can efficiently output surgical strategy alternatives in the treatment of AIS

Abstract:

Background:

Variability in surgical strategies for the treatment of adolescent idiopathic scoliosis (AIS) has been demonstrated despite the existence of classifications to guide selection of AIS curves to include in fusion. Decision trees and rule-based algorithms have demonstrated their potential to improve reliability of AIS classification because of their systematic approach and they have also been proposed in algorithms for selection of instrumentation levels in scoliosis. Our working hypothesis is that a rule-based algorithm with a knowledge base extracted from the literature can efficiently output surgical strategies alternatives for a given AIS case. Our objective is to develop a rule-based algorithm based on peer reviewed literature to output alternatives surgical strategies for approach and level of fusion.

Methods:

A literature search of all English Manuscripts published between 2000 and December 2009 with Pubmed and Google scholar electronic search using the following keywords: “adolescent idiopathic scoliosis” and “surgery” alternatively with “levels of fusion” or “approach”. All returned abstracts were screened for contents that could contain rules to include in the knowledge base. A dataset of 1556 AIS cases treated surgically was used to test the surgical strategy rule-based algorithm (SSRBA) and evaluate how many surgical treatments are covered by the algorithm. The SSRBA was programmed using Matlab. Descriptive statistic was used to evaluate the ability of the rule based algorithm to cover all treatment alternatives.

Results:

A SSRBA was successfully developed following Lenke classification’s concept that the spine is divided into three curves segments (proximal thoracic (PT), main thoracic (MT) and thoraco-lumbar/lumbar (TL)). Each of the 1556 AIS patient in the dataset was ran through the SSRBA. It proposed an average of 3.78 (+/- 2.06) surgical strategies per case. Overall the SSRBA is able to match the treatment offered by the surgeon in approach and level of fusion 70% of the time (with one vertebral level leeway).

Conclusion:

This study is to the author’s knowledge the first attempt at proposing an algorithm to output all surgical alternatives for a given AIS case. It uses a rule-based algorithm with a knowledge base extracted

from peer-reviewed literature in an area with great variability. When tested against a database of AIS patients treated surgically, the SSRBA developed has the ability to propose a surgical plan with respect to approach and levels of fusion that matches the surgeon plan in a great majority of cases. Since this SSRBA seems to output multiple valid surgical strategies, it could allow the comparisons of various strategies for a given case and guide surgical treatment.

Keyword: adolescent idiopathic scoliosis, algorithms, surgical treatment planning

Introduction:

Variability in surgical strategies for the treatment of adolescent idiopathic scoliosis (AIS) has been demonstrated [1-4] despite the existence of classifications to guide selection of AIS curves to include in fusion [5, 6]. As stated by Lenke et al [1], "best surgical treatment" for each AIS patient will require " a classification and grading system of AIS that allows similar curves to be grouped together to critically and objectively evaluate the variable treatments used for each particular curve patterns". Much research is undertaken to develop such a classification system [7-10], which would also include tri-dimensional features now available with advanced imaging systems and 3D-reconstructions. Different objectives for correction, known inter-observer variability of current classification systems, personal surgeon's preferences based on their previous experience, and/or the current lack of clearly defined guidelines were enumerated by Aubin et al, as potential sources of treatment variability [2]. Decision trees and rules-based algorithms have demonstrated their potential to improve reliability of AIS classification because of their systematic approach [9, 11, 12]; they have also been proposed in algorithms for selection of instrumentation levels in scoliosis which could prevent post-operative imbalance [13]. The purpose in properly selecting those levels of fusions is to minimize the length of the fusion to keep maximum mobility while allowing optimal correction of balance and deformity. Post-operative complication such as decompensation resulting in imbalance, junctional deformity, or unsatisfactory clinical results such as shoulder imbalance or residual gibosity should also be avoided by properly selecting those levels of fusion.

To date, most algorithms so select AIS surgical strategy have aimed at following one philosophy and compare cases following that philosophy to those that didn't. No algorithms have yet been published to enumerate alternatives surgical strategies for a given curve type according to Lenke classification. Such an algorithm would be required to find the "best surgical treatment". Our working hypothesis is that a rule-based algorithm with a knowledge base extracted from the literature can efficiently output surgical strategies alternatives for a given AIS case. Our objective is to develop a surgical strategy rule-based algorithm (SSRBA) based on peer reviewed literature to output alternatives surgical strategies for approach and level of fusion. We will then test that SSRBA's ability to output all considerable surgical strategies by testing it on a large multi-centric database of AIS cases treated surgically.

Materials and Methods:

Literature review and rule extraction

To identify recent published data on surgical strategies in treating AIS, we performed a literature search of all English Manuscripts published between 2000 and December 2009 with Pubmed and Google scholar electronic search using the following keywords: "adolescent idiopathic scoliosis" and "surgery" alternatively with "levels of fusion" or "approach". All returned abstracts were screened for contents that could contain rules to include in the rule-based algorithm; this included review papers, surgical techniques and original papers. Rules were also retained only if they were applicable to a case based on its Lenke classification. The totality of those rules formed the knowledge base for the rule-based algorithm. Case reports and small case series were nonetheless excluded to avoid inclusion of rules that were experimental and not adequately demonstrated due to small patient sample or short follow-up (less than 24 months).

Development of a rule-based algorithm

Rule-based systems represent a very simple technique, which uses a knowledge base of simple rules. Three components are required to create a rule based system [14, 15]:

1- A database, which contains a set of facts that represents the initial working memory. In our case our database of AIS cases was used to test the rule-based algorithm developed.

2- A knowledge base, which is a set of rules that should encompass any actions that should be taken within the scope of a problem, and is extracted from the literature review.

3- A rule interpreter, which controls the problem solving, process and determinates that one or many solutions have been found. In our case we have developed an algorithm based on the Lenke classification to act as the rule interpreter.

Given the known variability in surgical treatment of AIS, the goal in developing a SSRBA with multiple outputs is to be able to enumerate all possible surgical strategies alternatives based on published data for a given case. The SSRBA was developed following Lenke classification's concept that the spine is divided into three curves segments (proximal thoracic (PT), main thoracic (MT) and thoraco-lumbar/lumbar (TL)). This segmental approach determines whether a curve is structural or not and determines whether a fusion of the curve is required. While following in part this concept about Lenke's classification, rules were also included to evaluate the possibility to fuse a non-structural curve or leave a structural curve unfused based on additional clinical and radiological findings.

Results:

SSRBA designed from the knowledge base:

344 abstracts were returned from our literature search. 47 papers containing data on surgical strategies (approaches and levels of fusion) were retained. 40 rules, concerning surgical treatment strategy based on curve segment structurality, risk of junctional instability, deformation or clinical features were extracted from those papers and integrated in the SSRBA. Many rules overlapped and in general, followed the Lenke classification principle.

The SSRBA is separated into 3 parts (fig. 1), each part leading to a decision on the need or not to include a curve segment into the fusion. The SSRBA starts with an evaluation of the PT curve (Part I), if the curve is structural then posterior selective fusion (PSF) should be considered and the upper-instrumented vertebra (UIV) can be determined and go onto part III to determine the LIV or whether selective ASF is possible. If the PT curve is not structural, then we evaluate the MT structurality (Part II). If the MT curve is structural, we then determine the PSF UIV at the MT curve, and go onto part III but if it is not, then we need to see whether the TL curve is amenable to a selective fusion. In Part III, we already know that either the PT or the MT are structural and the PSF UIV determined, we need to decide on whether the TL curve is structural and its need to be included in the fusion or not. If so, only a PSF is possible and the lower-instrumented vertebra (LIV) determined. If not MT selective fusion should be considered.

For each part, the decision on curve structurality, the possibility for a selective fusion and the extent of fusion is based on rules extracted in the literature, summarized in figure 2 and each part detailed in the following paragraphs.

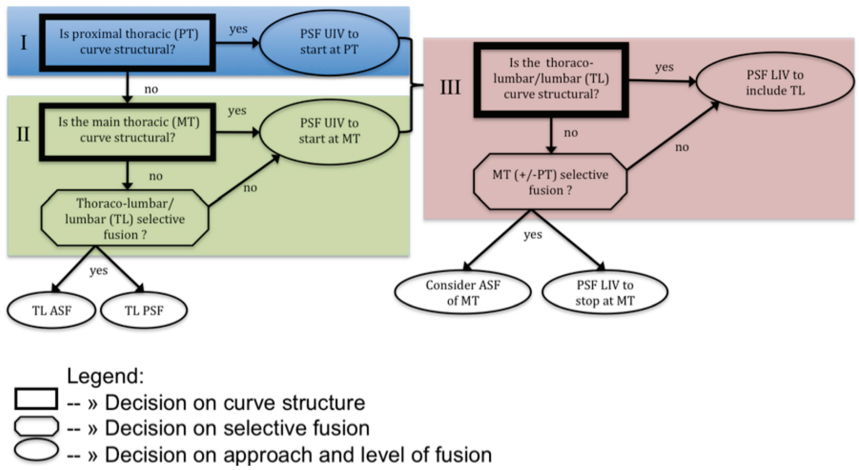


Figure 1: SSRBA mainframe to determine levels of fusion and approaches based on curve segment structurality. PSF: posterior spinal fusion ASF: anterior spinal fusion PT: proximal thoracic MT: main thoracic TL: thoraco-lumbar/lumbar UIV: upper instrumented vertebra LIV: lower instrumented vertebra

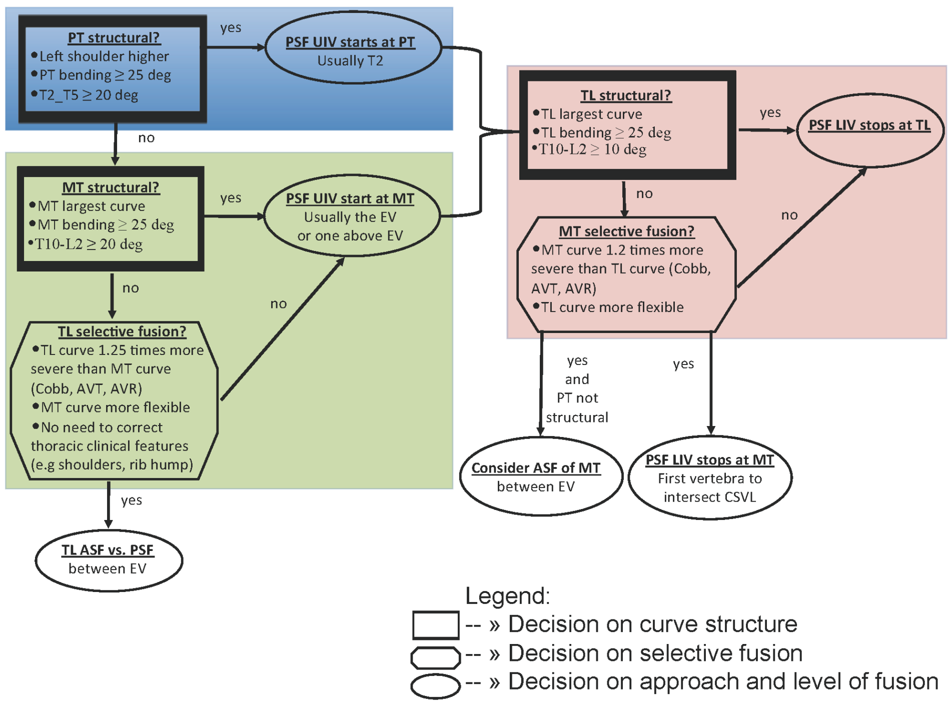
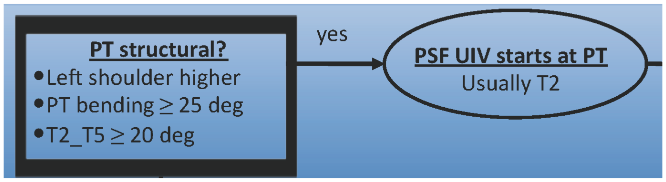


Figure 2: SSRBA including criteria for structurality and common rules for level of fusion.

In order to cover all possible surgical strategies, each decision in the SSRBA can go more than one way based on the criteria present at each step. For each decision on selective fusion, if all conditions are respected for a selective fusion, the SSRBA proposes that alternative and no other. If one or more of the selective fusion criteria are not met, non-selective fusion is also proposed. It should be noted that in testing our SSRBA, if data was missing in the database, the condition was not considered and decision on selective fusion was based on the remaining criteria to avoid excessive strategy suggestion for each case.

Part I: Definition of PT structurality and determination of the upper-instrumented vertebra

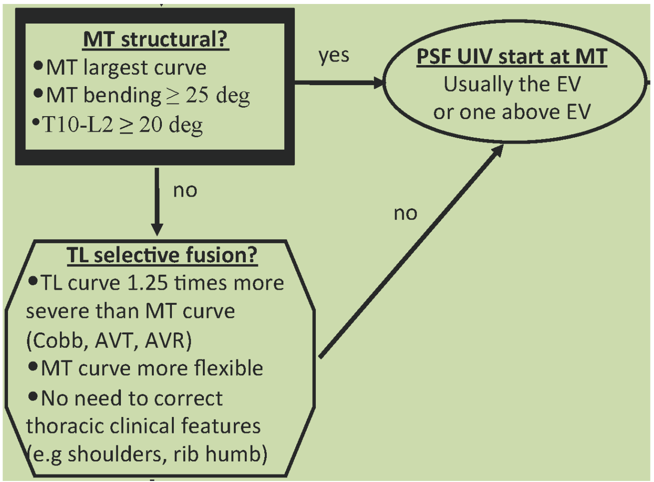


Proximal thoracic (PT) structurality defines the need to extend the fusion up to the upper instrumented vertebra usually between T1 and T3. A proximal thoracic curve is considered structural according to Lenke classification [6], if the PT curve is greater or equal to 25 degrees on AP bending X-ray films or T2-T5 Cobb angle on lateral X-rays is greater or equal to 20 degrees. The extent of the fusion to the upper-instrumented vertebra (UIV) then depends on shoulder height (Table 1). Overcorrection of the MT curve with segmental instrumentation increases the risk of PT curve decompensating and can result in elevation of the shoulder contralateral to the MT curve post-operatively. Therefore, Suk et al. proposed to include the proximal thoracic curve based on broader criteria than the Lenke classification does [19]. For non-structural curves based on Lenke classifications but having PT Cobb angle ≥ 25 on AP and left shoulder higher or level with right shoulder, clinician preference and judgment on the amount of correction applied to the main thoracic curve will define the need to include the PT curve or not.

Source	Criteria of structurality	Other criteria to determine UIV	PSF UIV to start at PT
[6, 20-22] [23]	Lenke type 2 or 4 PT Cobb angle on bending x-ray ≥ 25 Or T2-T5 Cobb angle on lateral x-ray ≥ + 20	Left shoulder higher than right shoulder *	T2
		Otherwise	T2 or T3
[19]	PT Cobb angle on AP x-ray ≥ 25 and left shoulder higher or level with right shoulder *		T1 or T2

Table 1: Definition of a structural proximal thoracic curve and fusion extent
* for right main thoracic curve

Part II: Definition of MT structurality, TL selective fusion and determination of the levels of fusion for selective TL fusion and UIV in MT fusion



As defined by Lenke classification [1, 6, 21], a MT curve is structural if its Cobb angle is the largest, it does not reduce below 25 degrees on bending or the T10-L2 sagittal Cobb angle is greater than 20 degrees (table 2). If any of those conditions is fulfilled, the MT curve should be included in the fusion. The MT curve should also be included in the fusion if a selective TL/L fusion is not amenable (Table 3). Following the algorithm, the PT is not structural and therefore the UIV is set to stop at the MT end vertebra[24,27] or one level above[24] particularly in the presence of an hypokyphotic thoracic curve [25] (Table 4).

If a MT curve is not structural, a selective TL/L fusion should be considered. In order to avoid decompensation of the unfused MT curve following selective TL/L fusion, attention should be paid to ensure that the TL curve is larger, less flexible, more rotated and translated than the MT curve. In addition, specific attention should be given to the TL/L junction, which should be included in the fusion if greater than 20 degrees to avoid development of junctional kyphosis. When a selective TL/L fusion is decided, several options are possible. An anterior spinal fusion (ASF) has the advantage of saving levels of fusion, particularly when the Hall's concept of overcorrection is applied (table 5). Attention should be paid to the contra-indication for ASF regarding immature skeletal age and regional kyphosis[26-28] [29-

34]. In a TL/L ASF, the TL/L curve is usually fused between the end vertebra, when Hall's concept is applied, a shorter fusion can be achieved within the end vertebra depending on the localization of the apex. Hall's concept should only be applied for TL curve with apex between T11 and L1, which are more than 50% flexible on bending and lack regional kyphosis. When an ASF is not amenable, a PSF is also possible between the end vertebras if there is no junctional kyphosis. In case of junctional kyphosis with sagittal Cobb angle T10-L2 > 20 degrees, the MT curve should be included in the fusion. Depending on the remaining criteria of the MT curve, shall the surgeon decide to still select a selective TL fusion; the TL junction should be included with a fusion from T8 or T9 down to the TL stable vertebra.

Source	Criteria of structurality of MT curves
[6]	If any of the following - MT Cobb angle largest - MT Side bending Cobb ≥ 25 deg. - T10-L2 kyphosis ≥ 20 deg.

Table 2: criteria for structural main thoracic curve

Source	Criteria for TL selective fusion
[35, 36]	Radiological criteria: Ratio criteria (TL/L:MT) > 1.25 Cobb AVT AVR MT flexibility > TL/L (ideally MT S.B. >25°) Lack of TL junctional kyphosis (T10–L2 < +20°) TL = thoracolumbar; L = lumbar; MT = main thoracic; AVT = apical vertebral translation; AVR = apical vertebral rotation.
	Clinical criteria: Shoulders level or left shoulder high TL/L trunk shift > MT trunk shift TL/L scoliometer measurement > MT scoliometer measurement by 1.2 ratio Thoracic rib prominence acceptable to patient, parent, and surgeon preoperatively, because thoracic rib cage will undergo minimal change postoperative TL = thoracolumbar; L = lumbar; MT = main thoracic

Table 3: Radiological and clinical criteria required for a TL selective fusion (from [35], permission pending)

Source	Criteria for UIV selection	UIV
[24]	Selective fusion of MT (not including the PT)	One level higher than MT end vertebra
[25, 37]	Same	UIV is the upper EV of the MT

Table 4: Determination of PSF UIV in structural MT curve with non-structural PT curve

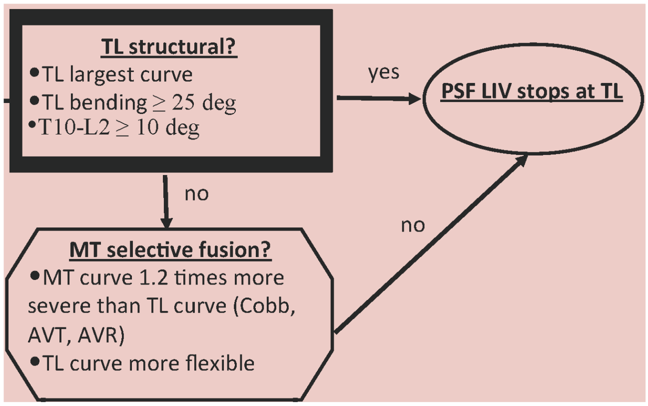
Selection of instrumented vertebra based on end vertebra:			
Source	**Criteria for this selection**	**UIV**	**LIV**
[26-28] [29-34]	Contra-indication to ASF for TL/L curve: - Tri-radiate cartilage still opened [34] - Risser grade 0 or 1 [35] - Thoracic curve hyperkyphotic (Sagittal Cobb T5-T12 > 40) → In those cases consider PSF	TL/L UEV	TL/L LEV
Hall concept: Overcorrection of the apical segments Prerequesite [38]: - Apex T11-L1 - Upper and lower curves correct to at least 50% on bending X-rays - Less than 10 deg of kyphosis in thoracic spine over length of instrumentation - Less than 60 deg of kyphosis on thoracic curve above			
Source	**Criteria for this selection**	**UIV**	**LIV**
[22, 38-40]	Apex is a vertebra	One level proximal to TL/L apex	One level distal to TL/L apex
	Apex is a disc	Two levels proximal to TL/L apex	Two levels distal to TL/L apex
[26, 27]	Hall concept based on EV	One level distal to TL EV TL/L UEV +1	One level proximal to TL EV TL/L LEV-1

Table 5: Anterior Selective Fusion of the TL/L curve

Source	Criteria for this selection	UIV	LIV
[41]	In case of junctional kyphosis (T10-L2 >20 degrees)	T8 or T9	TL SV
[27, 28, 39, 42, 43]	All pedicle screws constructs	TL/L UEV	TL/L LEV

Table 6: Posterior Selective Fusion of the TL/L curve

Part III: Definition of structural thoraco-lumbar/lumbar curve and determination of the lower-instrumented vertebra



As defined by Lenke classification [1, 6, 21], a TL curve is structural if its Cobb angle is the largest, it does not reduce below 25 degrees on bending or the T10-L2 sagittal Cobb angle is greater than 20 degrees (table 7). If the TL curve is structural then the LIV for a PSF remains to be set. Several rules have been extracted to choose the LIV. Commonly, the LIV is set at L3 or L4 for scoliosis with double curves and several rules exist concerning which of the two vertebras to choose from (table 8).

If the TL curve is not structural, a selective MT fusion should be considered. In order to avoid decompensation of the unfused TL curve, inversely to a selective TL fusion, attention should be paid to ensure that the MT curve is larger, less flexible, more rotated and translated than the TL/L curve. In the presence of junctional kyphosis, the TL junction should be included and fusion extended to include that junction, usually down to L1 or L2 (Table 8). In order to accomplish a MT selective fusion ASF or PSF are possible. ASF is particularly suited for hypokyphotic thoracic spines, skeletally immature patients to avoid Krankshaft phenomenon and allows good spontaneous correction of Lenke “C” lumbar modifier curves while saving 1 to 3 levels of fusion compared to a posterior fusion. Nonetheless, several contra-indications related to patient curve magnitude, local kyphosis, pulmonary function, patient weight and compliance particularly when a thoracoscopic techinique is used have to be checked to consider an ASF (table 10). ASF is usually done between the MT end-vertebra. If PSF is chosen the fusion is usually extended to the last vertebra touched by the CSVL or chosen in relation to the neutral vertebra (table 11).

Source	Criteria of structurality of TL curves
[6]	If any of the following - TL Cobb angle is the largest - TL Side bending Cobb ≥ 25 deg. - T10-L2 kyphosis ≥ 20 deg.
[44, 45]	T10-L2 kyphosis ≥ 10 deg.

Table 7: criteria for structural Thoraco-Lumbar/Lumbar curve

Source	Criteria for this LIV selection	Lower Instrumented Vertebra (LIV)
[20]	For Lenke curve type 3, 6 (double major) or 4 (triple major)	L3 or L4 with the level determined by the most proximal lumbar level intersected by the CSVL
[21]	For Lenke curve type 3, 6 and 4, if any of the following: - apex of the TL/L curve is L2 or caudad, - the L3-4 disc is convex or open on the convexity of the TL/L curve - L4 is a grade I Nash-Moe rotation or greater	L4
[21]	For Lenke curve type 3, 6 and , if any of the following - apex is the L1-2 disc or cephalad - the L3-4 disc is neutral or closed on the convex side of the TL/L curve - L3 is a grade 1.5 or less Nash-Moe rotation	L3
[44]	If T10-L2 kyphosis ≥ 10 deg then PSF should include the junctional level to avoid DJK	MT end-vertebra + 1 or 2 levels distal (usually L1 or L2)

Table 8: Determination of PSF LIV in structural MT and TL curves

Source	Criteria of structurality of MT curves
[35, 36]	Radiological criteria: Ratio criteria (MT:TL/L) > 1.2 Cobb AVT AVR TL/L flexibility > T (ideally TL/L S.B. <25°) Lack of TL junctional kyphosis (T10–L2 < +10°) MT = main thoracic; TL = thoracolumbar; L = lumbar; AVT = apical vertebral translation; AVR = apical vertebral rotation. Clinical criteria: Right shoulder high or shoulders level Thoracic trunk shift > lumbar waistline asymmetry Thoracic scoliometer measurement > lumbar scoliometer measurement minimum 1.2 ratio

Table 9: Radiological and clinical criteria required for a MT selective fusion (from [35], permission pending)

<table>
<tr><td colspan="4">Indications and advantages for ASF alone [29, 41, 46]:
- Lenke “-“ sagittal thoracic modifier
- “C” lumbar modifier to optimize spontaneous lumbar correction
- Skeletally immature patients at risk for crankshaft with PSF alone
- Ability to save 1 to 3 lumbar fusion level</td></tr>
<tr><td>Source</td><td>Criteria for this selection</td><td>UIV</td><td>LIV</td></tr>
<tr><td>[29, 32, 41, 47, 48]</td><td>Contra-indication to OPEN ASF for MT curves
- pre-operative hyperkyphosis:
T5-T12 > 30 [49] [50] [51, 52], T5-T12 > 40 [32]
- curve too great: > 80 [48] [6]
- Weight < 70 kg [32]
(relative, particularly for single rod instrumentation)
- Smoking
- T1 tilt > 5 deg and Left shoulder elevated on PE [53]
or SH > 5mm → PSF to T1 [54]
- More than one structural curve</td><td>MT UEV</td><td>MT LEV as distal as possible if two vertebras are parallel</td></tr>
<tr><td>[51, 52, 55]</td><td>Selection criteria for thoracoscopic ASF for MT curves
From [51, 52]:
Girl (adolescent rather than juvénile)
- Type 1- (A, B ou C) [26]
- MT < 70
- Sagittal T5-T12 < 30
From [55]:
- Structural thoracic Adolescent or Adult idiopathic scoliosis with normal bone density
- MT between 40 and 70
- MT on bending <30
- End vertebra less than 8 vertebras apart
- Limited within T4-L1
- Contra-indication:
o Rigid MT > 70
o Sagittal T5-T12 < 40 [56]
o Previous thoracic surgery
o History of recurrent pneumonia, TB or abnormal lung function
o Seizure disorder or non-compliance with post-op instructions</td><td>MT UEV</td><td>MT LEV as distal as possible if two vertebras are parallel</td></tr>
</table>

Table 10: Anterior Selective Fusion of the MT curve

<table>
<tr><td colspan="3">Indication for PSF alone:
- Lenke “N” or “+” sagittal thoracic modifier
- Large patient size
- Fusion to same distal vertebra as ASF</td></tr>
<tr><th>Source</th><th>Criteria for this selection</th><th>LIV</th></tr>
<tr><td>[26, 57]</td><td>Fusion up to the last vertebra to touch the CSVL</td><td>Usually
MT LEV + 1</td></tr>
<tr><td rowspan="2">[58] [19]</td><td rowspan="2">Fusion based on the Neutral vertebra</td><td>MT end vertebra and MT neutral vertebra no more than 2 vertebra apart → fusion to neutral vertebra</td></tr>
<tr><td>MT end vertebra and MT neutral vertebra more than 2 vertebra apart → fusion to 1 level above neutral vertebra</td></tr>
</table>

Table 11: Posterior Selective Fusion of the MT curve Posterior Selective Fusion of the MT curve Posterior Selective Fusion of the MT curve

The dataset:

This dataset was complete for all radiographic measurements related to Lenke classification determination (this includes AP standing and bending PT, MT and TL/L Cobb angle as well as sagittal T2-T5 and T10-L2 Cobb angles) but partial for other radiographic measurements and some clinical data (table 12). As specified above, when the SSRBA is tested against the data set, lacking data is neutralized so that decision is based on remaining available data. In cases where critical data was missing, such as shoulder height, AVT or AVR, which are occasionally single elements required to determine selective fusion or the levels of fusion, both treatment alternatives are proposed by the algorithm. It can be noticed that radiographic data are more consistently complete than clinical data and that for a same clinical measurement (scoliometer reading) is not reported as completely for all curves. Incompleteness of the dataset was handled to limit consequences on the SSRBA testing as described above.

Data	Cobb angle for Lenke classification (PT, MT, TL/L upright and bending) and sagittal Cobb angles	Apical vertebral translation (MT and TL)	Apical vertebral rotation (MT and TL)	Radiographic Shoulder height	Scoliometer reading for PT/MT/TL
Total record complete	1556	1556	1461	978	785/1239/1126
Percentage	100%	100%	93%	62%	50%/80%/72%

Table 12: Completeness of dataset for variables used for decision

Testing of the SSRBA:

Each of the 1556 AIS patient in the dataset was ran through the algorithm. It proposed an average of 3.78 (+/- 2.06) surgical strategies per case. Subdivision on the number of proposition per Lenke class is displayed in table 14. Overall the SSRBA is able to match the treatment offered by the surgeon in approach and level of fusion 70% of the time (with one vertebral level leeway). The SSRBA outputted more consistent levels of fusion for the LIV (91.9%) than the UIV (77.5%). Propositions were more likely to match with surgeon treatment for Lenke type 1 (74.8%), type 2 (72.6%) and type 5 (74.7%) while Lenke type 3 (45%), type 4 (40.4%) and type 6(62%) were more often treated differently than proposed by the SSRBA output.

Single curve types were the one with the most propositions per cases on average Lenke curve type 1 (4.64 propositions per cases) and curve type 5 (5.08 propositions per cases) while multiple curve patterns all had less than 3 propositions per cases on average.

	One SSRBA proposition match surgeon treatment	No match for any of the propositions with surgeon treatment
Approach with UIV and LIV	70% (1089 / 1556)	30% (467/1556)
Approach and UIV	77.5% (1206/1556)	22.5% (350/1556)
Approach and LIV	91.9% (1417 /1556)	8.9% (139/1556)

Table 13: Ability of the SSRBA to match with one of the surgeon surgical strategy for approach and levels of fusion

Lenke curve type	Number of cases	Mean number of propositions per cases	Standard deviation	SSRBA proposition matching surgeon treatment
1	715	4.64	2.12	74.8%
2	339	2.62	1.09	72.6%
3	111	1.86	0.88	45%
4	52	1.35	0.48	40.4%
5	214	5.08	1.51	74.7%
6	125	2.51	1.05	62%
Overall	1556	3.78	2.06	70%

Table 14: SSRBA proposition matching surgeon treatment by Lenke class

Discussion

This study is to the author's knowledge the first attempt at proposing an algorithm to output all surgical alternatives for a given AIS case. The Lenke classification system is the benchmark system and most of the current literature proposes recommendations based on it. Therefore we used it as a backbone to develop that SSRBA. Yet, as stated by Trobisch et al[59], existing treatment algorithms do not account for every exception, and further research is required to improve long-term surgical outcomes. It is with this goal in mind that this study was undertaken.

In developing the SSRBA, segmentation of the spine into three segments permitted to extract rules related to each Lenke curve types and keep the structure of the Lenke classification. In recent review papers based solely on Lenke classification stating the author's preference in selecting fusion levels in patients with AIS[20-22, 59, 60], it was found that our algorithm includes a great majority of the rules stated by each of those papers but also includes many additional rules published and on which other surgeons might base their surgical strategy. In this respect this SSRBA fulfills its rules in offering as many alternative strategies as possible.

When comparing surgeon treatment with outputs from the SSRBA, results do show an overall good coverage of all surgical strategies (70%). It is important to highlight that this study used a one level leeway in order to accept a surgeon strategy as similar to one of the outputs from the SSRBA. Most studies compare the inclusion or exclusion of each of the curves when comparing strategies[61-63]. This level of accuracy in determining the surgical strategy was wished by the author in order to use the rules which are usually based on specific vertebras as precisely as possible. In this study, we found that simple curve types (type 1,2 and 5) had more surgical strategies published in the literature than complex curve types (type 3,4,6). Also, anterior approach for fusion is reserved to a specific subpopulation of simple curve types and not applicable to complex curve types. Finally, our algorithms will tend to non-selective fusion if any of the selective fusion criteria is not fulfilled. This resulted in many more propositions by cases for simple curve types than complex ones but also a higher match rate between surgeon strategy and output from the SSRBA for simple curve types.

In recent years, there has been a shift toward shorter fusion given the powerful correction that can be achieved by all posterior pedicle screw constructs and the development of derotation techniques[64]. Therefore due to ongoing improvements in instrumentation and classification, protocols often are outdated before they have been validated[59]. In doing an extensive literature review and including all peer-reviewed validated rules, that SSRBA was developed, yet some rules such as the extension of the distal level of fusion to L3 or L4 in complex curve types are still heavily debated. Some consider that fusion down to L4 should be only reserved if a level disk is to be achieved but avoided to prevent accelerated wear of the remaining L5-S1 segment.

Limitations of this study include the analysis done from a database of radiographic measurements rather than from the x-ray themselves. This has played a role in the determination of the UIV and LIV because some rules rely on specific radiographic findings which were not in the database such as “the last vertebra touched by the CSVL”, instead we had to rely on common rules on the position of that last vertebra to cross the CSVL in relation to the reference vertebra such as the end, neutral or stable vertebra. Also the database was not complete as stated in table 12. The missing data will likely have led to some inaccuracies in the ability of our SSRBA to properly output a surgical strategy that could have matched the surgeon’s.

Conclusion

In this study we have successfully developed a SSRBA able to output multiple surgical strategies based on rules extracted from the literature. The surgical strategies from the SSRBA matched the surgeon's plan in 70% of cases on average with respect to approach, UIV and LIV at one vertebra level leeway. Surgical strategies were better matched for simple curve types as opposed to complex ones for which less surgical strategies were proposed and for which the literature is less extensive. The development of SSRBAs able to output surgical strategy alternatives should allow the comparisons of various strategies for a given case and guide treatment for those cases that do not fit in typical curve types[59, 61, 62].

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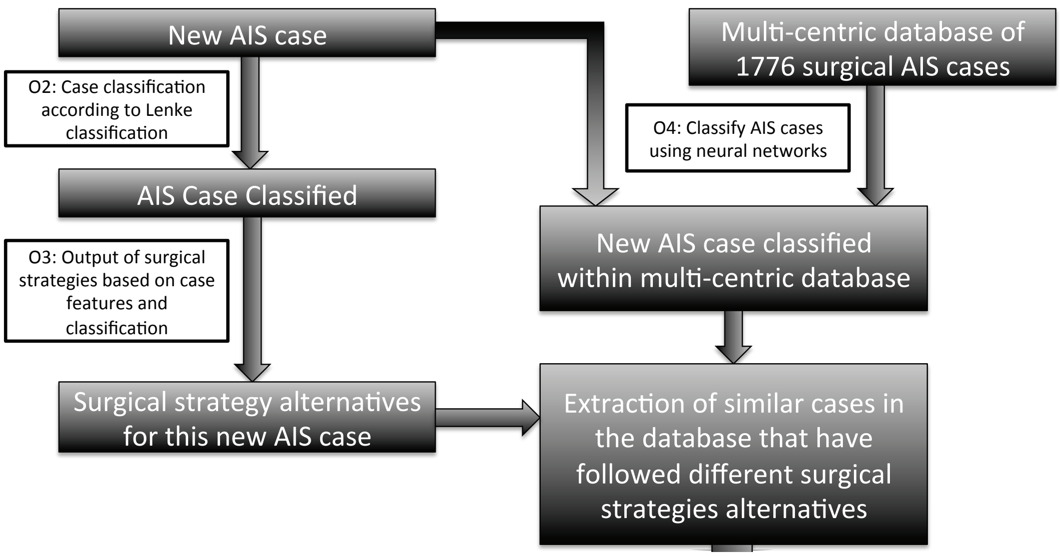
Chapter 6. Use of Kohonen Self-Organizing-Maps to classify AIS and analyse treatment patterns.

This chapter includes the fourth and fifth articles of this thesis.

Both articles present the classification for AIS using a Kohonen Self-Organizing-Map.

The fourth article presents the technical aspect of the classification and its validation while the fifth article focuses on its clinical implications and how it highlights treatment variability based on curve types.

Those articles answer objective 4.



<u>Mezghani N, Phan P, Mitiche A, Labelle H, de Guise JA.</u>

<u>A Kohonen neural network description of scoliosis fused regions and their corresponding Lenke classification. Int J Comput Assist Radiol Surg. 2012 Mar;7(2):257–64.</u>

<u>Authors' contribution:</u>

Mezghani N: Literature review, Neural Network programing, statistical analysis, manuscript writing, submission and revision

Phan P: Manuscript editing, clinical interpretation of results

Mitiche A: Input on Neural Network programing.

de Guise JA: Revision of manuscript, project funding

Labelle H: Revision of manuscript, project funding

Phan P, Mezghani N, Wai EK, de Guise J, Labelle H.
Artificial neural networks assessing adolescent idiopathic scoliosis: comparison with Lenke classification. The spine journal : official journal of the North American Spine Society. 2013 Nov;13(11):1527–33.

Authors' contribution:

Phan P: Literature review, Neural Network analysis with Kappa statistic maps, statistical analysis, manuscript writing, submission and revision

Mezghani N: Neural Network programming, manuscript editing

Wai EK: Manuscript editing and revision

de Guise JA: Manuscript revision, project funding

Labelle H: Data clinical interpretation, manuscript revision, project funding

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ORIGINAL ARTICLE

A Kohonen neural network description of scoliosis fused regions and their corresponding Lenke classification

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Abstract
Purpose Surgical instrumentation for adolescent idiopathic scoliosis (AIS) is a complex procedure where selection of the appropriate curve segment to fuse, i.e., fusion region, is a challenging decision in scoliosis surgery. Currently, the Lenke classification model is used for fusion region evaluation and surgical planning. Retrospective evaluation of Lenke classification and fusion region results was performed.
Methods Using a database of 1,776 surgically treated AIS cases, we investigated a topologically ordered self organizing Kohonen network, trained using Cobb angle measurements, to determine the relationship between the Lenke class and the fusion region selection. Specifically, the purpose was twofold (1) produce two spatially matched maps, one of Lenke classes and the other of fusion regions, and (2) associate these two maps to determine where the Lenke classes correlate with the fused spine regions.
Results Topologically ordered maps obtained using a multi-center database of surgically treated AIS cases, show that the recommended fusion region agrees with the Lenke class except near boundaries between Lenke map classes. Overall agreement was 88%.
Conclusion The Lenke classification and fusion region agree in the majority of adolescent idiopathic scoliosis when reviewed retrospectively. The results indicate the need for spinal fixation instrumentation variation associated with the Lenke classification.

[redacted]

Keywords Adolescent idiopathic scoliosis · Neural network · Lenke classification · Fusion level · Computer-aided decision

Introduction

Adolescent idiopathic scoliosis (AIS) is a complex three-dimensional (3D) deformation of the natural shape of the spinal column. AIS patients have pathological spinal curves in the coronal plane, alterations of the kyphosis or lordosis in the sagittal plane, and rotations of the vertebrae. The surgical instrumentation for the AIS is a complex procedure involving many difficult decisions, such as the spinal segments to instrument, the type/location/number of hooks or screws, the rod diameter/length/shape, the implant attachment order, and the amount of rod rotation [1]. The goal of the surgery is to perform a stable correction of the spinal deformity while leaving as many mobile spinal segments as possible. The selection of the appropriate spinal region to be fused remains a challenging decision in scoliosis surgery. As an illustration of this challenge, Fig. 1 shows a radiograph of a spine severely deformed by scoliosis (Fig. 1a) and a series of radiographs in which spines are straightened using different instrumentations (Fig. 1b–e). The attachments vary according the location as well as the severity and the geometry of the deformity.

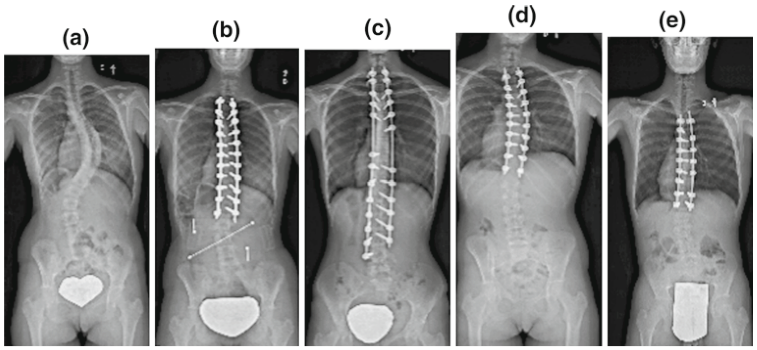
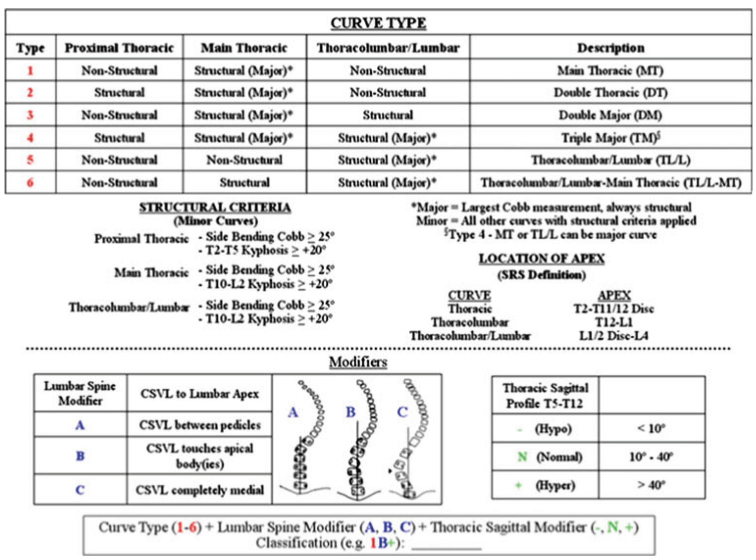


Fig. 1 **a** Pre-surgery severely deformed scoliotic spine; **b** surgery corrected spine by implants at selected appropriate segments; **c–e** three different cases of surgery corrected scoliosis spines



CURVE TYPE

Type	Proximal Thoracic	Main Thoracic	Thoracolumbar/Lumbar	Description
1	Non-Structural	Structural (Major)*	Non-Structural	Main Thoracic (MT)
2	Structural	Structural (Major)*	Non-Structural	Double Thoracic (DT)
3	Non-Structural	Structural (Major)*	Structural	Double Major (DM)
4	Structural	Structural (Major)*	Structural (Major)*	Triple Major (TM)§
5	Non-Structural	Non-Structural	Structural (Major)*	Thoracolumbar/Lumbar (TL/L)
6	Non-Structural	Structural	Structural (Major)*	Thoracolumbar/Lumbar-Main Thoracic (TL/L-MT)

STRUCTURAL CRITERIA
(Minor Curves)

Proximal Thoracic - Side Bending Cobb $\geq 25°$
- T2-T5 Kyphosis $\geq +20°$

Main Thoracic - Side Bending Cobb $\geq 25°$
- T10-L2 Kyphosis $\geq +20°$

Thoracolumbar/Lumbar - Side Bending Cobb $\geq 25°$
- T10-L2 Kyphosis $\geq +20°$

*Major = Largest Cobb measurement, always structural
Minor = All other curves with structural criteria applied
§Type 4 - MT or TL/L can be major curve

LOCATION OF APEX
(SRS Definition)

CURVE	APEX
Thoracic	T2-T11/12 Disc
Thoracolumbar	T12-L1
Thoracolumbar/Lumbar	L1/2 Disc-L4

Modifiers

Lumbar Spine Modifier	CSVL to Lumbar Apex
A	CSVL between pedicles
B	CSVL touches apical body(ies)
C	CSVL completely medial

Thoracic Sagittal Profile T5-T12	
- (Hypo)	< 10°
N (Normal)	10° - 40°
+ (Hyper)	> 40°

Curve Type (1-6) + Lumbar Spine Modifier (A, B, C) + Thoracic Sagittal Modifier (-, N, +)
Classification (e.g. 1B+): ________

Fig. 2 The chart describing the criteria of the Lenke curve classification [10]

Currently, the Lenke classification model is prevalent in surgical planning to determine the appropriate region of the spine to be fused. The Lenke model is described by a chart, called the Lenke chart, which specifies the criteria to separate the spine curve shapes into six different types. A Cobb angle characterizes the spine curve in one of three spine regions, namely, the proximal thoracic (PT) defined between the 2nd and 5th thoracic vertebrae (T2-5), the main thoracic (MT) defined between the 5th and 12th thoracic vertebrae (T5-12), and the thoracolumbar/lumbar (TL/L) between the 10th thoracic and the 2nd lumbar vertebrae (T10-L2).

As shown in Fig. 2, the curves are classified as major or minor, with the largest curve by Cobb angle measurement being designated the major curve. The minor curves are further classified as structural or non-structural depending on the curve flexibility and sagittal alignment. The classification is performed using *strict cut-offs* of the Cobb angle measurements on the coronal and the sagittal X-rays. However, there is a well known *variability* in Cobb angle measurements, which some studies have evaluated to be up to 10° [2,13]. Therefore, and paradoxically, the Lenke classification relies on strict rules applied to measurements subject to high variability. *In turn, this can cause an undesirable variability in the treatment*.

For instance, according to this chart, a difference of as little as one degree in the T10-L2 kyphosis measurement (structural criteria in Fig. 2) can turn a Lenke 4 classification into a Lenke 2, resulting into two different fusion recommendations. Such a variability in surgical planing and treatment of AIS has been of concern in clinical practice [1,22]. For instance, in [22], five AIS cases have been proposed to thirty-two experienced spinal deformity surgeons for surgical planning. The authors demonstrated a high variability in the number of implants used and in the fusion region selected. The Lenke et al. [11] study found that the Lenke classification system predicted the appropriate treatment of the fused region in only 90% of the 606 AIS cases treated surgically by multiple centers.

A few studies have investigated clustering of spinal geometrical 3D descriptions [5,24] to identify a number of AIS Lenke spine deformity classes and to classify the AIS cases according to their severity [16]. However, these studies did not address the relationship between the AIS classes and the surgical treatment.

Using a large database of surgically treated AIS cases, our present study investigates a topologically ordered self organizing Kohonen network, trained using Cobb angle measurements, to determine the relationship between the Lenke classification and the fusion level selection. There are two main benefits of using a Kohonen network. First, it is an efficient unsupervised classifier [6] and, second, it provides a two dimensional visual display of the results which can be convenient to clinicians.

Specifically, the purpose of this study is twofold (1) produce two spatially matched maps, one of Lenke classes and the other of fusion levels, and (2) associate these two maps to determine where the Lenke classes correlate with the fused spine regions and where they do not. Our hypothesis is that comparing topologically ordered self organizing neural maps of AIS Lenke classes and their corresponding fusion region selections can afford a useful description of the instrumentation variability. In a clinical application, the Kohonen maps can be used to determine, for a given AIS case to treat, which cases of the database are most similar and, therefore, which surgical treatment is most appropriate because these maps not only show the Lenke classes similarity but also the corresponding fusion region region variability.

The remainder of this paper is organized as follows: The second section explains the Kohonen neural network. The third section describes the database and the fourth section presents results. Finally, the fifth section contains a discussion, a conclusion, and an outlook on future work.

The Kohonen neural network

The Kohonen neural network [6], also called the Kohonen associative memory, and self organizing map (SOM), has been the focus of an impressive number of studies in a variety of fields such as optimization, pattern recognition, image processing, and robotics. The bibliography of Oja et al. [19] for instance, gives an addendum of 2,096 references to a previous compilation of 5,384 scientific papers where the Kohonen network is used.

The Kohonen neural network [6], implements a clustering algorithm similar to K-means [4,12,21]. It is also a vector quantizer because it represents a given large collection of data patterns by a small set of representative patterns of the same dimension [7,16,17,23]. In coding theory these representative elements are often called code words and form the code book. The nodes in a Kohonen network are organized in a one- or two-dimensional array as shown in Fig. 3. The network can be viewed as an associative memory which encodes input patterns in the form of weight vectors stored at its nodes. The weight vectors are of the same dimension and nature as the input patterns. A characteristic of the Kohonen associative memory is its *self-organizing topological ordering*: neighboring nodes encode neighboring weight values, creating a spatial ordering among nodes.

The algorithm to build a Kohonen map from training data is given in the "Appendix".

Kohonen map quality: topographic error

A useful indicator to evaluate the quality of a trained Kohonen network is the topographic error. This error measures the

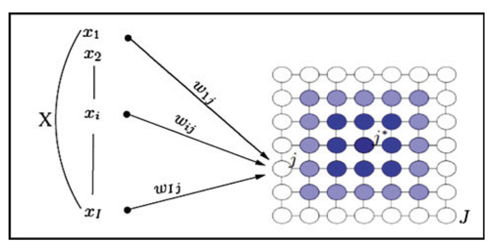


Fig. 3 A two-dimensional Kohonen memory of J nodes. $X = (x_1, x_2, ..., x_I)$ is an input data vector of dimension I and $W_j = (w_{1j}, \ldots, w_{Ij})$, the output of the training, are the weight vectors stored at nodes $j = 1, \ldots, J$. j^*, the winner node, contains the weight vector closest to the current input X

Table 1 Fusion region categories: five fusion patterns were determined based on which curve segments were fused, annotated F1–F5 [20]

Fusion region	Lenke class	Fused curve
F1	Lenke 1	MT
F2	Lenke 2	PT and MT
F3	Lenke 3 and Lenke 6	MT and TL/L
F4	Lenke 4	PT, MT and TL/L
F5	Lenke 5	TL/L

proportion of all data vectors for which the first and second best-matching units (BMU) are not adjacent vectors [25,27], i.e., the proportion of all data vectors for which the first and second nearest neighbor nodes are not adjacent nodes in the Kohonen map. The topographic error is calculated according the Eq. 1:

$$T\_\text{error} = \frac{1}{N}\sum_{i=1}^{N} u(X_i) \quad (1)$$

where the function $u(X_i)$ is equal to 1 if X_i data vector's first and second BMUs are adjacent, and 0 otherwise.

Kohonen agreement map

The Kohonen network is trained using the Cobb angles. The training algorithm does not use the Lenke class and the fusion region information. However after training, we project the Lenke classes to obtain a *Lenke class map*. We also project the fusion levels to obtain a spatially matched *fusion region map*. From these we build an *agreement map* as follows: let $l(j)$ be the Lenke class at node j, $f(j)$ the fusion level label, and $a(j)$ the agreement label. Then, $a(j) = 1$ if $l(j)$ agrees with $f(j)$ and 0 otherwise (Fig. 6a). Agreement is determined according the correspondence in Table 1.

The database

The Kohonen map is trained using a database of 1,776 surgically treated AIS cases. The cases were extracted from a multi-center collection developed by the members of the Spinal Deformity Study Group (SDSG). The database contains the patients complete information such as demographic characteristics, the deformity Lenke class, and surgical pre- and post-operative summary. The prevalence of the six Lenke classes in the database are different (Lenke 1: 46.2%, Lenke 2: 21.8%, Lenke 3: 7.3%, Lenke 4: 3.5%, Lenke 5: 12.8%, and Lenke 6: 7.5%).

The database also contains radiographic measurements, in particular the eight Cobb angles which we used to train the Kohonen maps, namely,

- On the coronal plane: Pt, Mt and Tt, which are the proximal thoracic, the main thoracic, and the thoraco-lumbar/lumbar angles, respectively.
- On side-bending radiographs on the coronal plane: Pt_B, Mt_B, and Tt_B which designate, respectively, the proximal thoracic, the main thoracic, and the thoracolumbar/lumbar angles.
- On the sagittal plane: Pt_H and Mt_H which, respectively, are the proximal thoracic and the main thoracic kyphosis angles.

For the Pt_H and the Mt_H angles, the sign is important because it differentiates between lordosis and kyphosis.

We generated five fusion region categories using criteria extracted from peer reviewed articles [3,8,14,15], confirmed by a senior orthopaedic surgeon (co-author H. Labelle), and compiled in [20]. The fusion regions are based on the curve segments fused as detailed in Table 1. PT curves were considered fused if the upper instrumented vertebra (UIV) was above or included T3. MT curves were considered fused if the UIV was between T4 and T9 and the lower instrumented vertebra (LIV) was above L2 included. TL/L curves were considered fused if the UIV was below T10 or the LIV was below or included L3. Specific clinical details on fusion region categories can be found in [9].

Experimental results

The Kohonen map is trained using the Cobb angle measurements in the database. Training required several experiments to determine the network size to obtain convergence of the weights to their final value and topological ordering. This is done by making several passes through the entire database of Cobb angles. Figure 4a, b show the Lenke class map after, respectively, one pass and ten passes, and Fig. 4c shows the final map.

The label in each node designates the Lenke class: it is the Cobb angle related class most frequently projected on the node. A node has no label as long as it has not been the site of a Cobb angle projection. Figure 4a–c illustrate the progressive appearance of clusters of nodes with the same label, i.e., the self organizing property of the Kohonen network. The trained map was a 9×8 (72 nodes) network of hexagonal nodes, obtained after a duration of 45 passes trough every item of the Cobb angle measurements database.

The size of the map is generally chosen empirically: several sizes are tried out and the one which produces the smallest topographic error (Eq. 1) is retained. The topographic error ($T_$error) for the trained map is 0.02, which means that for 2% of the training data, the first and second nearest neighbor nodes in the Kohonen map are not spatially adjacent.

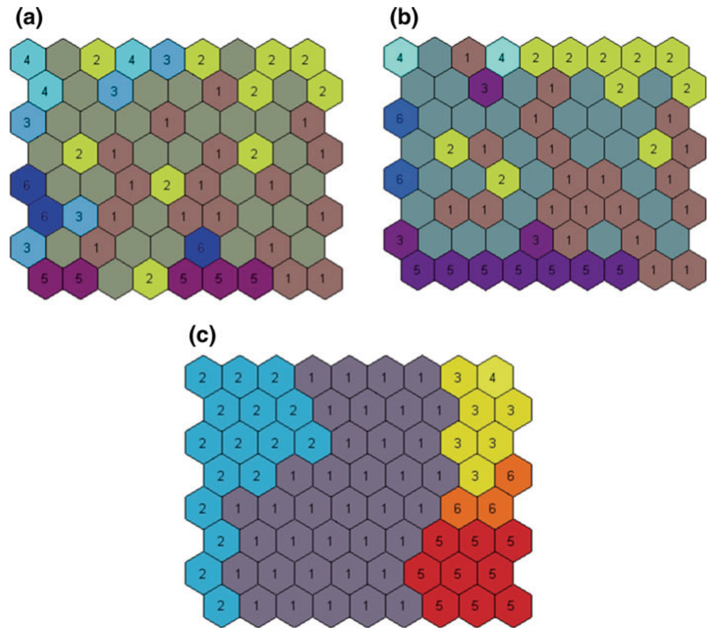


Fig. 4 The Lenke map training: **a** after one pass through the Cobb angle database, **b** after ten passes, and **c** the final map (after 45 passes)

Each of the eight first sub-figures of Fig. 5 corresponds to one of the Cobb angles. In each sub-figure, a hexagon is a node (map unit) containing a normalized angle value. The last sub-figure is the Lenke class map which we recall is determined using the vector of Cobb angles. For example, the map unit in the top left corner of the Lenke map is labeled as Lenke type 2. This map unit has high values of Mt (top row, second map) and Pt_B (second row, first map) but a relatively low Pt_H value (Third row, first map).

As mentioned earlier (Kohonen agreement map section), once the Kohonen network is trained, we project the Lenke classes to obtain the Lenke class map, and also project the fusion levels to obtain a spatially matched fusion region map. The node labels in Fig. 6 indicate the Lenke classes (Fig. 6a) and the fusion region categories (Fig. 6b). A node is labeled according to the most frequently projected class. Figure 6c is the agreement map. The agreement map is labeled "1" at a node where there is an agreement between the corresponding Lenke class and fusion region.

Table 2 is a confusion matrix resulting of the agreement map: the element of row r and column c indicates the number of network nodes (Fig. 6) assigned a fusion c for a Lenke class r. For instance, the first row shows that there are 26 nodes (out of 37) of Lenke 1 which agree with a Fusion 1. The other nodes do not agree with the Fusion 1 categorization. Instead, 6 nodes suggest a Fusion 2, 4 nodes a Fusion 3, and 1 node suggest a Fusion 5. This correspondence highlights the fusion region variabilities caused by the strict cut-off rules of the Lenke classification scheme. In contrast, all nodes for Lenke 5 agree with Fusion 5. Note that the Lenke 3 and the Lenke 6 classes are instrumented in the same way.

Discussion and conclusion

Figure 5 reveals that the Kohonen maps trained using the 8 cobb angles was able to automatically regroups AIS cases of the database into nodes which mainly conserved neighboring of similar curves. Each of The sub-figures of Fig. 5 corresponds to one of the Cobb angles. In general, the Cobb angle transitions in the map are smooth between neighboring nodes. This is in contrast with the strict cut-off rule used by the Lenke classification.

The spatial ordering of the maps is obvious in Fig. 6: In one map, Fig. 6a neighboring nodes have neighboring Lenke classes and, in the other map, Fig. 6b, neighboring nodes have neighboring fusion level categories. For example, in Fig. 6a, the Lenke 4 class (a triple major curve), at the upper right corner, is surrounded by Lenke 3 class nodes (double major curve). These two curve types are indeed similar. Each curve type is found in a specific area of the SOM when major

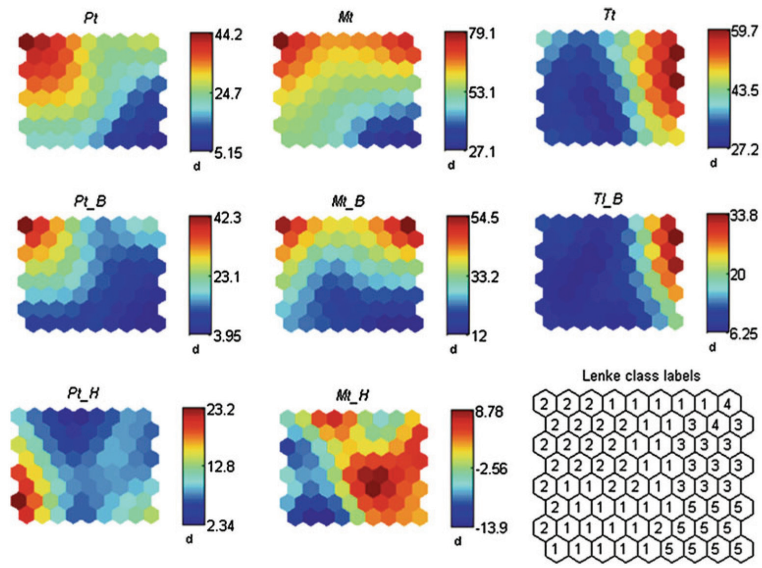


Fig. 5 Cobb angle map visualization: each of the first eight sub-figures corresponds to one of the Cobb angles. In each sub-figure, a hexagon is a node (map unit) containing a normalized angle value. The it last sub-figure corresponds to the Lenke classes

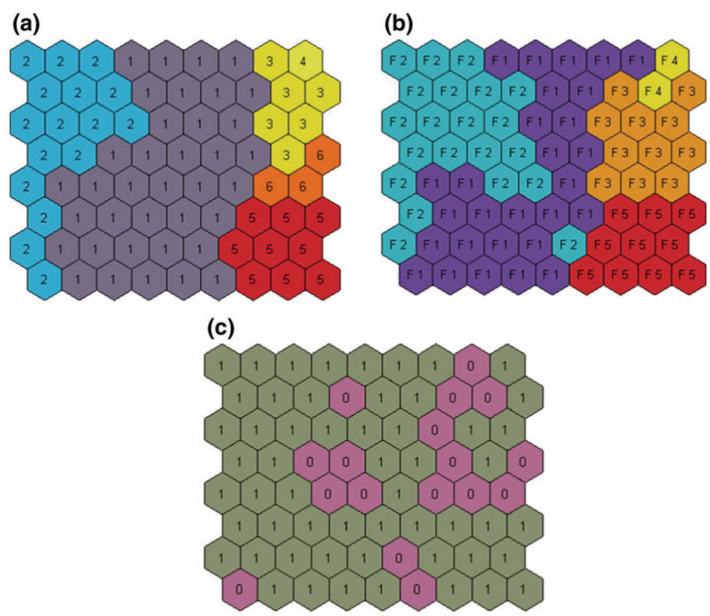


Fig. 6 **a** The Lenke map; the numbers correspond to the label of the Lenke class; **b** the fusion level map; the numbers correspond to the labels of the fusion region; **c** the agreement map: a label "1" at a node indicates an agreement between the corresponding Lenke class and fusion level at that node

Table 2 Confusion matrix resulting from the Lenke class map/fusion level map via the agreement map (Fig. 6c)

Lenke class label	Segment to be fused label				
	Fusion 1	Fusion 2	Fusion 3	Fusion 4	Fusion 5
Lenke 1	26	6	4	0	1
Lenke 2	1	15	0	0	0
Lenke 3 and 6	1	0	7	1	0
Lenke 4	0	0	0	1	0
Lenke 5	0	0	0	0	9

curve tagging is applied. Middle and left areas of the map are majorally composed of AIS cases with thoracic curves (Lenke 1 et Lenke 2). The right side of the map is mainly composed of curve types with lumbar and multiple segments curve types.

The association of the two maps which, we recall, have been trained on the 8 Cobb angles measurements, shows coincidence of the Lenke class and the proper fusion level category everywhere except at the borders between classes, i.e., the fusion region category variability occurs at the borders between the Lenke classes. Table 2 shows the count of agreements between the Lenke class map and the fusion category map. The agreement percentage is 88%. The 12% non-agreement highlight the fusion region variability caused by the strict cutoff rules of the Lenke classification scheme. Note that our results confirm the clinical study of Lenke [8], the subject of which was to test the ability of the Lenke classification model to correlate with regions of the scoliotic spine to be fused. Lenke reported an average agreement between the fused spine regions and the Lenke classes of 90% on a set of 606 AIS cases treated surgically by multiple centers.

In summary, we trained a network using a database of Cobb angle measurements which resulted in two spatially matched maps, one of Lenke classification and the other of fusion region category. The association of the two maps showed that the Lenke class coincides with the proper fusion level category except at the borders between classes., i.e., the fusion level category selection variability occurs at the borders between the Lenke classes. Therefore, surgery planning could benefit from such map associations, by comparing treatment outcome from similar patients receiving different treatment.

This study can be improved by training on a larger database according to the prevalence of the six Lenke classes reported in the literature [11] and by investigating finer map labeling which would reflect the finer categorization of the lumbar spine modifier (A, B, or C), and the sagittal thoracic modifier (−, N, or +) to the Lenke classes.

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Conflict of interest None.

Appendix: Kohonen map training algorithm

Let $X = (x_1, x_2, \ldots, x_I)$ be an input data vector of dimension I. The Kohonen training algorithm is based on competitive learning [18,21]. The weight vectors $W_j = (w_{1j}, \ldots, w_{Ij})$ stored at nodes $j = 1, \ldots, J$ are the output of the training. The nodes are organized in a two-dimensional $[N_l \times N_c]$ matrix. After the weights are initialized to small random values, the training process iterates two steps until convergence, one to find the node, j^*, that contains the weight vector closest to the current input X, and the other to update the weight vectors at each node j of the memory according to:

$$w_{ij}(n+1) = w_{ij}(n) + \epsilon(n)h(n)^{j,j^*}(x_i(n) - w_{ij}(n)) \quad (2)$$

where n is the iteration number and,

$$h^{j,j^*}(n) = \exp - \frac{||j - j^*||^2}{2\sigma(n)^2} \quad (3)$$

$$\epsilon(n) = \epsilon_1 \left(\frac{\epsilon_2}{\epsilon_1}\right)^{\frac{n}{n_{\max}}}, \quad \sigma(n) = \sigma_1 \left(\frac{\sigma_2}{\sigma_1}\right)^{\frac{n}{n_{\max}}} \quad (4)$$

We used the Euclidian distance to measure weight vectors proximity.

$$d(X, W_j)^2 = \sum_{i=1}^{I} (x_i - w_{ij})^2 \quad (5)$$

Function h^{j,j^*}, called the *neighborhood function*, acts as a smoothing kernel and defines the influence of node j^* on node j during update at j. It decreases with increasing grid distance between nodes j^* and j. It depends on a parameter $\sigma(n)$ which decreases with the number of iterations between values σ_1 (initial value) and σ_2 (final value) (Eq. 4). The $\epsilon(n)$ parameter modulates the update amount of the weights; it varies with the number of iterations from ϵ_1 (initial value) to ϵ_2 (final value) (Eq. 4). σ_1, σ_2 and ϵ_1, ϵ_2 affect both the initial conditions and the duration of the update iterations. Therefore, they affect the algorithm convergence and topological ordering. They must be chosen appropriately, and this is done empirically.

Once the training is performed, the map nodes are labeled using the training data. The training data are projected on the Kohonen map and a node is labeled according to the most frequently projected class, a procedure known as majority voting [26].

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Technical Report

Artificial neural networks assessing adolescent idiopathic scoliosis: comparison with Lenke classification

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Abstract

BACKGROUND CONTEXT: Variability in classifying and selecting levels of fusion in adolescent idiopathic scoliosis (AIS) has been repeatedly documented. Several computer algorithms have been used to classify AIS based on the geometrical features, but none have attempted to analyze its treatment patterns.

PURPOSE: To use self-organizing maps (SOM), a kind of artificial neural networks, to reliably classify AIS cases from a large database. To analyze surgeon's treatment pattern in selecting curve regions to fuse in AIS using Lenke classification and SOM.

STUDY DESIGN: This is a technical concept article on the possibility and benefits of using neural networks to classify AIS and a retrospective analysis of AIS curve regions selected for fusion.

PATIENT SAMPLE: A total of 1,776 patients surgically treated for AIS were prospectively enrolled in a multicentric database. Cobb angles were measured on AIS patient spine radiographies, and patients were classified according to Lenke classification.

OUTCOME MEASURES: For each patient in the database, surgical approach and levels of fusion selected by the treating surgeon were recorded.

METHODS: A Kohonen SOM was generated using 1,776 surgically treated AIS cases. The quality of the SOM was tested using topological error. Percentages of prediction of fusion based on Lenke classification for each patient in the database and for each node in the SOM were calculated. Lenke curve types, treatment pattern, and kappa statistics for agreement between fusion realized and fusion recommended by Lenke classification were plotted on each node of the map.

RESULTS: The topographic error for the SOM generated was 0.02, which demonstrates high accuracy. The SOM differentiates clear clusters of curve type nodes on the map. The SOM also shows epicenters for main thoracic, double thoracic, and thoracolumbar/lumbar curve types and transition zones between clusters. When cases are taken individually, Lenke classification predicted curve regions fused by the surgeon in 46% of cases. When those cases are reorganized by the SOM into

FDA device/drug status: Not applicable.

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[redacted]

nodes, Lenke classification predicted the curve regions to fuse in 82% of the nodes. Agreement with Lenke classification principles was high in epicenters for curve types 1, 2, and 5, moderate in cluster for curve types 3, 4, and 6, and low in transition zones between curve types.

CONCLUSIONS: An AIS SOM with high accuracy was successfully generated. Lenke classification principles are followed in 46% of the cases but in 82% of the nodes on the SOM. The SOM highlights the tendency of surgeons to follow Lenke classification principles for similar curves on the SOM. Self-organizing map classification of AIS could be valuable to surgeons because it bypasses the limitations imposed by rigid classification such as cutoff values on Cobb angle to define curve types. It can extract similar cases from large databases to analyze and guide treatment.

Keywords: Adolescent idiopathic scoliosis; Surgical treatment; Lenke classification; Neural networks; Kohonen self-organizing maps

Introduction

Adolescent idiopathic scoliosis (AIS) is a complex three-dimensional deformity of the spine. Lenke classification for AIS [1] classifies it based on the six curve types according to the degree of deformity and the flexibility of each curve region (proximal thoracic, main thoracic, thoracolumbar/lumbar); this is done using cutoff criteria on Cobb angles measured on anteroposterior and sagittal X-rays. Curve regions included in the fusion are recommended based on the curve types. There is a know variability in the classification [2], surgical planning, and goals in the treatment of AIS [3] that could be accentuated by Cobb angle measurement variability evaluated to be up to 10° in scoliosis cases [4]. Several computer algorithms [5] have been used to classify AIS based on geometrical features. Those novel classifications have shown AIS subtypes and allowed a better assessment of AIS severity, but none of them have attempted to analyze AIS treatment patterns.

Our working hypothesis is that self-organizing maps (SOM), a kind of neural network and artificial intelligence algorithm, can reliably classify AIS and highlight treatment patterns. Our first objective is to use SOM to reliably classify AIS cases from a large database. Our second objective is to analyze surgeon's treatment pattern in selecting curve regions to fuse in AIS using Lenke classification and the SOM.

Methods

Data set

A complete data set of 1,776 AIS cases from 30 hospitals worldwide treated surgically by 63 surgeons between 2002 and 2008 was extracted from the Spinal Deformity Study Group database of AIS cases. A validated software by a third-party company (DrPro; PhDx, Albuquerque, NM, USA) was used to measure the eight basic Cobb angles used in the Lenke classification to define curve types from digitalized preoperative X-rays. For each AIS patient, levels of fusion were also retrieved, and the patients were classified according to Lenke classification by a systematic algorithm [6].

Classification and treatment association using SOM Kohonen maps

SOM Kohonen maps implement an algorithm of the clustering paradigm where large data patterns are mapped onto a small set of representative categories using a training process. Details on the algorithm used for this classification can be found in a former publication [7]. To evaluate the quality of a trained Kohonen network, the topological error is measured and represents the proportion of all nodes for which first and second-most similar nodes are not adjacent in the Kohonen map.

Matlab software (Mathworks, Inc., Natick, MA, USA) with Neural Network Toolbox was used to create an SOM based on the basic eight Cobb angles of each patient in the data set. Each node contains a weight vector of the eight basic Cobb angles, which were set by competitive training to optimize classification of each case from the database into a corresponding node. Neighboring nodes on the SOM have therefore characteristics differing only slightly for each of the eight Cobb angles. Lenke curve type was not used as an input to generate the SOM. The levels of fusion are divided into five categories based on the curve regions fused [8,9] (Table 1).

Statistical analysis

Descriptive statistics were used to calculate the ability of Lenke classification and the SOM to predict curve regions of the spine to be fused. Kappa statistical analysis at each node for agreement between fusion realized and fusion recommended by the Lenke classification for all cases in that

Table 1
Criteria for the determination of spine curve fusion

Regional curves	Vertebra selected for determination of curve fusion
PT	UIV higher or equal to T3
MT	UIV higher than T9 and LIV higher or equal to L2
TL/L	UIV lower or equal to T10 and/or LIV lower or equal to L3

PT, proximal thoracic; MT, main thoracic; TL/L, thoracolumbar; UIV, upper instrumented vertebra; LIV, lower instrumented vertebra.

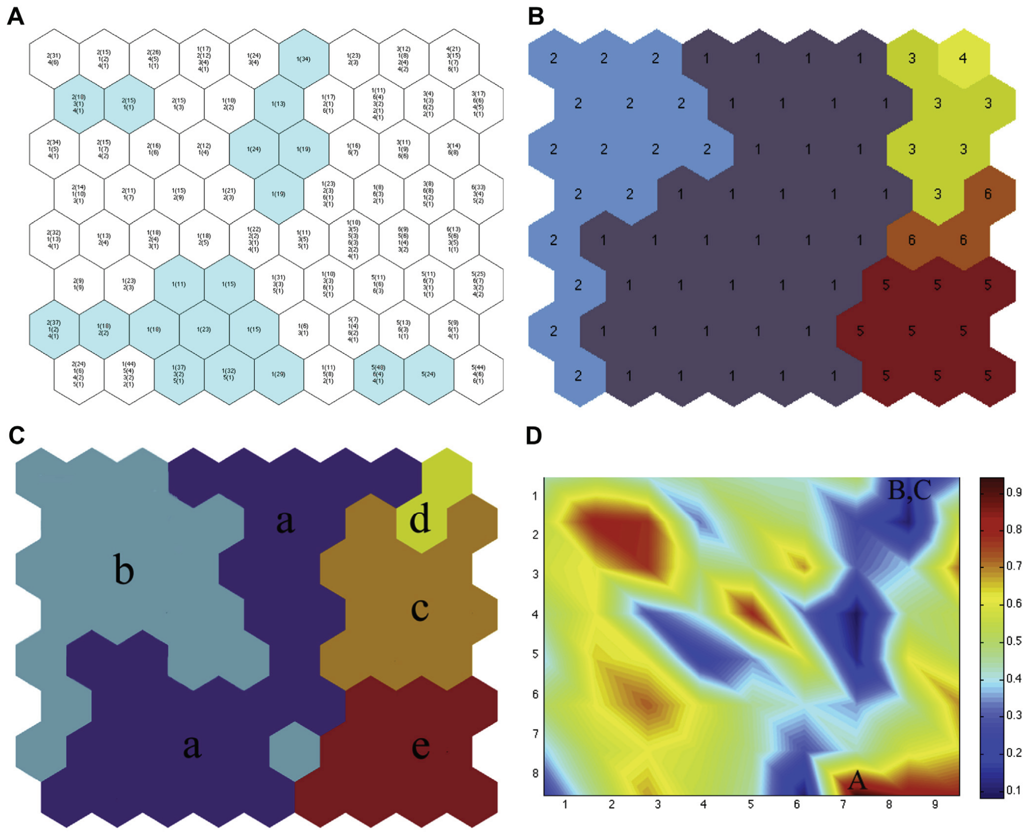

Fig. 1. (A) Self-organizing maps with adolescent idiopathic scoliosis (AIS) Lenke curve type frequencies in each of the nodes (epicenters with >90% of same curve types in blue). Each node contains the curve type followed by the number of subjects from the database assigned to this node with this curve type in parenthesis. (B) Self-organizing maps with each node tagged with the major AIS Lenke curve type. (C) Self-organizing maps with each node tagged with the major fusion pattern. (D) Matrix using edge gradient with kappa value for agreement between surgical treatment and recommendation by Lenke classification in each node. A kappa value scale is displayed on the right.

node is displayed in an agreement map of the SOM with edge gradient.

Results

Kohonen maps

A very accurate SOM was obtained; its topological error is 0.02. This demonstrates proper ordering of the nodes on the map, adequate neighboring, and very good accuracy of the classification [7]. Curve pattern clusters are visible on the SOM when each node is tagged with the major curve type in that node (Fig. 1, A and B).

Most nodes comprised mixed curve types, but 20 nodes comprised at least 90% of the same curve types (1, 2, and 5) and will be called epicenters. Using the major fusion pattern to tag each node, a harmonious distribution of curve fusion pattern is also obtained (Fig. 1, C) despite complete heterogeneity of treatment pattern in each node.

Table 2
Recommendation for fusion levels according to the Lenke classification principles

Lenke curve types	Fusion patterns	Structural curves to include in fusion
1 (MT)	a	MT
2 (double thoracic)	b	PT+MT
3 (double major)	c	MT+TL/L
4 (triple major)	d	PT+MT+TL/L
5 (TL/L)	e	TL/L
6 (TL/L-MT)	c	MT+TL/L

MT, main thoracic; PT, proximal thoracic; TL/L, thoracolumbar/lumbar.

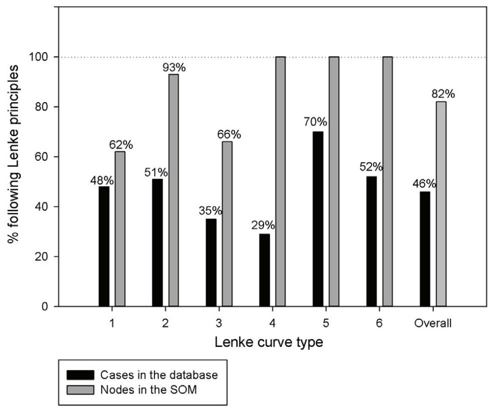

Fig. 2. Comparison of proportion of cases in the database and nodes in the self-organizing maps (SOM) following Lenke classification principles of curve fusion for adolescent idiopathic scoliosis.

Statistical analysis

Only 46% of cases followed Lenke classification principles for fusion (Table 2). When those same patients are plotted on the SOM, 82% of the nodes followed Lenke classification for fusion (Fig. 2).

The agreement map (Fig. 1, D) demonstrated almost perfect agreement (kappa >0.8) in the epicenters of curve types 1, 2 and 5; those clusters have high agreement between levels of fusion recommended by the Lenke classification and fusion performed on those patients. Between those epicenters, transition zones with low agreement (kappa between 0 and 0.2) are seen. For multiple region curve types (3, 6, and 4), nodes with fair to moderate agreement (kappa between 0.21 and 0.6) are observed.

Discussion

The complexity of AIS has led to the development of several clinical and computer-generated classifications to guide its evaluation and treatment. The Lenke classification for AIS is commonly used nowadays, but its reliability has been challenged [1,2]. A source of error can be the variability in Cobb angle measurement. Self-organizing maps can compensate for measurement variability by placing nodes with similar characteristics closer on the map. This study aimed at developing an SOM that could improve classification accuracy and study treatment variability.

A highly accurate AIS SOM was successfully developed. Because a computer does the classification, the SOM will consistently classify a patient to a node with perfect reproducibility. The reliability of this classification is

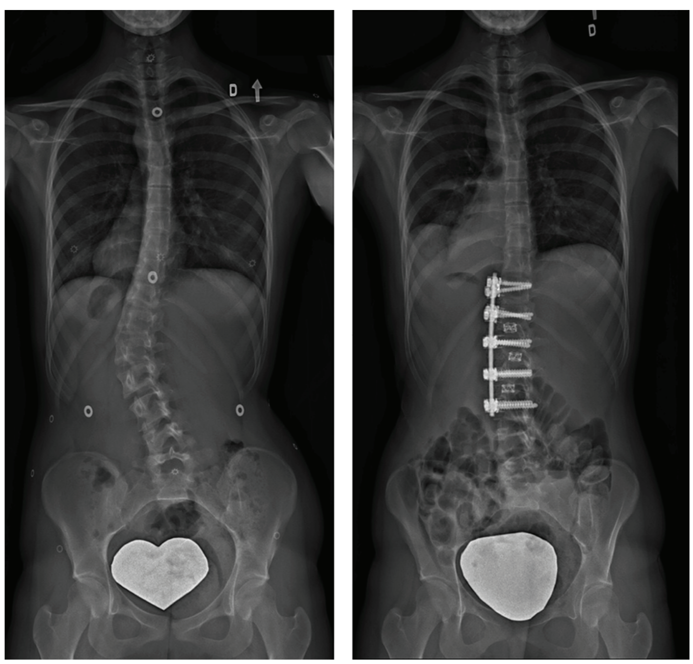

Fig. 3. Case A: 19 year-old woman with Lenke curve type 5 was treated with an anterior fusion of the thoracolumbar curve from T11 to L3.

only dependent on the Cobb angle measurements. Two neighboring nodes in the map are likely to contain the most similar patients in the database compared with nonadjacent nodes; therefore, the SOM can compensate for Cobb angle measurement variability. In the original article by Lenke et al. [1], high reliability in classification was found for curve types 1, 2, and 5 (kappa value >0.7) for which the SOM also defined epicenters. This suggests that those curve types have features that are well distinguished by humans and by the neural network alike.

In this study, we realized that surgeons tend to follow Lenke classification principles when treating similar curves on the SOM, but the exact curve type does not always dictate the fusion type. From the database, surgeons followed Lenke classification principles of fusion in 46% of cases but 82% of the nodes followed those principles in the SOM. This is in contrast with Lenke et al. [10] who describe 90% cases following those principles. Discrepancy for those results is suspected to arise from the methodology in the determination of region fused and the worldwide multicentric nature of the Spinal Deformity Study Group database, while Lenke et al. [10] studied five American centers, which might have more consistent approach to AIS treatment. Lenke principles are followed almost perfectly in epicenters for curve types 1, 2, and 5, regions with high kappa values on the agreement maps. Kappa values were lower for multiple curve types (Lenke 3, 6, and 4) and lowest in transition zones. Although intuitive, to our knowledge, this is the first description of such correlations between Lenke curve type and surgical treatment.

A possible limitation of this study is the determination of regions fused based on the vertebral levels included in the fusion. Nonetheless, this method has been accepted in several former peer-reviewed articles [8,9] from which we extracted the criteria used to determine which curves were fused. To optimize geometric regrouping, other parameters such as maximum plane of deformity, apical vertebral translation, or Lenke modifiers could have been used as additional inputs. Nonetheless, this study focused on the correlation of Lenke curve types and fusion patterns, and we decided to limit the input parameters to Cobb angles.

With the increase of large clinical databases, SOM could be used as search motors to extract similar patients and compare surgical strategies. Practically, given a new AIS patient, the surgeon can input her eight Cobb angles into the SOM, which returns its localization on the map and similar patients from the same and neighboring nodes. If the new patient is classified to an epicenter, surgical strategy has little variability and treatment suggested by Lenke principle can be applied with confidence. If the patient is classified to a node with low kappa, different surgical strategies applied to similar cases can be compared to extract the optimal treatment.

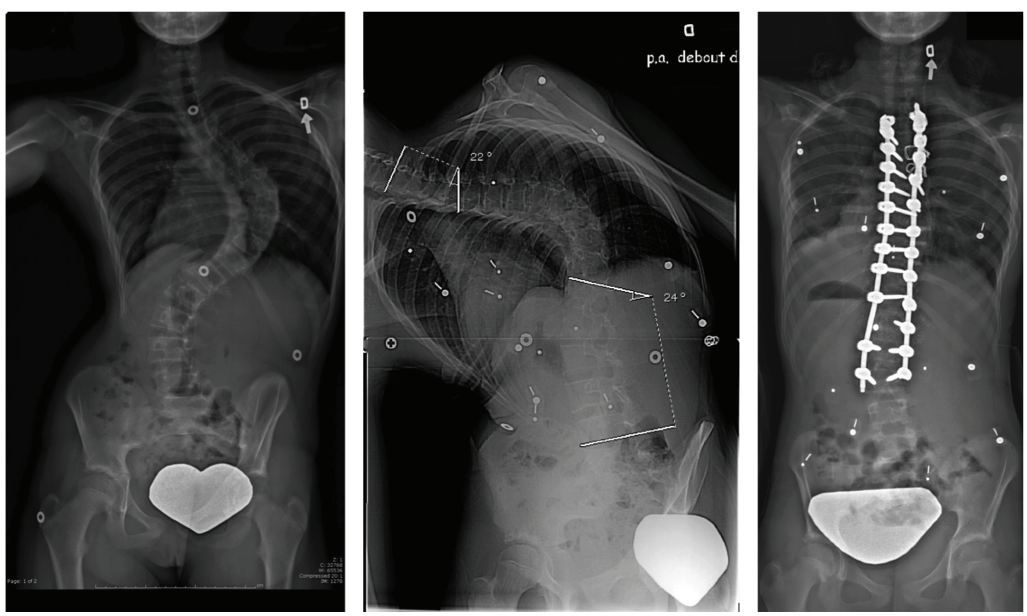

Fig. 4. Case B: 12-year-old female with Lenke curve type 1. On bending X-rays, proximal thoracic and thoracolumbar/lumbar curves correct just below 25°, making them nonstructural. Patient B was treated with a fusion of all three curve segments from T3 to L3.

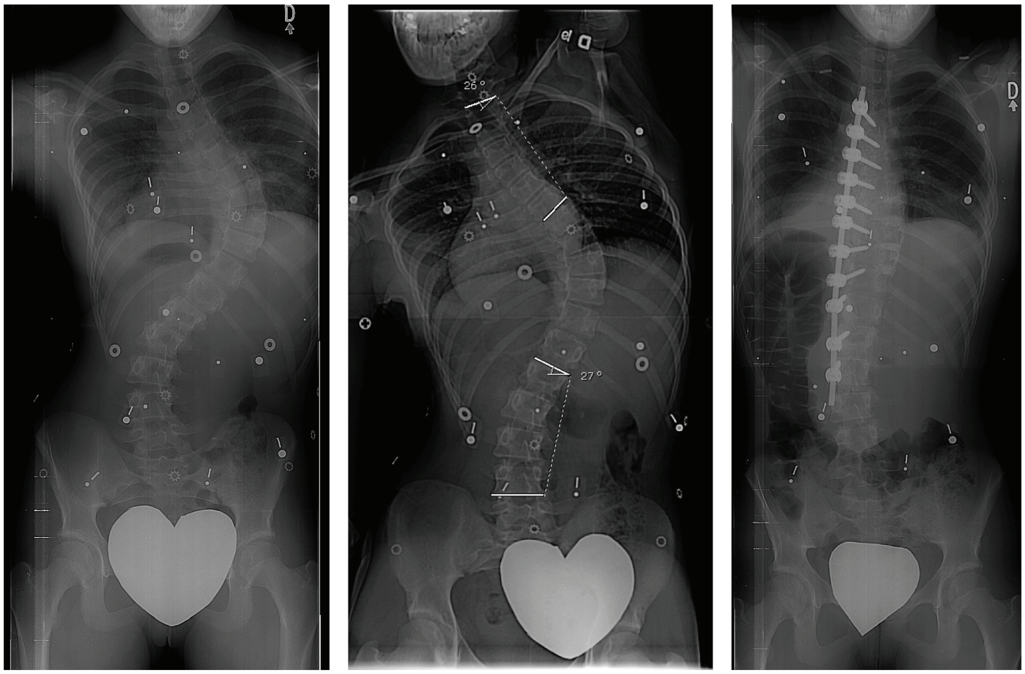

Fig. 5. Case C: 14-year-old female with Lenke curve type 4. On bending X-rays, Cobb angles of proximal thoracic and thoracolumbar/lumbar corrected to just above 25°; those curves are therefore considered structural. Patient C was treated with fusion of the main thoracic curve from T4 to L2.

Illustration of the cases

Patient A (Fig. 3) has a typical thoracolumbar curve, Lenke curve type 5, and was treated with a selective fusion by an anterior approach. She is at the epicenter of the curve type 5 on the SOM (Fig. 1, B) in a node with high kappa value on the agreement map (Fig. 1, D) confirming that her treatment is not controversial. Patient B (Fig. 4) has a Lenke curve type 1 (Fig. 1, B and D) but was treated with a fusion of all three curve segments. From this same node, patient C (Fig. 5) has Lenke curve type 4 (Fig. 1, B and D) and was treated with fusion of the main thoracic curve only. Both these patients are on a borderline node with high treatment variability and comprised Lenke 1, 2, 3, and 4 curve types (Fig. 1, A) for which all fusion patterns were applied. Patients B and C have Cobb angles on bending X-ray that are very close to the 25° cutoff that determines whether a curve is structural. The SOM is able to gather cases that are similar based on input parameters without cutoff values.

Conclusions

An AIS SOM with high accuracy was successfully generated and can compensate for variability in Cobb angle measurements. Cases with similar curve types were automatically grouped into clusters, and epicenters were defined. Lenke classification principles are followed in 46% of the cases but in 82% of the nodes on the SOM. Cases within epicenters were treated with high agreement with those principles. Using an unsupervised algorithm, the SOM highlights the tendency of surgeons to follow Lenke classification principle for similar curves on the SOM. Self-organizing map classification of AIS could be valuable to surgeons because it bypasses the limitations imposed by rigid classification such as cutoff values on Cobb angle to define curve types. It can extract similar cases from large databases to analyze and guide treatment.

References

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Chapter 7. Presentation of a software to assist AIS surgical planning (SAASP)

In this chapter the software developped (SAASP) using all the former studies will be presented. First a description of the integration of each of the algorithms developped into the platform will be performed, then a statistical analysis comparing outcome from surgeries following the most recommended strategy by the software and outcome from surgeries that did not follow the software recommendation will be undertaken.

7.1 Introduction and background

Several computer algorithms [125-127] and software[156, 157] have been developed in order to guide surgical treatment of AIS. Nonetheless none of them is widely used in the clinical setting. In order to highlight the limitations of those applications a literature review on recent applications developed to assist AIS management was undertaken[158]. It concluded that a major limitation of computer applications aiming at guiding treatment is the lack of proper justifications to get acceptance from clinicians for a decision. In an evolving medical field toward evidence-based medicine, many algorithms display outputs that are the result of an average of rule as it can be the case of fuzzy logic[126] or resulting from a learning process. This results in a major limitation, which can be described as a "black box" effect, representing the algorithm, where there is no justification of output in relation to the input.

Since decision trees and computer assisted rule based algorithms have demonstrated to be beneficial in classifying AIS in the area of King's classification [5, 52, 53], a classifier decision tree (CDT) for Lenke classification[33] and a computerized surgical strategy rule-based algorithm (SSRBA) [159] were developed. In addition, the existence of large multi-centric databases of AIS patients has motivated to find methods to seek similar patients to a new treated patient in order to compare treatment. Current classifications reliability is limited by the existence of cut-off values on Cobb angle measurement which variability has been documented to be as high as 5 degrees intra-observer[47]. Therefore, a Kohonen self-organizing-map (SOM) classification for AIS based on the angle used for Lenke classification was developed [160] and demonstrated a good ability to extract similar patients from a large database while avoiding the limitations imposed by cut-off values from the Cobb angle.

The working hypothesis is that software based on the above-described applications [33, 159, 160] can guide surgeons in their surgical strategy planning and ultimately could optimize surgical treatment.

The objective of this work is to develop a comprehensive and user-friendly software platform based on artificial intelligence tools to guide surgeons in their selection of approach and levels of fusion for surgical treatment of AIS.

7.2 Method

7.2.1 Software platform and programming

A graphic user interface (GUI) was developed in Matlab software (Mathworks, Inc., Natick, MA, USA). Matlab script was used to integrate algorithms from the Lenke CDT, the SSRBA and Kohonen SOM.

The software was built with an iterative process. A software engineer accomplished feature integration. A clinical user gave feedback to improve the software that was again reprogrammed iteratively until satisfactory result was obtained.

Integration of the Lenke CDT simply required input of 8 Cobb angles in order to determine the Lenke curve type. A form including those Cobb angles as well as other information required for determination of the surgical strategy was developed. The CDT was used to feed the Lenke curve type to the SSRBA.

Integration of the SSRBA into the software required much programming in order to translate rules extracted from the literature into encoded rules. Data required as input are fetched from the CDT with Cobb angles and Lenke curve type. Any additional data necessary by the SSRBA can be inputted upfront or is prompted as decision is taken along the algorithm structure. As noticed in our literature review[158], a limitation to use applications was the time required to input or treat data by some applications making them non-implantable in busy clinics. The 8 Cobb angles for Lenke classification are regularly measured when assessing AIS, only necessary data required for decision is thereafter prompted but can also be inputted upfront in the GUI if desired. Attention was paid to build a surgical strategy script with complete justification for each of the strategy proposed based on patient characteristics and the adequate literature represented by rules leading to that proposition. Scoring for each proposition was done in order to favour least levels of fusions while ensuring that indications and contra-indications to selective fusion are respected. Therefore anterior fusion over posterior fusion was favoured as long as none of the contra-indications to anterior fusion was present.

The SOM was integrated and used the 8 Cobb angles from the CDT to extract 20 neighbour cases which level of fusion are displayed on a 3D map with UIV in the x-axis, LIV in the y-axis and the number of neighbour who underwent those levels of fusion in the z-axis. That map allows a quick overview of the surgical strategy applied to the neighbours to a new case on the SOM (figure 16, 17, 18, section 3a).

7.2.2 Outcome measures and statistical analysis

In order to test the efficacy of the software to output proper surgical strategies, statistical analysis comparing the outcome from the surgery following the strategy most recommended by the software and the outcome from surgeries that did not will be undertaken. It was considered that the surgical treatment recommended by the SSRBA was similar to the one received by the patient when the approach, the UIV and LIV with one level leeway matched. The outcomes measured will be the magnitude of the curves as measured by the Cobb-angle, the correction achieved for each of the curves and the patient balance. Mann-Whitney-U and Chi-Square statistics with alpha set at 0.05 is adjusted with Bonferonni correction to alpha = 0.005 since we test multiple variables at a time.

The outcomes compared will include the Cobb angle measurement for each of the three curves, the correction for each of those curves and the coronal and sagittal balance. The correction for each of the curves is measured according to the following equation[161]:

Curve correction = (preoperative standing Cobb angle — postoperative standing Cobb angle) / (preoperative standing Cobb angle) * 100%.

In order to compare balance outcome, patients will be classified as imbalanced if absolute value of coronal balance is greater than 2 centimeters and absolute value of sagittal balance greater than 6 centimetres [1]. Chi-Square statistic will be used to compare balance outcome.

7.3 Results

7.3.1 GUI

The GUI is composed of 3 main areas each of which corresponds to one of the applications (CDT, SSRBA, SOM). Figure 22, represents the empty GUI with area 1 representing the case with its radiological measurements and its Lenke classification as determined by the CDT. Area 2 represents the SSRBA; surgical strategy alternatives including the approach and levels of fusion suggested are displayed. A score represents the level of recommendation of that strategy based on the body of literature suggesting that strategy, the number of levels of fusion saved, the presence or absence of contra-indication to selective fusion. Area 3 represents the SOM, neighbours to the new case from the database and the level of fusion that were chosen for their surgeries will be displayed in a 3D map as described in the method section. Figure 23 represents the data entry form, only the 8 Cobb angles needed for Lenke classification are required to start processing the case. All other additional data field can also be inputted, but necessary data to establish the surgical strategy will be requested during SSRBA processing.

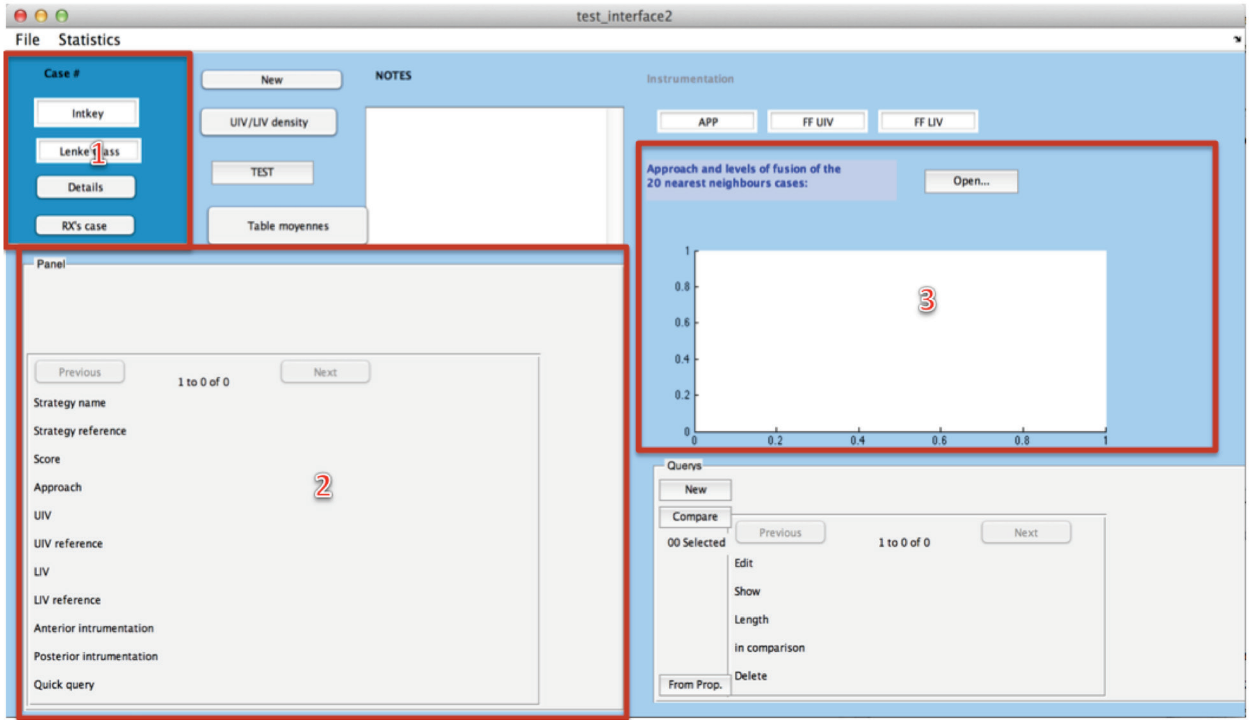

Figure 14: Empty GUI before patient data is entered with the 3 algorithms output area, each of which represent an application developed in the thesis.

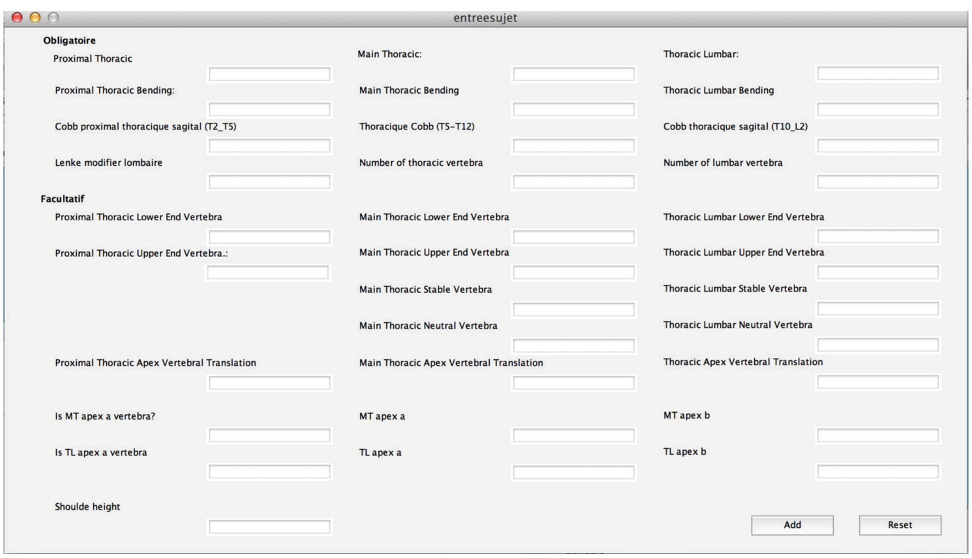

Figure 15: Data entry form for a new case

7.3.2 Case presentation

In order to display the software features, we will present 2 AIS cases displaying various features of the platform.

Case 1: Lenke 1AN

This first case is a single main thoracic curve Lenke 1AN. GUI output (fig. 16) presents the case classification and radiologic measurements (area 1a and 1b). Surgical management by the spinal deformity surgeon was a posterior fusion from T4 to T12 (area 2c).

Surgical strategy proposed by the SSRBA (area 2a) includes first an anterior spinal fusion (ASF) from T5 to T11 since the patient does not have any contra-indications (area 2b: “MT ASF: OK”). Also proposed by the SSRBA are posterior spinal fusions from T3 or T4 to T11 or T12 (area 2b). Complete justification of those propositions can be found in the surgical strategy script in the annexe of this chapter (7.4.1). It can be noted that a total of 4 surgical strategies are proposed for this patient. While all strategies are consistent with a selective fusion of the main thoracic curve, the multiplicity of the propositions is due to the several rules from the literature in choosing the level of fusion based on the various reference vertebras and the permutation between UIV and LIV.

Results from the SOM are presented in area 3. The 3D map demonstrates that the 20 closest neighbours to this patient were instrumented between T2 and T6 down to T10 and L4 (area 3a). Now based on the UIV and LIV density statistics (area 3b), we can see that instrumentations for similar cases followed a “normal-shaped distribution” centered on T3 and T12. This fits similar findings when the patient is plotted on the SOM (fig 27) which shows that it is located in the epicenter of Lenke 1 curve type that surgical treatment with selective fusion of the main thoracic curve as proposed by Lenke classification does not show much variability amongst surgeon as demonstrated by the Kappa Map.

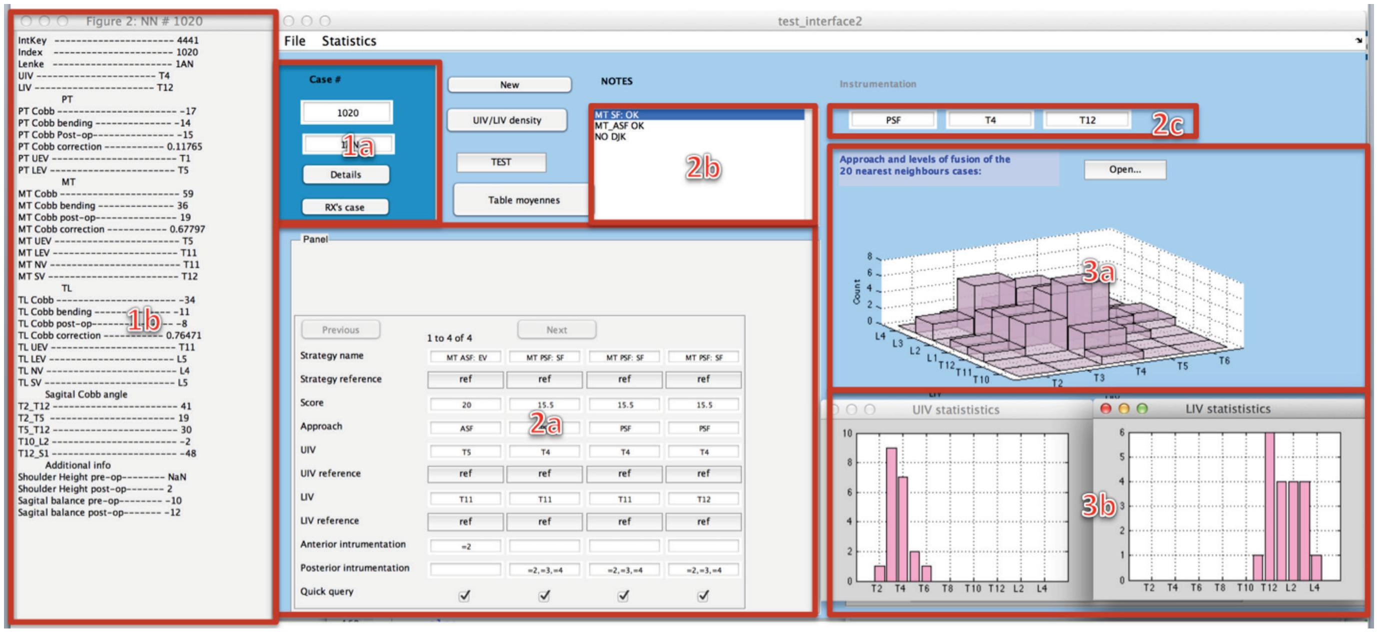

Figure 16 : GUI output for patient #1020 with AIS curve type1AN

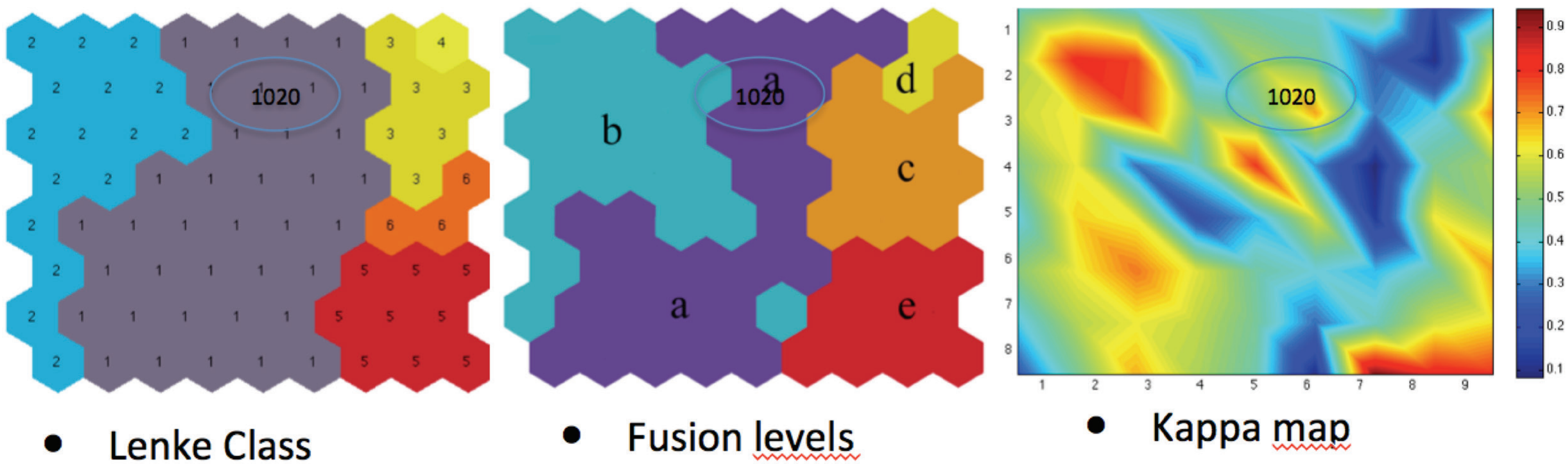

Figure 17: Position of patient (#1020) on the SOM shows that it is located in the epicenter of Lenke 1 curve type that surgical treatment with selective fusion of the main thoracic curve as proposed by Lenke classification does not show much variability amongst surgeon as demonstrated by the Kappa Map

Case 2: Lenke 1CN

This second case is a single main thoracic curve Lenke 1CN. GUI output (fig. 18) presents the case classification and radiologic measurements (area 1a and 1b). We can notice that in fact the Cobb angle measured for the MT and TL curves are both equal to 43 degrees. And that classification of this curve type as either a Lenke curve type 1 or 5 could simply be secondary to Cobb angle measurement variability.

Surgical management by the spinal deformity surgeon was a posterior fusion from T5 to L3 (area 2c).

Surgical strategy proposed by the SSRBA (area 2a) includes first two strategies leading to fusion of both thoraco and lumbar curves from T4 to L3 or L4 despite the lenke curve type 1 for which selective fusion of the main thoracic curve is recommended according to the Lenke classification. The reason why selective fusion should be avoided is displayed in the notes section (area 2b), where it is stated that many parameters go against a selective fusion. Those parameters include MT and TL/L curves with similar curve magnitude, lack of flexibility of the TL curve as compared to the MT and superior rotation of the TL/L as opposed to the MT. Full description of the rules and literature leading to those surgical strategies can be found in the annexe 7.4.2. Of note, the last proposition offered by the SSRBA is a selective fusion of the MT from T4 to L5. The LIV is a database error where the patient MT stable vertebra was stored as L5 and demonstrates some of the errors that can occur in large databases.

Results from the SOM are presented in area 3 of fig 18. The 3D map demonstrates that the 20 closest neighbours to this patient were treated with either MT selective fusion, TL/L selective fusion or fusion of both MT and TL curves. In fact when this curve is plotted on the SOM it's in a transition zone between Lenke curve type 1, 5 and 6 (fig 19). When comparing Lenke classification recommendation with actual surgical treatment undertaken, there is little agreement as demonstrated by this case and the Kappa map.

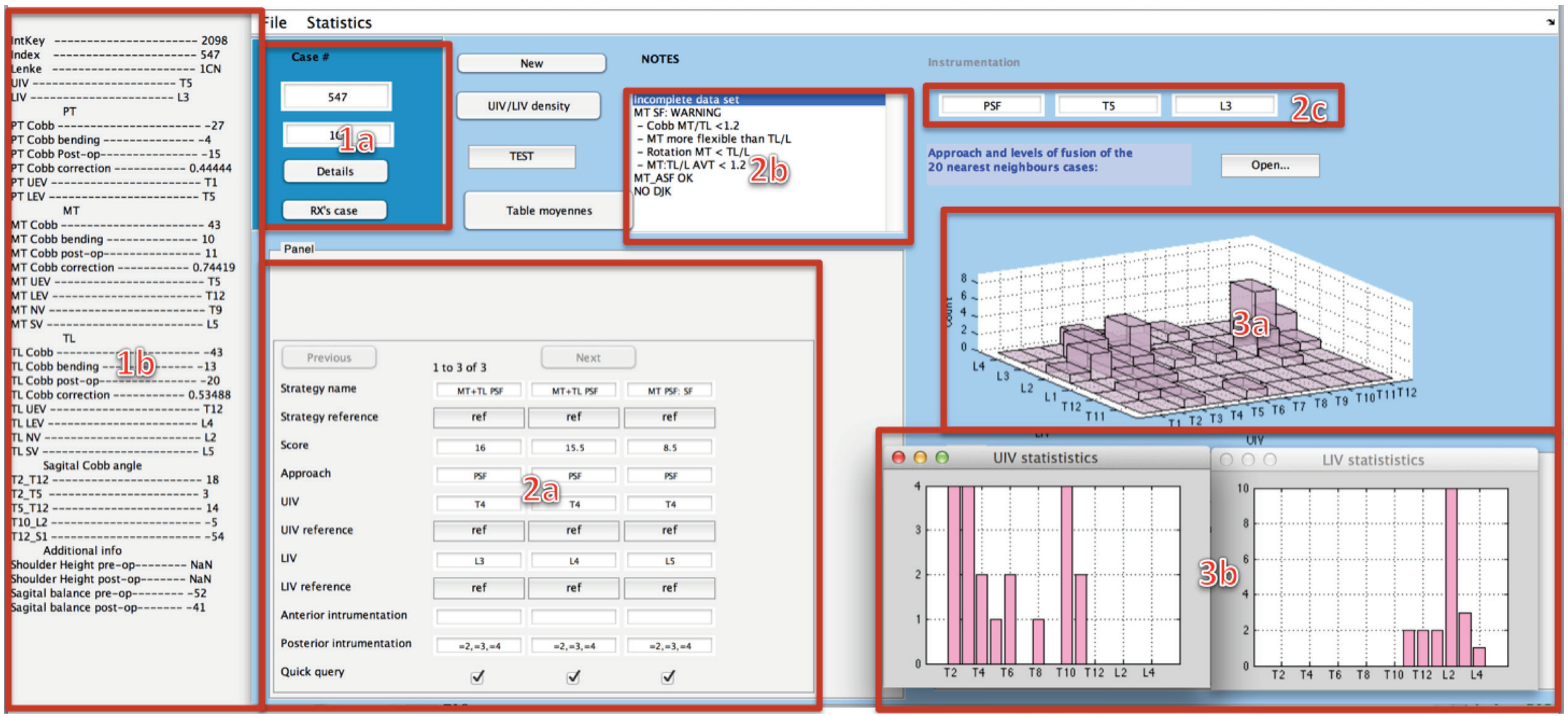

Figure 18 : GUI output for patient #547 with AIS curve type1CN

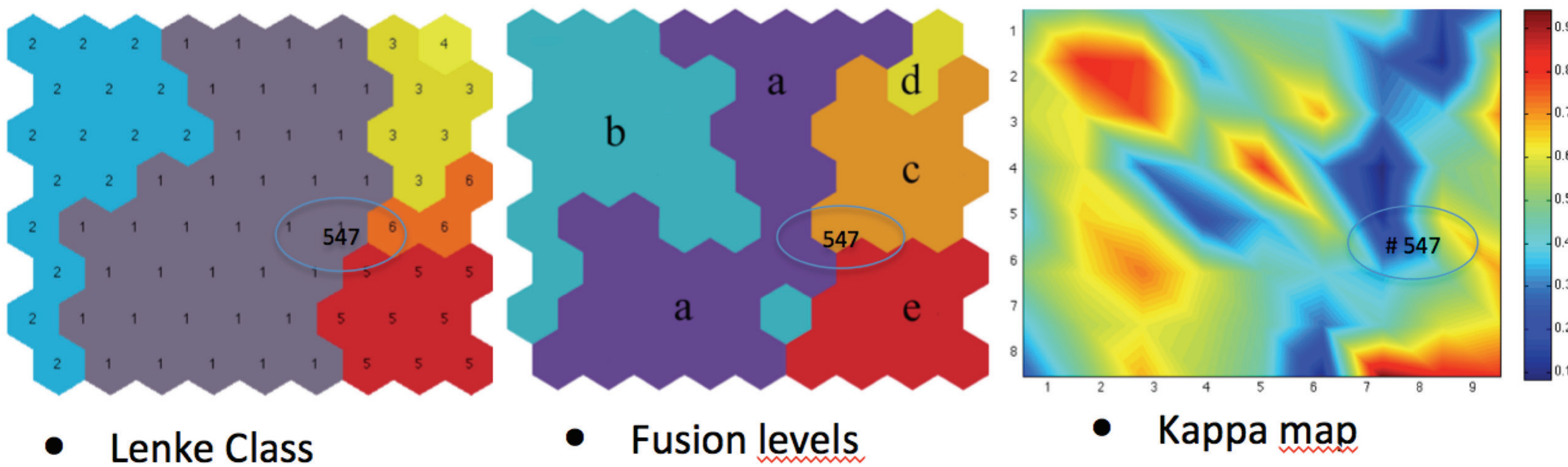

Figure 19: Position of patient (#547) on the SOM shows that it is located in a transition zone between curve types 1, 5 and 6. SOM shows that surgical treatment is highly variable for that kind of curve types and not correlate well with Lenke classification recommendation as demonstrated with the low Kappa value in this region

7.3.3 GUI: neighbour comparison

Further functions were developed in the GUI in order to permit comparison of a new patient with its nearest neighbours. As seen in fig 16 and fig 18, the 20 nearest neighbours to any given patients are plotted on a 3D map to compare surgical strategy and level of fusions. Detailed data on each of those neighbours can be displayed for case comparison, fig 28. In addition, statistical analysis on radiographic measurements of patients following various surgical strategies can be done and statistical results displayed fig. 29. While integrated in the GUI those features were developed to the prototyping stage only and not tested thoroughly.

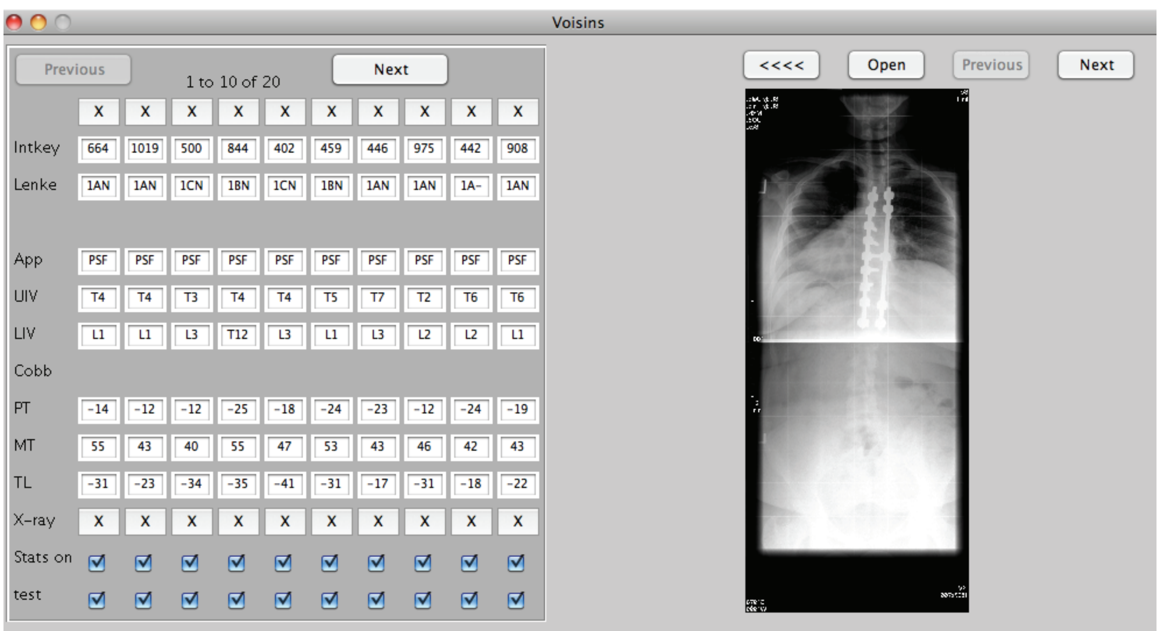

Figure 20: GUI to display neighbour data for case comparison.

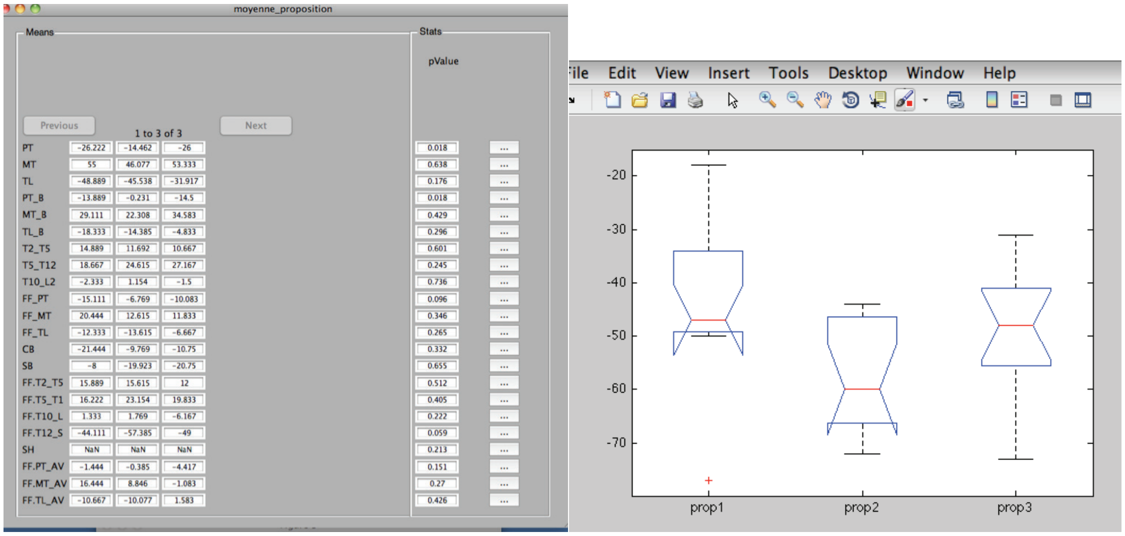

Figure 21: GUI for statistical analysis comparing outcome for various surgical strategies used in neighbours of a given case.

7.3.3 Statistical analysis

Statistical analysis comparing the outcome from surgeries following the first surgical strategy recommended by the software (with the highest score) and the outcome from surgeries that did not follow any of the surgical strategy outputs was done.

Radiographic measurements at 1 year were used since insufficient data was available at two years (less than 20% follow-up). Statistical analysis of pre-operative and first follow-up (usually at 6 weeks) measurements did not demonstrate any difference between the two groups.

Comparison of radiographic measurements at one year are displayed in table 2 :

Radiographic at one year follow-up	AIS patients following SSRBA most recommended treatment N =108/1058	AIS patients with treatment different from the SSRBA output N=950/1058	p-value
PT	-11.7 (+/-11.3)	-11.5(+/-11.03)	0.40
PT correction	0.16 (+/-0.31)	0.30(+/- 0.65)	0.126
MT	18.5 (+/-18.4)	19.9 (+/-19.7)	0.165
MT correction	0.50 (+/- 0.22)	0.50(+/-0.24)	0.600
TL/L	-11.9(+/-16.5)	-13.7(+/-16.3)	0.058
TL/L correction	0.54(+/-0.24)	0.49(+/-0.36)	0.037
Coronal balance (C7PL) Imbalance if > 2 cm	-6.8 (+/- 12.9) 1% imbalanced	-7.2 (+/- 15) 6.5% imbalanced	0.023
Sagittal balance (C7) Imbalance if > 6 cm	-17.04 (+/- 31.08) 11% imbalanced	-18.35 (+/- 31.7) 21% imbalanced	0.049

Table 2: Statistical analysis comparing outcome from surgeries following SSRBA most recommended strategy with outcome from surgeries that did not follow that strategy.

Based on this analysis, and using an alpha value = 0.005 after Benferonni correction, there was no statistical difference in outcome between the strategy most recommended by the SSRBA and other strategies. Nonetheless, it should be pointed, that limited data was available due to discontinuation of the database and that only 60% of patients from the original database had complete data at one year. While there was strictly no difference in measurements at first follow-up, we can see a trend in TL curve correction, coronal and sagittal balance at one year. It is suspected that difference between the groups could increase with longer follow-up.

7.4 Annexe

7.4.1 Surgical strategy script for case 1

```
This is instrumentation report for case 1020 (Lenke: 1AN)

----------Surgical strategies------------

 Proposition # 1: MT ASF: EV
Approche ASF UIV: T5 LIV: T11
Reference:
ASF between the End Vertebras can be done in this patient according to Betz(1999 ref.2) Lenke(1999, ref7) and others
It can be done opened with succesfull series from  Hurtford(2006 ref.23) with dual rods and no pseudoarthrosis
It can be done thoracoscopically  with the following selection criteria Newton (2005, ref. 10) and Lonner (2007 ref.24)
    - MT < 70 and MTb <30
    - Sagital T5-T12 < 30 (Newton) ou <40 (Lonner)
    - End vertebra less than 8 vertebras apart
    - Limited whithin T4-L1
    - CI: previous thoracic surgeries, reccurent pneumonia, TB, Abnormal lung fcn
    - CI: seizure dz or non-compliance post-op limitations
UIV justification:
In this patient: MT UEV=T5
LIV justification:
In this patient: MT LEV=T11
NB: If two end vertbras are parallel, the most distal one should be chosen

 Proposition # 2: MT PSF: SF
Approche PSF UIV: T4 LIV: T12
Reference:
Treatment with a selective fusion of the MT, like a Lenke 1 curve type
Successful treatment with "Significantly better main thoracic and spontaneous lumbar fractional curve correction than rigid single-rod
ASF"
for the treatment of Lenke type I main thoracic curves based on Potter(2005, ref11)
Selective thoracic fusion with segmental pedicle screw fixation in thoracic idiopathic scoliosis had satisfactory radiographic and
clinical outcomes
after sur- gery and has been well-maintained for minimum 5-year follow-up, According to SUK(2005, ref15)
UIV justification:
This is a fusion by PSF with UIV one level above MT UEV (Suk et al, Spine 2005, ref.1,6,15)
LIV justification:
Selective fusion to the most cephalad vertebra in the TL/L region that is AT LEAST intersected by CSVL
usually one level below LEV of the MT curve or one or two above true stable vertebra
The LIV is here one vertebral lower than the MT LEV  (Lenke 2007 ref.6 and Suk 2005 ref.15)

 Proposition # 3: MT PSF: SF
Approche PSF UIV: T4 LIV: T11
Reference:
Treatment with a selective fusion of the MT, like a Lenke 1 curve type
Successful treatment with "Significantly better main thoracic and spontaneous lumbar fractional curve correction than rigid single-rod
ASF"
for the treatment of Lenke type I main thoracic curves based on Potter(2005, ref11)
Selective thoracic fusion with segmental pedicle screw fixation in thoracic idiopathic scoliosis had satisfactory radiographic and
clinical outcomes
after sur- gery and has been well-maintained for minimum 5-year follow-up, According to SUK(2005, ref15)
UIV justification:
This is a fusion by PSF with UIV one level above MT UEV (Suk et al, Spine 2005, ref.1,6,15)
LIV justification:
Selective fusion to the most cephalad vertebra in the TL/L region that is AT LEAST intersected by CSVL usually one level below LEV of
the MT curve or one or two above true stable vertebra
The LIV is here  one vertebra above the true MT SV  (Lenke 2007 ref.6 and Suk 2005 ref.15)

 Proposition # 4: MT PSF: SF
Approche PSF UIV: T4 LIV: T11
Reference:
Treatment with a selective fusion of the MT, like a Lenke 1 curve type
Successful treatment with "Significantly better main thoracic and spontaneous lumbar fractional curve correction than rigid single-rod
ASF"
for the treatment of Lenke type I main thoracic curves based on Potter(2005, ref11)
Selective thoracic fusion with segmental pedicle screw fixation in thoracic idiopathic scoliosis had satisfactory radiographic and
clinical outcomes
after sur- gery and has been well-maintained for minimum 5-year follow-up, According to SUK(2005, ref15)
UIV justification:
This is a fusion by PSF with UIV one level above MT UEV (Suk et al, Spine 2005, ref.1,6,15)
LIV justification:
When preoperative NV was the same as or one level distal to EV , the curve should be fused down to NV
LIV is the MT neutral vertebra (Suk,2003 ref.16)
```

```
----------NOTES and Flags------------


NOTE:  MT SF: OK
 Radiographic and clincal parameters should be checked before proceding to Selective Fusion (Lenke 2003, ref.13)
 MT:TL/L Cobb angle ratio should be above 1.2
 MT:TL/L AVT distance ratio should be above 1.2
 Sagittal Cobb T10_L2 should be < 10
 We should have MT rotation < TL/L rotation
 TL flexibility should be > MT flexibility
 Selective fusion of MT and not TL could be adequate for this patient based on the criteria above
 With a score of: 5

NOTE:  MT_ASF OK
 In order to proceed with anterior fusion of the MT curve:
 There should not be any thoracic kyphosis (T5_t12 < 40)
       according to Sucato(2008, ref.19), Sweet(2001, ref.20) and others
 Curve should not be too great for ASF correction (MT < 80),
       accordingly to according to Betz(1999, ref.2), Lenke(2001, ref.21) and others
 There should not be more than one curve according to Lowe(2000, ref.22)
 There should not be a Shoulder higher by 5mm on the other side from the curve according to SUK(2000, ref.14)
 Based on those criteria, anterior fusion of the MT is here appropriate

NOTE:  NO DJK
 Patient not at risk of DJK based on sagital measurement of Cobb T5_T12 and T10_L2

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7.4.2 Surgical strategy script for case 2

```
This is instrumentation report for case 547 (Lenke: 1CN)

----------Surgical strategies------------

 Proposition # 1: MT PSF: SF
Approche PSF UIV: T4 LIV: L5
Reference:
Treatment with a selective fusion of the MT, like a Lenke 1 curve type
Successful treatment with "Significantly better main thoracic and spontaneous lumbar fractional curve correction than rigid single-rod ASF"
for the treatment of Lenke type I main thoracic curves based on Potter(2005, ref11)
Selective thoracic fusion with segmental pedicle screw fixation in thoracic idiopathic scoliosis had satisfactory radiographic and clinical outcomes
after sur- gery and has been well-maintained for minimum 5-year follow-up, According to SUK(2005, ref15)
UIV justification:
This is a fusion by PSF with UIV one level above MT UEV (Suk et al, Spine 2005, ref.1,6,15)
LIV justification:
This is the MT SV (Arlet 2007)
Distal level of fusion should be at the Stable vertebra but no lower (Arlet 2007 ref. 1)
Posterior treatment using pedicle screw constructs usually involves fusion down to the true stable vertebra at T11 (rarely), T12, or L1 (Lenke 2007 Ref.6)

 Proposition # 2: MT+TL PSF
Approche PSF UIV: T4 LIV: L3
Reference:
According to Arlet(2007, ref.1):
double major curves of Lenke type C remain beyond the possibility of single selective thoracic fusion.
For a long time, large Lenke type IC and Lenke type III curves (double major curves) have been treated by posterior spine fusion
addressing both curves down to L4.
When looking at the result of long fusion in AIS and the presence of back pain, it has been reported that fusion to L4 is more likely
to be associated with pain than fusion to L3.
Shortening the fusion length must not, however, be done to the detriment of an imbalanced result, a marked wedging of the disc space,
or persistent and marked rotation under the bottom instrumented vertebra
UIV justification:
This is a fusion by PSF with UIV one level above MT UEV (Suk et al, Spine 2005, ref.1,6,15)
LIV justification:
For double curves, Lenke 3 or 6, The LIV usually needs to extend to L3 or L4 (Lenke 2007, ref.6)
In this case, apex of TL/L higher than the L1/L2 disk space, making it a candidate for fusion to L3
but two more criterai should be checked!
L3-4 disc is neutral or closed on the convex side of the TL/L curve
AND L3 is a grade 1.5 or less Nash-Moe rotation

 Proposition # 3: MT+TL PSF
Approche PSF UIV: T4 LIV: L4
Reference:
According to Arlet(2007, ref.1):
double major curves of Lenke type C remain beyond the possibility of single selective thoracic fusion.
For a long time, large Lenke type IC and Lenke type III curves (double major curves) have been treated by posterior spine fusion
addressing both curves down to L4.
When looking at the result of long fusion in AIS and the presence of back pain, it has been reported that fusion to L4 is more likely
to be associated with pain than fusion to L3.
Shortening the fusion length must not, however, be done to the detriment of an imbalanced result, a marked wedging of the disc space,
or persistent and marked rotation under the bottom instrumented vertebra
UIV justification:
This is a fusion by PSF with UIV one level above MT UEV (Suk et al, Spine 2005, ref.1,6,15)
LIV justification:
For double curves, Lenke 3 or 6, The LIV usually needs to extend to L3 or L4 (Lenke 2007, ref.6)
If any of those criteria is true, fusion to L4 is required
Apex of TL/L lower or equal to L2
L3-4 disc on the convex or open side of the TL/L curve
OR L4 is a grade 1 or more Nash-Moe rotation
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NOTE:  Incomplete data set
 The missing variableSHis set by default to 0. Inclusion of the PT is therefore considered in strategies

NOTE:  MT SF: WARNING
 Radiographic and clincal parameters should be checked before proceding to Selective Fusion (Lenke 2003, ref.13)
 MT SF flags highlight that MT selective fusion is inadequate with a score -3
 - Cobb MT/TL <1.2
Radiographic and clincal parameters should be checked before proceding to Selective Fusion (Lenke 2003, ref.13)
MT:TL/L Cobb angle ratio should be above 1.2
In this cas, MT:TL/L Cobb = 1
Fusion of MT and TL should be considered

 - MT more flexible than TL/L
Radiographic and clinical parameters should be checked before proceding to Selective Fusion (Lenke 2003, ref.13)
MT flexibility should be less than TL/L flexibility
In this cas, (MT-MT_B)/MT = 0.76744 and (TL-TL_B)/TL 0.69767
Fusion of MT and TL should be considered

 - Rotation MT < TL/L
Radiographic and clincal parameters should be checked before proceding to Selective Fusion (Lenke 2003, ref.13)
Optimaly, we should have MT rotation >= TL/L rotation
In this cas, MT NashMoe = 0 and TL NashMoe = 1
Fusion should be considered

 - MT:TL/L AVT < 1.2
Radiographic and clincal parameters should be checked before proceding to Selective Fusion (Lenke 2003, ref.13)
MT:TL/L AVT distance ratio should be above 1.2
In this cas, MT:TL/L AVT = 1.0303
Fusion should be considered


NOTE:  MT_ASF OK
 In order to proceed with anterior fusion of the MT curve:
 There should not be any thoracic kyphosis (T5_t12 < 40)
       according to Sucato(2008, ref.19), Sweet(2001, ref.20) and others
 Curve should not be too great for ASF correction (MT < 80),
       accordingly to according to Betz(1999, ref.2), Lenke(2001, ref.21) and others
 There should not be more than one curve according to Lowe(2000, ref.22)
 There should not be a Shoulder higher by 5mm on the other side from the curve according to SUK(2000, ref.14)
 Based on those criteria, anterior fusion of the MT is here appropriate

NOTE:  NO DJK
 Patient not at risk of DJK based on sagital measurement of Cobb T5_T12 and T10_L2

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Chapter 8. Discussion and Conclusion

Surgical planning in AIS remains a difficult task due to the lack of guidelines and the pathology complexity. Many studies have aimed at guiding the selection of approach[98, 99, 162-164] and levels of fusion [36, 108, 112, 114, 116, 117, 119, 120, 165-167] and two major classifications have been developed to assist clinicians [36, 37]. With the increased use of computer applications in the clinical setting, several applications[125-127, 149, 151, 156, 168] were developed to assist surgeons with AIS surgical planning, yet no software are routinely used by surgeons. Particularly, applications based on artificial intelligence algorithms such as decision trees, rule-based algorithms [52] and neural networks [58, 64, 147] have shown great potential. This thesis aims at integrating artificial intelligence tools in a software platform to guide AIS surgical treatment. This chapter will discuss how our objectives were met and hypothesis tested while highlighting the limitations encountered.

8.1 Hypothesis 1 (H1) and Objective 1(O1)

Chapter 3 aimed at providing a critical appraisal of applications based on computer algorithms in the assessment and treatment of AIS. The objective was to review the literature, to extract features from successful applications that could be included in a software to guide surgeons in AIS surgical treatment while avoiding limitations from former applications. In the article presented[158], it was found that no clinically usable applications had been developed to guide selection of approach and levels of fusion for AIS. The only application available to clinicians is developed by the AOSpine under the name of Scolisoft [156] and represents a sophisticated repertory of AIS cases with pictures and data inputted by surgeons contributing to the database. No treatment proposition or background algorithm is used to guide surgical treatment. On the other hand Nault et. al [125-127] developed two fuzzy logics models, one for the proximal thoracic curve and one for the lumbar curves based on rules extracted from the literature to evaluate the need for curve fusion. While there was good agreement between the model and surgeon recommendations, the lack of clear justifications, since the model uses an average of the rules collected, was stated as a major limitation in case of disagreement and therefore difficult to integrate in clinics. From this review was concluded that many applications based on computer algorithms could bring great benefits to the management of AIS, yet they remain in the most part at the research stage due to a lack of usability, since there was no user interface development, and a common feature from those applications was the presence of a “black box”, where the output from the algorithm, lacked justifications in order to gain clinical acceptance. Therefore that article confirmed our first hypothesis that AI tools could improve AIS management but limitations such as usability and lack of clear justifications remained challenges to their clinical integration.

A successful application to guide AIS surgical treatment should therefore contain a user interface for clinical usability, have clear justifications from the literature to get acceptance from clinicians and could integrate artificial intelligence tools since they have shown to be beneficial in AIS management. All those features were taken into consideration in the subsequent work in this thesis.

Limitations from this study was the period reviewed, between 2001 and 2009, which corresponds to the start of this project and therefore does not include more recent literature. Nonetheless, a more recent manual review did not demonstrate any breakthrough in applications developed in the management of AIS. Also, it is noted that nearly 50 % of the articles retrieved from the literature and presented in chapter 3 represent the work from researchers from the region of Montreal, affiliated either with the University of Montreal, University of Quebec in Montreal and their engineering schools (École polytechnique and Ècole des techniques supérieures respectively) and Sainte-Justine Hospital. Those same institutions are involved in the work presented in this thesis. Given that the methodology in this literature review was rigorous, the many publications by the Montreal institutions around AIS result from a strong regional interest surrounding this pathology. In fact the unique interaction between surgeons, engineers and basic science researchers at Sainte-Justine hospital interested in the study of AIS has led to a pluri-disciplinary approach. First publication from that research group applying engineering techniques to AIS was in the mid 90's [169] and led twenty years later to the establishments of several laboratories in the same region studying AIS using a large array of techniques. This development was made possible through specific programs such as MENTOR (http://www.programmementor.ca/) under the Canadian Institutes of Health Research (CIHR) and financing projects using multi-disciplinary approach to apply new technologies in musculoskeletal research. In fact, the work presented in this thesis also results from the collaboration between surgeons and engineers sponsored by the Mentor program.

8.2 Hypothesis 2 (H2) and Objective 2 (O2) and 3 (O3)

Former simple rule-based algorithms have demonstrated their utility in classifying AIS according to King's classification [5, 52, 53] and in guiding the selection of levels of fusion [117]. With the widespread use of Lenke classification in recent years, a CDT[33] was developed and successfully improved classification accuracy in the clinical setting independently of levels of training and knowledge about AIS, which fulfilled our second objective (O2). While classifier decision tree can be subject to advanced learning mechanisms to optimize classification, the CDT was simplified in order to make it more accessible in the clinical setting. Stokes et al. [53] demonstrated how a rule-based algorithm can identify sources of variability in King's classification. The systematic approach used with the Lenke CDT algorithm led to increased classification accuracy that is proportional to the time spent classifying, a novel findings that has not yet been described in the literature about classification of spinal pathologies. The transition from a computer algorithm for AIS to the clinical setting was therefore successful and confirmed the first part of our second hypothesis (H2) that such classifications can assist clinicians in the classification of AIS.

Features retained from our critical appraisal of the literature [158] , were used in order to choose an algorithm that could guide surgical management of AIS. First, that algorithm should avoid the "black-box" effect, where output generated is linked to the input by a trained algorithm using data and rules for learning purposes but cannot generate justifications that clinicians can confidently rely on for decision-making. Second, in a medical world strongly emphasizing evidence-based-medicine, propositions from the algorithm should be based on evidence extracted from current literature as suggested by Nault et al[125] as opposed to personal experience as some algorithms have done in the past [117]. Third, in an area of great variability with respect to surgical treatment for a given case[12, 13, 77], and the lack of gold standard, that algorithm should be able to output several alternatives on which optimization could be done. Based on its successful applications in the past, a rule-based algorithm based on the literature was selected. It does not have the uncertainty associated with "black-box" algorithms, it can keep track of rules to justify the output and is one of the rare algorithms to allow several outputs for a given input. The Lenke classification for AIS was used as a frame for that algorithm given its dominant use in the literature and to maximize rule extraction from the literature. The SSRBA generated is able to output adequate surgical strategies and covers 70% of the surgical strategies used in the database with an average of 3.78 (+/- 2.06) propositions per case with respect to approach and exact level of fusion with a one level leeway. All those surgical strategies are proposed based on each patient clinical and radiological characteristics and rules extracted from the literature based on well-developed and adapted justifications. This is the first time an algorithm is described with the ability to output such surgical strategies and it fulfills our third objective (O3) and second half of our second hypothesis (H2).

Limitations from the SSRBA include its development framed upon the Lenke classification and the integration of rules onto the algorithm without optimization or learning process. As stated, the Lenke classification principles dividing the spine into three segments and considering whether a curve is structural or not to decide about fusion are used to build the SSRBA. On top of this frame, rules extracted from the literature were added and adjusted to the SSRBA. A complete use of artificial intelligence could have included a step where weight could be added for each step of the algorithm based on patient characteristics. Those weights could have been assigned following a learning process from a database of patients. Such a step should be considered in the future for outcome optimization purposes.

8.3 Hypothesis 3 (H3) and Objective 4 (O4)

As stated by Lenke et al [14], “best surgical treatment” for each AIS patient will require “ a classification and grading system of AIS that allows similar curves to be grouped together”. As described in our literature review, a suspected major reason for the variability in

Lenke classification [38, 41] is the variability in Cobb angle measurement [45, 47]. While that variability might be lowered with the area of digital imaging [8, 9], another way to improve AIS classification is to bypass cut-off values in order to group similar curves together. By using a SOM, gradients of Cobb angles are used rather than cut-off values in order to classify AIS curves. This allowed the distinction of epicenters for curve types and transition zones, which had not been described in the past. Interestingly, correlation of Lenke classification fusion recommendation with surgery undertaken was high in the epicenters and much lower in the transition zones. The classification created using the SOM was therefore able to highlight treatment patterns and extract similar cases from a large database without the limitations of Cobb angle measurement variation, which fulfills O4 and confirms H3.

A major limitation from that study is that it only uses Cobb angles to achieve classification. In fact, in order to correlate treatment patterns with the Lenke classification surgical recommendation, only the 8 Cobb angles used in curve type determination were used. It is probable that additional radiographic parameters could have brought more precise neighbouring, particularly in respect to three-dimensional neighbouring. In an experiment [170], when using 71 patients from our institution with three-dimensional reconstruction of the spine, the closest neighbour based on a 3D reconstruction of the spine (a spline)[138], was found 70% of the time in the same or a neighbouring node on the SOM. Future classification should therefore aim at improving that three-dimensional neighbouring since curve characteristics guide surgical treatment. [171]

8.4 Hypothesis 4 (H4) and Objective 5 (O5)

In answer to the article on SOM [160], Kang et al. [105] stated : “Ultimately, a humanized front-end software module or interface must be developed to collect data and to deliver an understandable output to the practicing surgeon.”. Without knowledge of our current project those authors had confirmed the need for a platform oriented toward clinicians to integrate algorithms such as the SOM. Using scripting software, Matlab, for experimental and scientific computing, a GUI was successfully developed and was able to integrate all the algorithms developed in this thesis to classify AIS and guide its surgical treatment. That platform, SAASP, allows a new case to be inputted into the GUI with a user front end. The new patient is then classified according to Lenke classification and surgical strategies are proposed based on the SSRBA. Using the SOM, neighbour patients can be extracted from the database. Outcomes from surgical strategy used for those patients can be compared by analysing radiological measurements at follow-up. Therefore, a comprehensive platform integrating AI tools was successfully developed and could guide surgeons by outputting viable surgical alternatives for a given case and compare those strategies based on similar cases from a large database.

Many applications have been developed to guide AIS surgical treatment, under the form of a collective database [156], a model using fuzzy logic and rules form the literature to guide curve fusion [125] or simulators to predict surgical corrective result [149]. Some systems integrating patient databases and artificial intelligence tools to guide AIS surgical treatment have also been developed but their findings unpublished[157]. SAASP represents a step closer to clinical usability and its features published and conceived with former applications limitations in mind.

Limitation of this software is its early development stage. While all the components have been published or submitted for publication, the platform itself remains in a scripting language, limiting its access to workstations with the Matlab software and requiring running the script and its associated database through that software. Also, due to the ceased contribution and accessibility of surgeons to the SDSG database, the database had remained to a static state with limited follow-up and numbers. Development of the current platform showed the vulnerability of such projects to the database on which they rely on. In fact, many challenges were encountered in order to translate data collected from the study group and stored in a statistical package such as SPSS or SAS into a database for computing use. With the increased interest to develop software integrating intelligent tools with databases to guide treatment[153, 156, 157], attention should be given to adapt data collection and database storage to the software design, which requires considerations that are very different from collecting data for regular statistical analysis, which can be achieved through a statistical package.

In successfully developing the current software, the first part of H4 was confirmed. Surgical treatment optimization still remains to be achieved, since statistical analysis comparing outcome from the most recommended strategy by our platform with other strategies only showed a trend to better balance and lumbar curve correction without statistical significance. In order to achieve treatment optimization, the rule-based algorithm could follow a learning process based on a large database of AIS cases aiming at optimizing outcome measures. Such process would require long-term follow-up data in order to obtain significant results.

8.5 Conclusion

On order to develop comprehensive software to guide AIS surgical treatment, a literature review was undertaken, a Lenke classification decision tree, an AIS surgical strategy rule-based algorithm and a SOM classifications were developed. The Lenke classification decision tree showed that algorithms adapted to the clinical setting could be beneficial by improving classification accuracy independent of the level of training. The rule-based algorithm was the first attempt at outputting multiple surgical strategies based on rules extracted from the literature for a given AIS case and is able to match strategies undertaken by surgeons in a large multicentre database. Classification of AIS using neural network has shown great potential in bypassing the limitations imposed by the use of cut-off values on Cobb angle, which measurement is known to have variability leading to AIS classification variability. Furthermore, the ability to develop analysis maps over the classification map, such as the Kappa map has permitted to analyse surgeon treatment variability when compared to Lenke classification recommendation and showed regions, epicenters of curve types, where treatment is in great agreement while others, transition zones, contained much variability in treatment. The software developed has integrated all those algorithms and the GUI allows the user to input a new case, get it classified by the decision tree, have surgical alternatives proposed by the rule-based algorithm and see what has been done for similar cases in a large multicentre database using the SOM. Using AI tools to guide AIS management has proven beneficial in former work and this thesis confirms that such tools can be integrated in clinically oriented software to guide surgical treatment.

Based on the work presented in this thesis and the development of multi-centric databases, software using advanced algorithms can be developed to guide surgical treatment.

While preliminary analysis presented in this thesis shows the potential for surgical optimization based on software output, further research is required to benefits the benefits in using such software.

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