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Three-Dimensional Classification of Spinal Deformities Using Fuzzy Clustering

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Study Design. A prospective study of a large set of three-dimensional (3D) reconstructions of spinal deformities in adolescent idiopathic scoliosis (AIS).

Objectives. To determine the value of fuzzy clustering techniques to automatically detect clinically relevant 3D curve patterns within this set of 3D spine models.

Summary of Background Data. Classification is important for the assessment of AIS and has been mainly used to guide surgical treatment. Current classification systems are based on visual curve pattern identification using two-dimensional radiologic measurements but remain controversial because of their low interobserver and intraobserver reliability. A clinically useful 3D classification remains to be found.

Methods. An unsupervised learning algorithm, fuzzy k-means clustering, was applied on 409 3D spine models. Analysis of data distribution using clinical parameters was performed by studying similar curve patterns, near each cluster center identified.

Results. The algorithm determined that the entire sample of models could be segmented in five easily differentiated curve patterns similar to those of the Lenke and King classifications. Furthermore, a system with 12 classes made possible the identification of subpatterns of spinal deformity with true 3D components.

Conclusions. Automatic and clinically relevant 3D classification of AIS is possible using an unsupervised learning algorithm. This approach can now be used to build a relevant 3D classification of AIS using appropriate key features of 3D models selected by a panel of expert spinal deformity surgeons.

Key words: cluster analysis, adolescent idiopathic scoliosis, pattern recognition. **Spine 2006;31:923–930**

Adolescent idiopathic scoliosis (AIS) involves a three-dimensional (3D) deformity of the spine. The current gold standard for the evaluation of curve severity is the measurement of Cobb angles in the frontal plane.[1] Curves in the sagittal plane, namely, kyphosis and lordosis, are also generally evaluated to characterize the sagittal profile. For most patients who develop severe scoliosis, surgical correction is required, with the goals of achieving spinal realignment with various implants and maintaining the correction achieved by bone fusion within the instrumented spinal segment.

Classification is crucial for the proper assessment of AIS. The first classification system widely used was purely descriptive, based on the visual pattern identification of thoracic, lumbar, thoracolumbar, or double major curves. Current systems,[2] such as the King classification[3] and more recently the Lenke classification,[4] are aimed at guiding surgical treatment by selection of the appropriate fusion and instrumentation levels. Both systems are based on the manual measurement of two-dimensional (2D) geometric indexes such as Cobb angle or central sacral vertebral line on spinal radiographs. Although very useful, these systems have been shown to have poor reproducibility due to a relatively high interobserver and intraobserver variation.[4,5] Furthermore, these measurements are based on the 2D projection of the spine on radiographs and represent a simplification of the 3D spinal deformity involved in scoliosis. To overcome this limitation, Poncet *et al* have proposed to classify curves according to the pattern of geometric torsion measured on 3D geometric reconstructions of the spine.[6] This proposal has not gained wide acceptance because of the inherent complexity associated with torsion measurements and perhaps more importantly because geometric torsion is not an intuitive measurement for clinicians and cannot be related to any usual curve pattern identification on radiographs. Furthermore, the equipment necessary to obtain 3D reconstructions of the spine in the standing position is not readily available to a majority of clinicians and has been used up to now mostly in a research context.[7–9] This last example illustrates why a true 3D classification system of scoliotic deformities has yet to be discovered: 3D reconstructions of the spine are difficult to obtain and add an unlimited number of planes and measurements to take into account, a task that makes standard visual curve pattern identification a very difficult, complex, and perhaps impossible task.

Fortunately, modern diagnostic tools are now based on the processing power of computers and combined to the wider availability of digital radiography, the equipment and software necessary to obtain fast and accurate 3D reconstructions is now within the reach of clinicians.[10] Algorithms can be specifically designed for a given task and can be executed with a higher reproducibility than manual measurements. Such a deterministic approach using a rule-based algorithm to infer the King

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classification system has been recently explored to improve classification accuracy.[11] Although based on quantitative rules, this technique considers only hard threshold values (such as for example > or < than 40° Cobb angle) for decision-making and unfortunately can still fail to classify borderline curve patterns. On the other hand, other mathematical algorithms based on unsupervised learning techniques have been described to overcome these limitations and classify data without any a priori knowledge of the class distribution. Clustering techniques are such an example and are typically used to estimate iteratively the regrouping of data samples in a high dimensional space (n-D) according to several observations (features).[12] In the field of orthopedic rehabilitation, fuzzy clustering methods have been used in gait analysis of children with cerebral palsy, where the center of clusters identified from the stride length; cadence leg length and age have been analyzed[13] to assess the evolution or improvement of the clinical condition, using the transition between clusters over the time.

The goal of our study was therefore to evaluate the feasibility of using fuzzy clustering techniques to establish the basis of a 3D classification of spinal deformities in AIS. More specifically, the objective of this project was to determine the value of fuzzy clustering techniques to identify clinically relevant 3D curve patterns observed from a set of shape descriptors computed on 3D spine models in a cohort of subjects with AIS. Rather than being based on the review of radiographs by experts as described in previous studies on spine classification,[3,4] fuzzy clustering was applied without any *a priori* clinical knowledge with the hypothesis that it can define a clinically relevant classification system using the grouping of samples with similar features characterizing similar curve patterns.

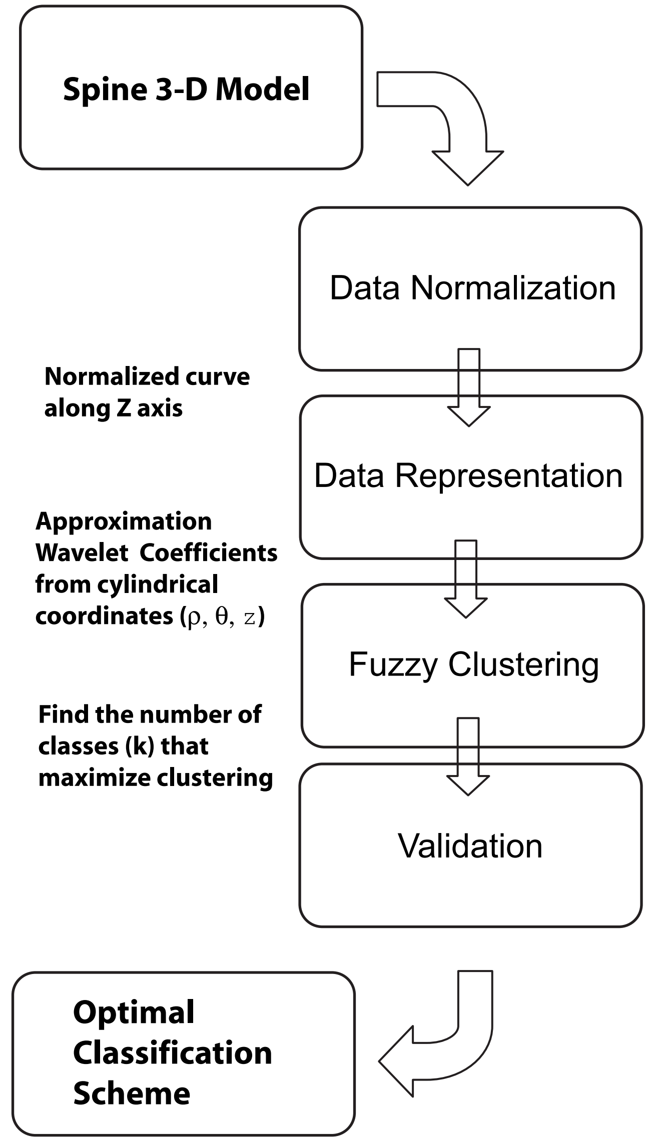

Figure 1. Block diagram of the system.

Materials and Methods

The proposed system, illustrated in Figure 1, can be summarized in four steps detailed in the following sections: data normalization, data representation, clustering, and validation. The first step in the process is to transform complex 3D spinal reconstructions into a simplified and normalized representation. A curve representing the deformity is modeled using a mathematical parametric 3D curve passing through the center of each vertebra. The second step is to reduce the number of inputs to model the curve with a limited number of parameters. As a third step, fuzzy k-means, a standard clustering technique, can then be applied on the samples to find the optimal regrouping of samples with similar features. The optimal number of clusters will regroup each member of a class with a strong similarity factor while keeping the centers of clusters as distinct as possible. For the final step, a dozen of each samples of 3D models located near the centers of the clusters were then submitted to an experienced spine surgeon for clinical evaluation and validation, based on the computation of standard clinical indexes and comparison to current classification systems. The processing and visualization software were developed using Matlab 6.1 (The Mathworks Inc., Natick, MA) using the statistical, wavelet, and fuzzy logic toolboxes.

Three-Dimensional Reconstruction of the Spine. A total of 409 spine models of patients with AIS were selected from a database of 1597 3D spine reconstructions that have been performed at our institution for various research projects over the past decade. The criteria for inclusion in the study were the following: 1) a diagnosis of AIS, 2) an age between 10 and 18 years when the radiographs were obtained, and 3) a Cobb angle measurement of the main curve greater than 40°. Patients with a previous spinal surgery or those currently treated with a brace were excluded. For each subject recruited in this study, a 3D reconstruction of the spine was done according to a technique previously reported in detail[7] and which has been validated over the past decade at our institution. Six points per vertebra (the inferior and superior tip of pedicles of each side of the vertebral body and the centers of the endplates) are manually identified on the radiographs as shown in Figure 2, and the 3D positions of each point are computed in the global reference frame. For easier clinical interpretation, a solid 3D model of vertebrae can be adjusted to each anatomic landmark with elastic registration techniques (Figure 2).

For the purpose of this project, the centroid of each vertebral body was computed using the average of the center of the

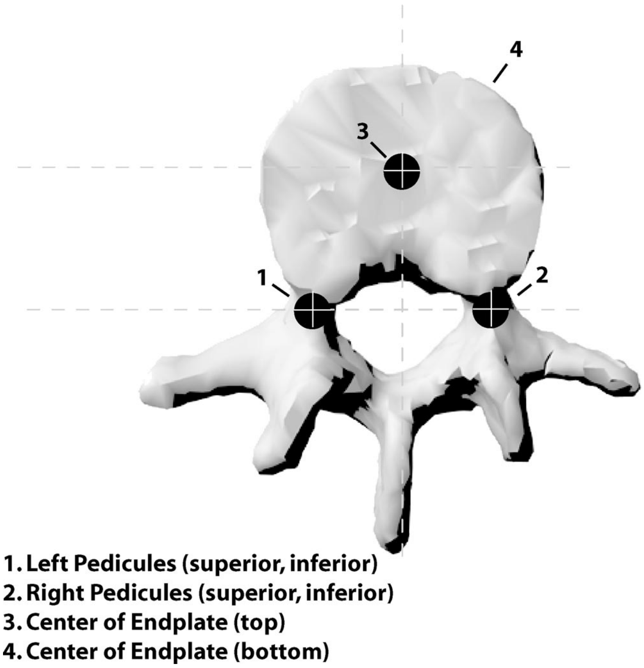

Figure 2. Digitization process: each vertebra is digitized using the inferior and superior tip of pedicles on each side of the vertebral body and the center of each endplate.

endplates to locate the position of vertebrae along the curvature. A rigid transformation was applied to consider the centroid of L5 as the origin of the reference frame. The reference frame used is the one defined by Stokes[8] with the x-axis orthogonal to the frontal plane and the z-axis directed toward the head. An isotropic scale factor along the z-axis was computed and applied to all spatial dimensions to maintain a unit aspect ratio and to ensure a proper comparison between patients.

Three-Dimensional Classifications. The analysis of a 3D spine model is a very complex task to perform, due to the infinite number of planes to consider. The complexity increases further when considering the infinite number of features (indexes) that can be studied. In order to simplify the recognition task, the global shape was first considered in our classification scheme. With the hypothesis that a large percentage of the 3D information of the curve lies in the global shape of the spinal curves, a first level of a multiscale classification was obtained using the analysis of 3D descriptors, without any regards to local features. This global approach allowed to greatly reduce the number of parameters to input, with a negligible error for classification from a global perspective while offering a better generalization of typical curve patterns in 3D. The feature strategy used to extract the shape of the curve consisted in the processing of the cylindrical coordinates along a regular interval of the parametric 3D curve (Figure 3). A wavelet-based compression technique was used to compress the huge amount of information and reduce the number of inputs in the clustering algorithm. A total of 20 wavelet approximation coefficients were stored as 3D descriptors for the spinal curve. Wavelet transform is widely used to compress image information[14] and has been successfully applied in several pattern recognition tasks to reduce the number of inputs.

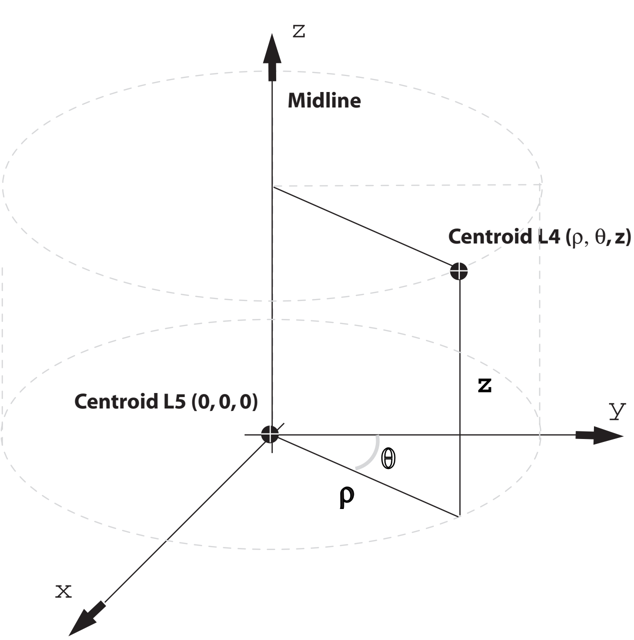

Figure 3. Cylindrical coordinates describing the centroid of each vertebra.

To further generalize the classification scheme, a fuzzy clustering technique was preferred over a "hard" clustering technique. The clustering algorithm used in this study consists of forming groups with similar features with a fuzzy margin, as opposed to using hard separation between the classes. The main advantage of this approach is to allow more flexibility. Basically, clustering will identify the mean samples in a large set of data according to the desired distribution (number of classes).

Validation. The classification proposed by the algorithm was evaluated using the Rand index, which consists of running the clustering algorithm with different random starting points in order to evaluate the consistency.[15] In addition, a dozen of each samples of 3D models located near the centers of the clusters were submitted to an experienced spine surgeon for clinical evaluation and validation of the clinical relevance of the patterns detected, based on the computation of standard clinical indexes and comparison to current classification systems. The clinical indexes considered were: 1) the Cobb angles of each curve in the frontal plane, 2) the Cobb angles of the thoracic kyphosis and lumbar lordosis, and 3) the computerized Cobb angles calculated in the planes of maximum and minimum curvature. To determine if any differences occur within each class, an analysis of variance was performed with the patient population broken down in each class.

■ Results

Wavelet decomposition allowed a compression of every spine curve from 17×3 spatial coordinates to 20 coefficients. The RMS error (2.0 mm) using only the 20 approximation coefficients to represent the 3D spine was in the same order of accuracy as for the 3D reconstruction technique.[7] Fuzzy clustering detected a classification with five classes that can divide the input space into well-defined clusters at a consistency rate of 100% computed on 20 trials with random starting points. In other words, the algorithm determined that the entire sample of 409 3D reconstructions could be segmented in five easily differentiated curve patterns (Figure 4).

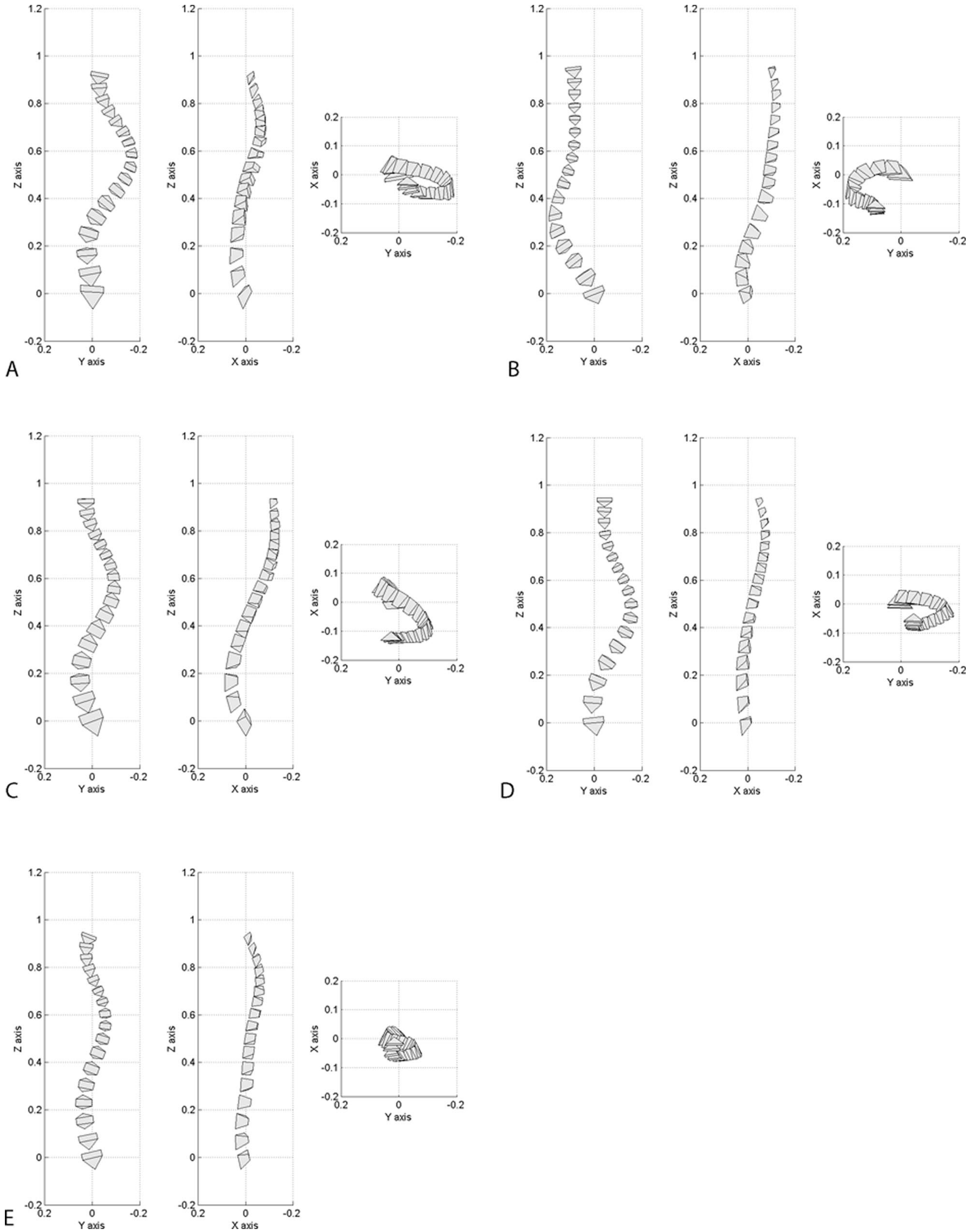

Figure 4. Samples nearest from the center of cluster. **A**, The first class represents a King Type III or Lenke Type 1 thoracic curve. **B**, The second class presents a Lenke Type 5 lumbar/thoracolumbar curve. **C**, The third class consists of a King Type I or II, or Lenke Type 3 thoracic and lumbar curves. **D**, The fourth class presented a King Type IV curve pattern. **E**, The final pattern is a flat back with a King Type V or Lenke Type 2 double thoracic curve.

Table 1. Clinical Indices of Center of Clusters

Clinical Indices (k = 5)	Class 1	Class 2	Class 3	Class 4	Class 5
Cobb angle (PA)*	26 ± 11	14 ± 11	28 ± 14	30 ± 11	25 ± 12
Cobb angle (PA)*	43 ± 10	26 ± 17	41 ± 13	44 ± 11	42 ± 8
Plane of maximum curvature†	35 ± 10	19 ± 11	34 ± 13	36 ± 10	30 ± 12
Plane of maximum curvature†	48 ± 8	28 ± 12	43 ± 10	47 ± 11	40 ± 9
Plane of minimum curvature‡	1 ± 1	1 ± 0	1 ± 0	1 ± 1	1 ± 1
Plane of minimum curvature‡	3 ± 2	4 ± 7	2 ± 1	2 ± 1	3 ± 2
Kyphosis	25 ± 15	31 ± 11	29 ± 13	22 ± 13	23 ± 11
Lordosis	38 ± 17	39 ± 15	33 ± 14	36 ± 12	30 ± 14

Values are mean ± SD (°).
*Cobb angles of the largest curve computed in the PA view.
†Cobb angles of the largest curve in the plane of the maximum curvature.
‡Cobb angles of the largest curve computed in the plane of the minimum curvature.

The first class identified is a single thoracic curve pattern similar to a King Type III or a Lenke Type 1 curve, with thoracic hypokyphosis and lumbar hypolordosis in the sagittal plane (Figure 4A). The apical view of the reconstruction demonstrates that the deformity is mainly located in the frontal plane. The second pattern identified is a lumbar/thoracolumbar curve similar to a Lenke Type 5 (Figure 4B). The third class represents a thoracic and lumbar curve patterns (Figure 4C) similar to the King Type I or II, or Lenke Type 3 curves. The fourth class is similar to a King Type IV curve, with the apex located slightly lower in the thoracic segment and a flat back in the sagittal plane (Figure 4D). The last pattern is a double thoracic curve (Figure 4E) that can be associated to a King Type V or Lenke Type 2 curves. Details of the clinical indexes of the center of clusters are presented in Table 1. The center of each cluster can be associated with the mean representative of each class.

Fuzzy clustering also detected that a classification of the 409 3D spine reconstructions in 12 classes can divide the input space into well-defined clusters at a consistency rate of 92% computed on 20 trials with random starting points. The 12 curves patterns detected are presented in Figure 5. It can be seen that the five basic frontal curve patterns identified in the preceding cluster analysis are found again, but this time, they are divided in subgroups according to changes in the other planes of the spinal deformity. For example, the first and seventh curve patterns (Figures 4A, G) are single thoracic curve patterns (King Type III or Lenke Type 1) in the frontal plane but present different sagittal profiles: the first being associated with thoracic hypokyphosis and lumbar hypolordosis, and the seventh to thoracic hypokyphosis and normal lumbar lordosis. As another example, the second, fifth, and eight curve patterns (Figure 4B, E, I) are double thoracic curve patterns in the frontal plane but have different sagittal profiles. The second pattern is associated to global thoracic hypokyphosis and normal lumbar lordosis while the fifth and eight patterns are associated to a normal or increased thoracic kyphosis in the upper thoracic spine, and a flat thoracic and lumbar spine below. The fifth and eight patterns are further differentiated in the frontal plane, the fifth being a Lenke Type 2 double thoracic pattern while the eight is a Lenke Type 4 triple curve pattern, a pattern that was not detected in the 5 classes clustering.

The results of fuzzy clustering are presented in Table 2, for a class distribution of 5 and 12 samples, respectively. The results presented comprise the clinical indexes of the sample nearest from the center of clusters, the equivalent of the mean sample among the grouping. The details of intracluster and intercluster metrics evaluating the partition are presented in Tables 3 and 4. The analysis of variance is described in Table 5 and was successful in identifying a difference between each class as well as an intraclass, detected using standard clinical indexes. For the frontal Cobb angles and the plane of maximum curvature measurements, the results are statistically significant ($P < 0.05$) inside each grouping (Table 4). Kyphosis is statistically significant for the 12 classes.

■ Discussion

Classification is of paramount importance for the assessment of AIS, and up to now, has been mainly focused toward guiding surgical treatment. King *et al* have introduced the basis of the first knowledge based classification in terms of medical informatics. They have proposed a classification system of spinal deformities aimed at selecting the appropriate fusion and instrumentation levels for thoracic curves in AIS.[3] Using only seven clinical indexes, five thoracic spinal curves patterns were identified from the frontal plane radiographs assessment of 405 patients operated with the Harrington technique. Each curve pattern is associated to a specific treatment plan, thus guiding surgical practices and having a high clinical relevance. Unfortunately, this classification has several limitations: it can be used only for thoracic curves, it considers only the frontal plane component of the deformity, it has been based on treatment with the Harrington technique which is no longer used, and it has been shown to have a low interobserver and intraobserver reproducibility (64% and 69%).[4,5]

More recently, Lenke *et al* proposed a new and more comprehensive classification to overcome these limitations, which has now gained wide acceptance. The Lenke classification has the advantages over the King classification of

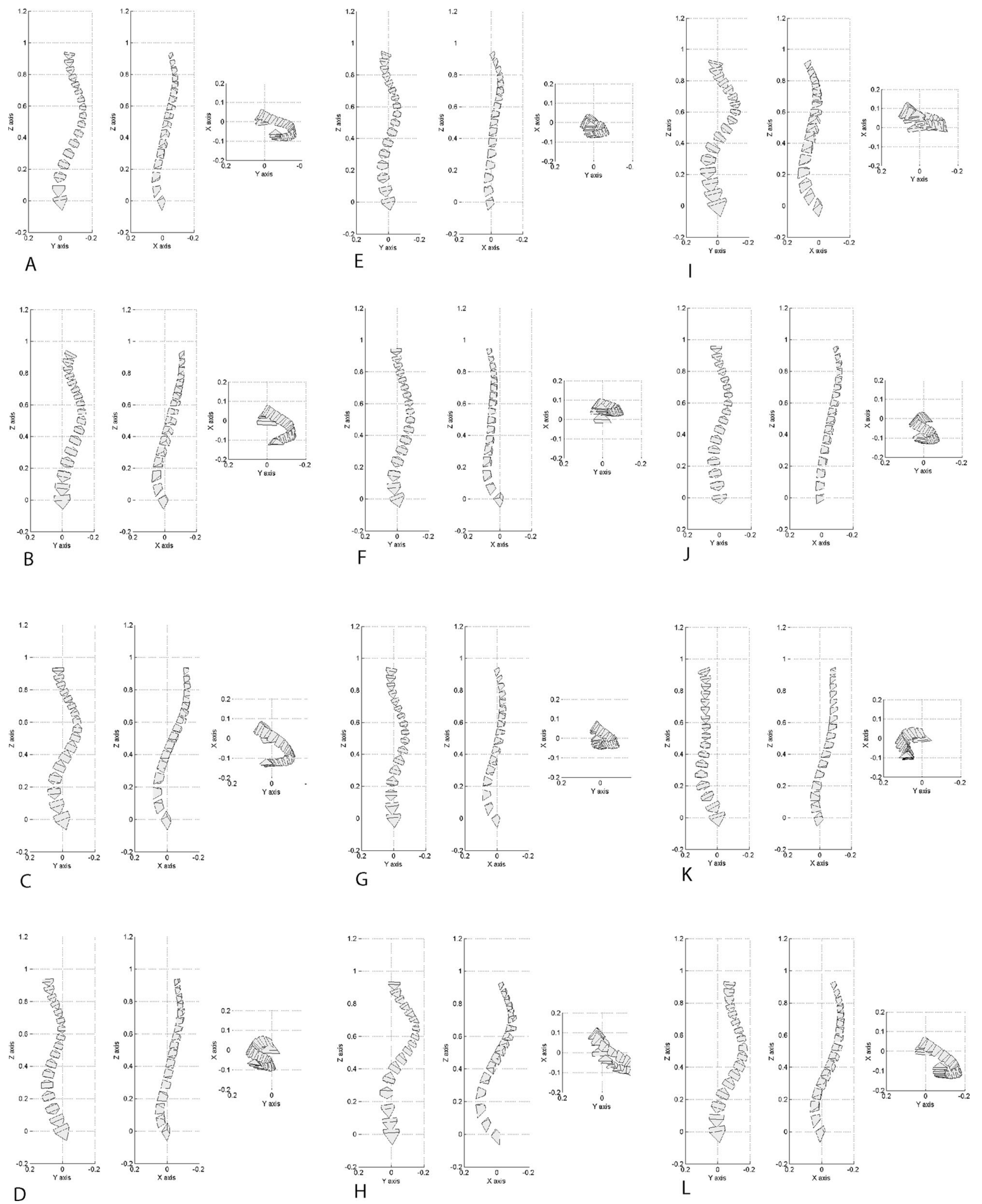

Figure 5. Samples nearest from the center of cluster for 12 classes.

covering a wider range of curve patterns, of having a fair to good reliability[4] and of considering some aspects of the curve patterns in the sagittal plane (sagittal modifiers). However, it still relies on the manual measurement of key radiographic 2D features by surgeons, which only partially cover the complex 3D curve patterns encountered in AIS.

Standard 2D measurements are not sufficient to fully characterize the spinal curve; hence, 3D descriptors have been defined to overcome this limitation. The plane of maximum curvature was proposed by Stokes *et al*[16] to describe the localization of a best-fit plane within a spinal curve where the angle of curvature is the greatest, and

Table 2. Grouping Distribution for 5 Classes and 12 Classes

Class	No. of Samples (k = 5)	No. of Samples (k = 12)
1	93	31
2	56	41
3	88	33
4	90	34
5	82	25
6	—	43
7	—	49
8	—	20
9	—	23
10	—	31
11	—	39
12	—	40
Rand Index	1.00	0.92

which cannot be seen in the frontal or sagittal planes. Perdriolle *et al*[17] have clearly shown that such an approach is absolutely necessary for adequate 3D evaluation of scoliotic deformities, since the regional planes of deformity in scoliosis are no longer aligned with the sagittal plane as in normal individuals, and are no longer related in space with the usual reference system (x, y, and z axis) of the body. In search for a true 3D classification, Poncet *et al* have proposed a set of 3D indexes that evaluate scoliosis as a torsion-like deformity,[6] based on measurements of geometric torsion using a computer algorithm and made on 3D model of the spine obtained by a stereo-radiographic technique. The concept of geometric torsion as a feature of any 3D curve in space is well known to engineers and has been recognized as a valid 3D measurement by the Scoliosis Research Society, but it is a difficult concept for clinicians to understand in relation to spinal deformity. For this reason, the classification has not gained a wide acceptance. This demonstrates that any attempt at 3D classification of spinal deformities must be based on clinical relevance and must rely on measures that clinicians can relate to in a 2D space, such as with frontal and sagittal radiographs. On the other hand, the establishment of a relevant 3D classification system based on the global 3D spinal geometry is a very difficult task if the only tools available are the frontal and sagittal radiographs. As previously stated, the use of 3D reconstructions of the spine is mandatory, but they add an unlimited number of planes and measurements of the deformity to take into account, a task that makes standard visual curve pattern identification a very difficult, complex, and perhaps impossible task.

Table 3. Cluster Analysis Using the Maximum, Minimum, and the Mean Distance From the Cluster Center

Class	Minimum	Mean	Maximum
1	2.71	6.14	8.93
2	0.93	3.60	6.80
3	0.74	2.37	4.70
4	0.16	1.02	5.23
5	0.37	1.40	3.62

Table 4. Cluster Analysis Using Intercluster Distance (k = 5)

Class	1	2	3	4	5
1	—	2.37	5.40	5.14	3.14
2	—	—	2.11	1.92	0.19
3	—	—	—	0.32	1.49
4	—	—	—	—	1.39
5	—	—	—	—	—

This article presents the first report on the use of an unsupervised learning algorithm to classify scoliotic deformities using a cohort of 409 subjects with AIS. We think that the proof of concept of using such an approach has been established, as opposed to the traditional method of visual curve pattern identification, which has been used in the literature so far, *i.e.*, using 2D geometric manual measurements made by surgeons on spine radiographs. We also think that our stated hypothesis that fuzzy clustering, without any *a priori* clinical knowledge, is an appropriate tool to define a clinically relevant classification of spinal deformities using the grouping of samples with similar features, has been demonstrated.

Clustering techniques were chosen for their proven ability to accomplish complex pattern recognition tasks and to provide a quantitative approach to solve the basic limitations of current classification systems based on visual curve pattern identification on radiographs. Compression using wavelet transform allowed to reduce significantly the number of inputs from the 3D reconstructions while still offering a good classification performance. Unsupervised learning techniques have the ability to provide insight on data distribution using a given set of shape descriptors and to deliver an automated approach that can reduce the intraobserver and interobserver variability associated with current visual classification systems.

Clinical evaluation by an expert spine surgeon revealed that the patterns detected without any clinical *a priori* knowledge other than the chosen shape descriptors of the curves were clinically relevant and, in the case of five classes cluster analysis, common curve patterns from the King and Lenke classifications were easily and automatically identified in the cohort studied. Furthermore, in the 12 classes cluster analysis, the five frontal

Table 5. Statistical Analysis Using ANOVA

Clinical Indices	k = 5	k = 12
Cobb angle (PA)*	<0.05	<0.05
Cobb angle (PA)*	<0.05	<0.05
Plane of maximum curvature†	<0.05	<0.05
Plane of maximum curvature†	<0.05	<0.05
Plane of minimum curvature‡	0.80	0.78
Plane of minimum curvature‡	0.62	0.54
Kyphosis	0.13	<0.05
Lordosis	0.32	0.09

*Cobb angles of the largest curve computed in the PA view.
†Cobb angles of the largest curve in the plane of the maximum curvature.
‡[5, 6] Cobb angles of the largest curve computed in the plane of the minimum curvature.

curve patterns observed in the five classes cluster analysis were again detected, with the addition of subtypes of these five basic patterns divided according to clinically identifiable changes in the sagittal plane, indicating that the approach does have the potential to classify in the three planes of the deformity. For example, the first and seventh curve patterns (Figure 4A, G) are single thoracic curve patterns in the frontal plane but present very different sagittal profiles, confirming the observations of Carpineta and Labelle[18] that statistically significant variations of sagittal configurations can be found within the King classification. This strongly suggests that a 3D classification of curve patterns in AIS is not only possible but that it can also be clinically relevant by defining subpatterns of the Lenke or King classifications that would need a different surgical strategy.

A small number of classes cannot allow the detection of subtypes in the classification while too many classes may regroup outliers and identify incorrect clusters, depending on the number of cases available in the cohort. Because of the relatively small number of 3D reconstructions available, this study considered only two class distributions ($k = 5$ and $k = 12$) that produced a uniform classification from the 3D descriptors with a consistency of 100% and 92%, respectively. The fact that a uniform number of samples in each class was found in the two class distributions, as shown in Table 2, suggests a well-defined and appropriate cluster distribution. In future studies, increasing the number of 3D reconstructions in the cohort with multicentric studies will be a crucial factor for the establishment of a more comprehensive 3D classification, as some significant curve patterns may not have been detected in this study if they were not present in a sufficient number of cases in the pool of reconstructions.

It should be reiterated that the selection of appropriate key features to extract from the 3D reconstructions is of crucial importance. This study should be seen as a preliminary trial demonstrating the validity and feasibility of the approach chosen, and not as presenting the definitive 3D classification of scoliotic deformities. The feature extraction strategy used in this study was simply the processing of cylindrical coordinates along a regular interval for each parametric 3D curve (Figure 3), but there are many other possible strategies to evaluate. The appropriate key features to select will now need to be determined by consensus among a panel of expert spine surgeons according to the goals of what a 3D classification should deliver, in order to ensure that the classification will be clinically relevant. A subcommittee of the Scoliosis Research Society Working Group on 3D Spinal Classification has been identified for this specific purpose and will be meeting in the near future to act as a panel of spinal deformity experts to accomplish this task.

■ Key Points

- Three-dimensional classification of adolescent idiopathic scoliosis was investigated using an unsupervised learning algorithm named fuzzy k-means clustering.
- Global shape descriptors from a large set of three-dimensional spine models were inputted in the algorithm to detect curve patterns.
- The algorithm was able to automatically segment the set of models in clinically relevant two-dimensional and three-dimensional curve patterns.
- This approach can be used to help build a relevant three-dimensional classification of adolescent idiopathic scoliosis.

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