REVIEW ARTICLE

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

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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.

**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

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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<br><br>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° ($r = 0.92$)<br><br>No definition of a critical SCI<br>No consideration for TL-L curve<br>Good reproducibility |
| Jaremko et al. [17–19] | 46 patients<br>1. 153 scans of 360° torso surface models from four laser scanners<br>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<br>0.1°±6.0° when compared to computer Cobb angle<br>0.8°±5.9° when compared to clinical Cobb angle |
| Ramirez et al. [21] | 111 AIS patients<br>1. 3D back shape from one single laser scanner<br>2. clinical parameters (trunk twist, cosmetic score, scoliometer) | Comparison of X-ray Cobb angle with Output from three types of classifiers<br>1. SVM (Support Vector Machine)<br>2. DT (Decision Tree)<br>3. LDA (Linear Discriminant Analysis) | Binary:<br>1 Mild (<30°)<br>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)<br>Number of progression patterns defined:<br>1. 10 for Cobb angle<br>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°)<br>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)<br>Two groups depending on Cobb angle increase between two visits<br>* Progression (>5°)<br>* 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:<br>1. Progression<br>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%.
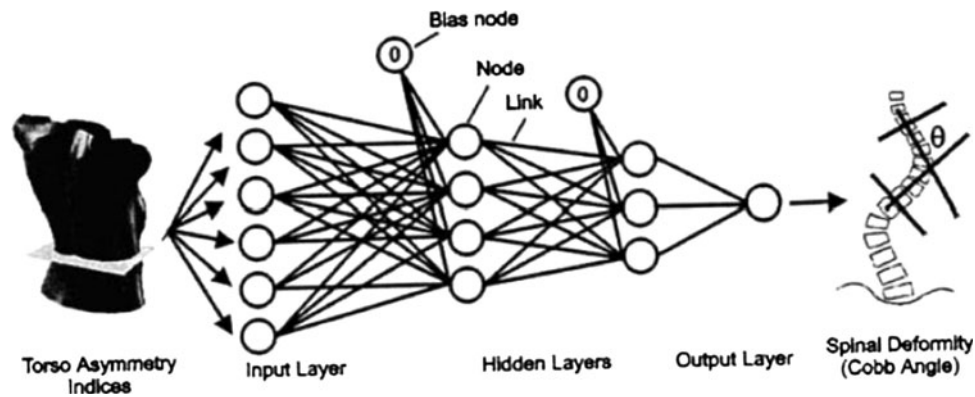
**Fig. 1** ANN to estimate the Cobb angle (*right*) from indices to torso asymmetry (*left*). Each node in the hidden layer takes a weighted sum of inputs and produces an output if the sum is greater than a threshold. The ANN "memory" is distributed through the link weights, which are modified to minimize 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
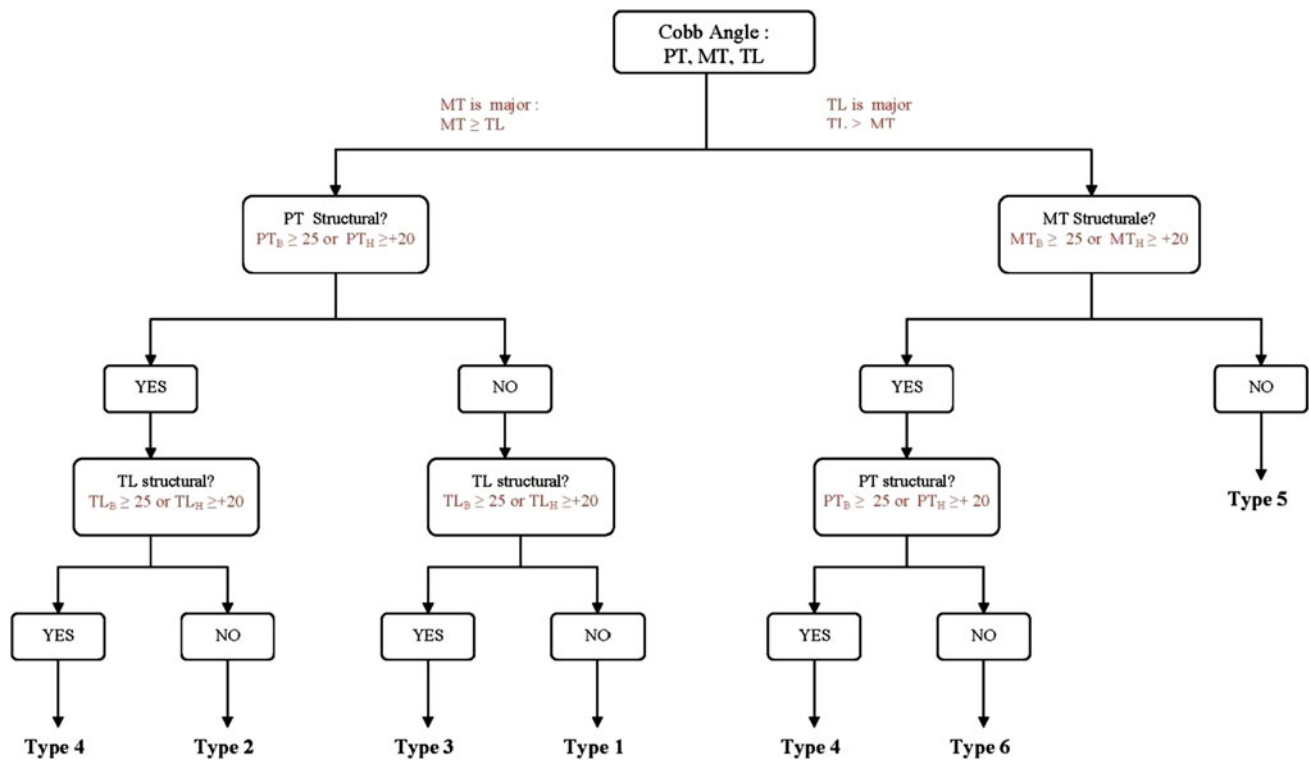
**Fig. 2** Decision tree developed to improve classification accuracy of AIS according to the Lenke scheme. *MT* main thoracic, *TL* thoracolumbar/lumbar, *PT* proximal thoracic indices, $X_B$ Cobb angle for curved spine. Poncet et al. [31] extracted three distinct segment X on bending PA X-ray, $X_H$ 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
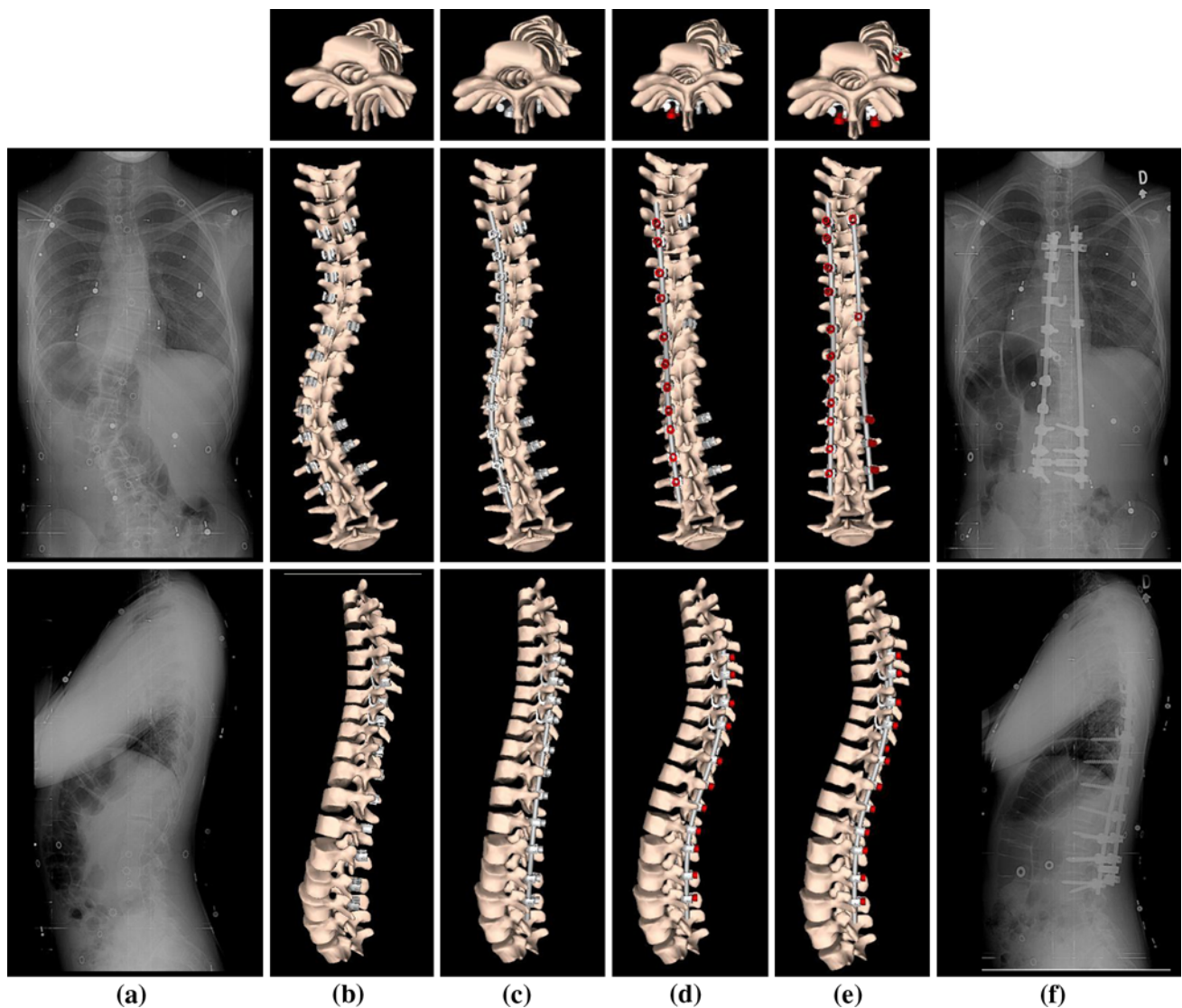
**Fig. 3** Representation of a patient with double major AIS spine and instrumentation during a simulation. **a** Preoperative radiographs, **b** initial geometry after the installation of the implants, **c** after the attachment of the first rod on the concave side of the spine deformity, **d** after 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.

**Conflict of interest** None.

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