Classification of three-dimensional thoracic deformities in adolescent idiopathic scoliosis from a multivariate analysis

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Abstract

Purpose Understanding how to classify and quantify three-dimensional (3D) spinal deformities remains an open question in adolescent idiopathic scoliosis. The objective of this study was to perform a 3D manifold characterization of scoliotic spines demonstrating thoracic deformations using a novel geometric and intuitive statistical tool to determine patterns in pathological cases.

Methods Personalized 3D reconstructions of thoracic (T)/lumbar (L) spines from a cohort of 170 Lenke Type-1 patients were analyzed with a non-linear manifold embedding algorithm in order to reduce the high-dimensionality of the data, using statistical properties of neighbouring spine models. We extracted sub-groups of the data from the underlying manifold structure using an unsupervised clustering algorithm to understand the inherent distribution and determine classes of pathologies which appear from the low-dimensional space.

Results For Lenke Type-1 patients, four clusters were detected from the low-dimensional manifold of 3D models: (1) normal kyphosis (T) with hyper-lordosis (L) and high Cobb angles (37 cases), (2) low kyphosis (T) and normal lordosis (L), with high rotation of plane of maximum

curvature (55 cases), (3) hypo-kyphotic (T) and hyper-lordosis (L) (21 cases) and (4) hyper-kyphotic (T) with strong vertebral rotation (57 cases). Results show the manifold representation can potentially be useful for classification of 3D spinal pathologies such as idiopathic scoliosis and serve as a tool for understanding the progression of deformities in longitudinal studies.

Conclusions Quantitative evaluation illustrates that the complex space of spine variability can be modeled by a low-dimensional manifold and shows the existence of an additional hyper-kyphotic subgroup from the cohort of 3D spine reconstructions of Lenke Type-1 patients when compared with previous findings on the 3D classification of spinal deformities.

Keywords Manifold embedding · Unsupervised clustering · 3D spine reconstruction · Adolescent idiopathic scoliosis · Classification

Introduction

Three-dimensional (3D) models of the spine have been used in numerous clinical studies in orthopedics for evaluating pathologies in spinal deformities such as adolescent idiopathic scoliosis (AIS). More recently, the 3D reconstruction of a patient's spine has been extremely useful in the undertaking of several studies such as the 3D evaluation of the immediate effect of the treatment with the Boston brace system [1], retrospective analysis on the effect of spinal instrumentation strategies [2] and the 3D progression of scoliosis [3]. Standard volumetric modalities such as magnetic resonance imaging (MRI) or computerized tomography (CT) are very attractive because of the increased accuracy they offer for modeling spinal

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geometry and obtaining precise representation of surgical implants. However, both modalities are not performed in the standing position. For these reasons, biplanar radiography is still the imaging technique which is most frequently used for the 3D clinical assessment of spinal deformities since it allows the acquisition of data in the natural standing posture [4].

While scoliosis is a recognized 3D deformation with a deviation not only in the coronal plane but also in the sagittal and transverse planes [5], the pathology is still measured and classified mainly with two-dimensional (2D) radiographic projections of the spine in the coronal and sagittal planes. Classification for AIS is not only useful for understanding the progression of the disease, but, more importantly, also for selecting the optimal surgical strategy based on patient-specific curvature profiles. Hence, by better assessing the type of deformation and risk of progression for a specific pattern, this increases the surgeon's chance of choosing the right instrumentation tools and surgical plan which will ultimately lead to improved patient outcomes. A first uni-planar classification (2D) was proposed by King et al. [6] and was mainly oriented towards the classification of thoracic curves in the coronal plane for selecting appropriate surgical instrumentation approaches. However, only 2D measurements in the coronal plane were considered to build the classification system without any consideration about the sagittal profile which demonstrated variability among King curve types. The Lenke classification system which was introduced in 1997, on the other hand, was a first-step attempt towards classifying scoliosis as a 3D deformity by incorporating both coronal and sagittal planes and demonstrated reasonably good reproducibility rating [7–9] as compared with the King classification system. It is now considered as the premier classification system and continues to be further developed with the addition of new indices such as the deformity score or the Lenke-Harms score [10]. Still misinterpretation in the different parameters makes the scheme subject to a wider differentiation form clinicians.

Due to the 3D nature of idiopathic scoliosis, the natural curvature properties of the spinal curve were also exploited with the goal of defining better indices to characterize the third dimension of scoliosis. Stokes et al. [11] first introduced axial rotation (AR) as a local measure evaluated in the transverse plane to assess the effect of derotation maneuvers in surgical procedures. Poncet et al. [12] proposed geometrical torsion, which is measured by the divergence of the spinal curve to the plane defined from the tangent and normal vectors, as a metric for determining patterns of deformation.

Understanding how to classify and quantify three-dimensional (3D) spinal deformities remains an open

question in adolescent idiopathic scoliosis. Recently, the Scoliosis Research Society (SRS) has recognized the need for 3D classification and mandated the 3D Scoliosis Committee to continue their efforts towards developing a 3D scheme for characterizing scoliosis. Duong et al. [13] proposed an unsupervised clustering technique in order to classify the 3D spine curve which extracts global shape descriptors derived from 3D reconstruction models of the spine. Sangole et al. [14] investigated the presence of subgroups within Lenke Type-1 curves from 3D reconstructions of the spine and proposed a new means to report 3D spinal deformities based on planes of maximal curvature. In this previous study, two distinct subgroups within the surgical cases (major curves) of Lenke Type-1 curves were found, thus suggesting that thoracic curves are not always hypo-kyphotic.

While these recent studies have investigated into pattern classification methods based on explicit parameters such as Cobb angles, kyphosis and planes of maximal deformity which are derived from the 3D geometry of the spine, an emerging trend, however, seeks to synthesize complex data in a sub-space of the conventional Euclidean coordinate system in order to capture the intrinsic variability of an anatomical shape. Indeed, methods have used linear statistics to understand the state of variation in a given class. The main limitation of the aforementioned method is that the high dimensionality and complex non-linear underlying structure unfortunately make the commonly used linear statistics [15] inapplicable for articulated structures such as the spine. Given the important and often un-correlated variations in the orientation and translation of the global spine shape, such statistics can only be performed locally within a sub-population of the entire data set. To overcome such a limitation, an alternative approach maps the high-dimensional observation data (3D spine population) that are presumed to lie on a nonlinear manifold, onto a single global coordinate system of lower dimensionality [16]. Therefore, it helps to preserve neighborhood relationships of similar deformed shapes, thereby revealing the underlying structure of the data which can be used for statistical modeling.

The objective of this study was to propose an algorithmic tool based on locally linear embedding [16] which simplifies the high-dimensionality of 3D spine models obtained from a group of patients (i.e. Lenke Type-1 patients) and evaluate the feasibility of using such a manifold embedding technique to establish the basis of a 3D classification for spinal deformities in AIS. More specifically, the goal of this work was to determine the value of data dimensionality reduction methods in order to identify typical 3D curve patterns observed from a set of intrinsic shape descriptors computed on 3D spine models with AIS. We analyzed populations of 3D scoliotic patients using a

novel geometrically intuitive statistical tool for pathological cases. Clustering was performed using an unsupervised *k*-means approach anchored on a custom-designed similarity metric specifically suited for spine models in order to demonstrate particular classes within studied population.

Materials and methods

The proposed method, illustrated in Fig. 1, can be summarized in four steps: 3D reconstruction, embedding of the high-dimensional data, clustering of points in a low-dimensional space and statistical analysis of the groups. We present in this section the methodology for these steps.

3D patient data

A cohort of 170 AIS preoperative patients with right thoracic deformations, classified as Lenke Type-1 by members of the 3D Scoliosis Committee of the SRS, were studied in this work. The average age at the time of the visit was

14 ± 2 years and the mean thoracic Cobb angle was $44 \pm 13^\circ$ (range, 11 – 76°). For each patient of the cohort, one postero-anterior (PA) and one lateral (LAT) X-ray image were acquired from the radiographic setup for the 3D reconstruction of the spine and pelvis. An image restoration filter based on partial differential equations was used in this study [17] in order to enhance the contrast in the X-rays. The biplanar X-ray images were subsequently calibrated with a self-calibration approach which optimizes the geometrical parameters of the radiographic setup, namely the extrinsic (rotation and translation) and intrinsic (principal points and distances) parameters [4].

To obtain a three-dimensional model of the patient's spine, six 3D anatomical landmarks (centers of superior and inferior vertebral endplates, and the tips of both pedicles) per vertebra (12 thoracic, five lumbar) were generated with a semi-supervised statistical image-based approach implemented in a custom-design software in C++ [18]. The method is summarized in Fig. 2. The method first estimates an initial statistical model based on the patient's centerline and then refines the vertebral geometries and landmarks using image features extracted from the X-ray images, such as intensity distributions and edge potential alignment. The method has shown accurate results with errors less than 3 mm compared with expert identification [18]. Landmarks were subsequently adjusted and matched by an expert to ensure validity. To reconstruct the sacrum, posterior, anterior, left and right extremities were identified as anatomical landmarks as shown in Fig. 3 in order to correctly represent the S1 vertebra. All 3D spine models were normalized with regard to their height and rigidly translated to a common referential at S1.

Manifold embedding of high-dimensional 3D reconstructions of the spine

Given the group of M (170) spine models reconstructed in 3D, we consider that if an adequate number of sample points are available, then the underlying manifold is considered to be “well-sampled”. Therefore, it can represent the underlying population structure. In the sub-cluster corresponding to a pathological population, each individual spine of the group set and its neighbors would lie within a locally linear distribution on the manifold [16]. The first step consists of selecting the N closest neighbors for each spine data point using a closeness measure computed between the 3D spine models of the data set. Standard distance metrics such as the Euclidean distance may not be suitable for evaluating the closeness between 3D spine models as they do not necessary lie in a conventional metric space. One must therefore utilize a metric which is more suited to the particular topology of the multi-object spine structure. Since spines can be described as articulated

Fig. 1 Workflow diagram of the proposed method. From a cohort of 3D spine reconstructions, the system sequentially (1) selects the closest neighbors for each patient, (2) embeds the data to a manifold embedding, (3) performs an unsupervised clustering of the data points and (4) analyzes the clusters based on a set of geometrical clinical parameters

Fig. 2 Illustration of the personalized 3D spine reconstruction from preoperative standing X-rays [18]

Fig. 3 Anatomical landmark identification on **a** the thoracic vertebra with endplate centers and pedicle extremity tips and **b** the pelvis with points on the S1 endplate

shape models (series of intervertebral translations and rotations), some statistical notions have to be generalized based on the concept of distance between articulated primitives.

We adopted the intrinsic nature of a Riemannian manifold geometry that allowed us to discern between articulated shape deformations in a topological invariant framework. The K closest neighbors Y_j were selected for each point Y_i using a distortion metric which is particularly suited for geodesic metrics, anchored on a custom-designed metric which allows us to evaluate the similarity between articulated shape deformations. The diffeomorphism metric $d_A(Y_i, Y_j)$ is defined as

$$d_A(Y_i, Y_j) = \sum_{k=1}^L \|t_k^i - t_k^j\| + d_G(R_k^i - R_k^j) \quad (1)$$

which estimates the distance between spine sample points. In sum, the distance measures the deviation in orientation and translation parameters for each vertebral level L of the spine. Hence, the first term evaluates the absolute distances which evaluate the inter-vertebral translations t . The second defines the deformation between rotation parameters R by estimating the amplitude of angulations between consecutive vertebrae using a geodesic unwrapping operation d_G . These articulated parameters were calculated using the method presented in [19].

The manifold weights were then estimated by assuming the local geometry of the samples can be described by linear coefficients that permit the reconstruction of every spine model from its neighbors. In order to determine the value of the weights assigned between each pair of points, a reconstruction error was minimized based on the difference between the absolute representation of the model's 3D landmark coordinates and the weighted neighbor's 3D landmarks for all data points. These weights represent the importance of a neighboring data point to the reconstruction of the element we seek to embed. The algorithm then maps each high-dimensional model to a low-dimensional point. At the end of the process, for each high-dimensional spine model, we obtained a simplified d -dimensional representation of that model denoted as $\mathbf{x}_i$ which we can plot in $\{1, 2, 3, \dots, d\}$ dimensions, based on the internal modes of variation. The manifold learning algorithm was implemented in C++. Additional details can be found in [16].

Unsupervised k -means clustering

We used a modified version of a k -means clustering method (Matlab R2009a, Mathworks inc, Natick, MA), based on a cluster analysis which aims to partition the M embedded data points into k clusters in which each observation belongs to the cluster with the nearest mean.

Initially, the data points were assigned at random to the k sets. In this initial step, the centroid was computed for each set. In the second step, every point was assigned to the cluster whose centroid is closest to that point. These two steps were alternated until a stopping criterion is met, i.e., when there is no further change in the assignment of the data points. Given a set of observations $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_M)$, where each observation is a d -dimensional real vector, k -means clustering aims to partition the M observations (sample spine points) into k sets ($k \leq M$). To ensure convergence, we iteratively reassigned random values to the data, running the algorithm multiple times with different starting conditions. While k is usually user-defined, we used a method to automatically determine the number of clusters based on intra-cluster and inter-cluster distance measures [20]. The basic procedure involves producing the classification for two clusters up to $K_{\max}$ clusters ($K_{\max} = 8$) which represents the upper limit on the number of clusters. Then the validity measure was calculated to determine which is the best clustering by finding the minimum value for the variance measure.

Clinical data analysis

We processed the Lenke Type-1 patients' cohort using the proposed non-linear manifold embedding algorithm in order to reduce the high-dimensionality of the 3D data, using statistical properties of neighbouring spine models to infer a global representation of the sub-population. Once the clustered embedding was obtained from the data set of spine models, we evaluated the clustered data points by analyzing the following 3D geometric indices for each spine:

1. Computed Cobb angle of the main thoracic (MT) curve in the coronal plane, which is similar to the standard radiographic Cobb angles, but computed from the coronal view of the 3D model.
2. Computed kyphosis constrained to the T4-T12 segment and calculated in a similar fashion to the computed 3D Cobb angle described above.
3. Computed lordosis angle measured between L1 and L5 in all 3D reconstructions.
4. Orientation of the plane of maximum curvature (PMC) of in the MT region, measured by the angle between the current plane and the sagittal plane. The orientation of the plane of maximum curvature is the plane rotation where the projected Cobb angle is maximum.
5. Axial orientation of the apical vertebra in the main thoracic region, measured by the Stokes method [21].

The variability and precision of these 3D geometric indices generated from the reconstructed spine models of scoliotic patients has been shown to be in the same range of

errors of similar clinical measurements taken from radiographs [22]. The graphical representations of these clinical indexes are shown in Fig. 4.

Results

To obtain manifold representations for the cohort of Lenke Type-1 patients, optimal sets of parameters must first be determined in order to appropriately model both the neighborhoods and the intrinsic dimensions of the population to demonstrate variability. We show the effect of varying the value of the N parameter which influences the number of selected neighbors for each spine model to build the subspace. This was determined from a series of experiments which evaluated the decrease in significant reconstruction weights for each value of N . This enabled us to detect when the distribution stabilizes based on the selection of its neighbors. In our experiments illustrated in Fig. 5a, we found that each spine should be reconstructed with its seven closest neighbors ($N = 7$). From these results, we see an optimal compromise must first be selected in order to obtain a low-dimensional representation which emphasizes the distribution. We then determined the size of the sub-dimension by computing the differences from the known model representation and its equivalence from the embedding algorithm. Residual variance values were plotted for the reconstruction of the models at each dimension parameter, with an absolute minimal value found at $d = 3$ as shown in Fig. 5b.

After the k -mean classification, four clusters ($k = 4$) were detected from the low-dimensional manifold of 3D models based on inter- and intra-cluster measures. The result from this classified embedding is presented in Fig. 6. The first group consisted in 37 patients with normal thoracic kyphosis profiles with hyper-lordosis and the highest levels in MT Cobb angles for all groups. The second group had 55 patients, mostly non-surgical (minor curves), with low thoracic kyphosis and normal lumbar lordosis values, but with the highest degree of rotation of the PMC from the sagittal plane. The third group had 21 cases with hypo-kyphotic and hyper-lordotic profiles. Finally, the fourth and last group included 57 patients with hyper-kyphotic thoracic profiles, with major surgical curves and demonstrating very high axial rotations in the apical vertebrae. These results show an additional group in contrast to the study by Sangole et al. which found hypo-kyphotic subgroups in a 3D analysis which used measures such as planes of maximal curvature and kyphosis as influential parameters that split the cases. Coronal and sagittal spine profiles, as well as the daVinci schemas [14] of the representative cases that were identified as the cluster centers are illustrated in Fig. 7. The average values of the geometrical indices

Fig. 4 Graphical representation of 3D clinical indices used for the evaluation of spinal deformities. **a** Computer Cobb angle in the coronal plane; **b** Kyphosis and lordosis in the sagittal plane; **c** Axial rotation of the apical vertebra; **d** Projection of the maximal curvature plane in 3D view; **e** Plane of maximal curvature in the top view

within each cluster differed (Table 1) and indicated the presence of these four groups.

To understand the meaning for each of the three dimensions of the manifold, we plotted trendlines of measurements for a series of clinical indices (MT Cobb angles, kyphosis, MT PMC and MT apex apical rotations) in order to determine any particular tendency with respect to a single axis of the manifold and assess the physical property of a particular dimension. Trendlines are presented in Fig. 8. If we analyze the first dimension, we can discern a significant tendency with regard to the amplitude of the MT Cobb angle and rotation of the PMC. Interestingly, as the Cobb measure steadily increases from one end of the spectrum to the other, the MT PMC rotation decreases. In the case of the second dimension, we observe an increase in the PMC rotation as well as steady increase

of the MT apex apical rotation, while the 3rd dimension shows again a decrease in PMC, this time linked with a decrease in thoracic kyphosis.

One-way ANOVA analysis (Statistica 5.5, Statsoft inc, Tulsa, OK) showed that all indices, except the lumbar lordosis index significantly influenced the grouping tendency ($P < 0.05$). The intergroup interactions showed a significant influence of all indices except for the MT Cobb measure which was nonsignificant in $C3$ and $C4$ ($P = 0.372$) as was expected because $C3$ and $C4$ have similar Cobb angles, but were identified as hypo- and hyper-kyphotic groups, respectively, due to the difference in the kyphosis and plane of maximum curvature. A non-significant finding in the lordosis measure for $C2$ and $C4$ was also found, but differentiated by the axial rotation of the apical vertebra.

Fig. 5 **a** Evolution of the percentage (%) increase of the number of significant weights with respect to the number of N neighbors. **b** Evolution of the residual variance with respect to the value of the lower dimension d

Discussion

With the intent of determining optimal surgical strategies and treatments for patients with AIS, classification systems

have received an increasing amount of attention because of their importance in assessing the severity and progression of the deformity. Lenke et al. [7] proposed a comprehensive classification system, covering a wider range of curve patterns and offer a fair to good reliability by considering some aspects of the curve patterns in the sagittal plane using sagittal modifiers. While radiographic 2D images only offers a limited representation of the complex 3D curve patterns encountered in AIS, 3D descriptors, such as the plane of maximum curvature, were proposed by Stokes et al. [22], describing the best-fit plane where the angle of curvature is the greatest. This was shown by Perdirolle et al. [23] to be a crucial parameter for adequately evaluating 3D scoliotic deformities since the regional planes of deformity in scoliosis are no longer aligned with the sagittal plane as in normal individuals. Other features such as geometric torsion [12], axial rotation [24] or curved planar reformation methods [25] were also developed towards that objective.

Still, quantification and classification of spinal deformities such as AIS in 3D remains challenging because of the difficulty of translating complex geometrical concepts into clinically applicable paradigms. Recent studies have investigated into pattern classification based on explicit parameters. Classification systems have therefore emerged from patterns detected on these 3D geometrical descriptors to discriminate various types of spine deformities. An emerging trend, however, seeks to simplify complex data to capture the intrinsic variability of anatomical shapes.

In this paper, we proposed a technique to perform a classification of 3D spine models by investigating and analyzing populations of 3D scoliotic patients using a

Fig. 6 Result of the low-dimensional manifold of 3D spine models from 170 Lenke Type-1 patients, clustering into four sub-groups. Cluster center points from these groups show (1) normal kyphosis with hyperlordosis, (2) low kyphosis and normal lordosis, with high rotation of plane of maximum curvature, (3) hypo-kyphotic and hyper-lordosis and (4) hyper-kyphotic cases

Fig. 7 Frontal, lateral and top view profiles with planes of maximal deformity (PMC) of the cluster centers for the four detected clusters. The respective da Vinci representations are also shown with

corresponding cases. **a** Cluster center from C1. **b** Cluster center from C2. **c** Cluster center from C3. **d** Cluster center from C4

Table 1 Average and standard deviation values of the thoracic and lumbar indices within all four groups

Parameter	Cluster I (n = 37)	Cluster II (n = 55)	Cluster III (n = 21)	Cluster IV (n = 57)	P value (Anova)
Coronal main thoracic (MT) Cobb angle (°)	53 ± 11	39 ± 9	45 ± 14	45 ± 9	SD (<0.01)
Kyphosis (°)	31 ± 15	26 ± 12	19 ± 12	39 ± 12	SD (<0.01)
Lordosis (°)	-39 ± 12	-32 ± 15	-38 ± 12	-33 ± 12	NS (0.284)
MT plane of maximum curvature (PMC) rotation (°)	61 ± 30	71 ± 31	45 ± 24	53 ± 25	SD (<0.001)
MT apical axial rotation (°)	-23 ± 11	-11 ± 8	-16 ± 8	-22 ± 8	SD (<0.001)

Levels of significance (*P*) for differences of geometric parameters between all groups based on Anova analysis are also shown

SD Significant difference, *NS* Non-significant difference

novel geometrically intuitive statistical tool in order to determine patterns in pathological cases. Hence, personalized 3D reconstructions of thoracic (T)/lumbar (L) spines obtained from a cohort of Lenke Type-1 patients were analyzed with a non-linear manifold embedding algorithm by reducing the high-dimensionality of the data, using statistical properties of neighbouring spine models. The algorithm incorporates a specific articulation-based

similarity measure to select neighbouring spine models, which are then used to create local patches where each spine data point is represented by a weight distribution of the neighborhood. We extract sub-groups of the low-dimensional data of the underlying manifold structure to understand the inherent distribution and determine classes of pathologies which appear from the low-dimensional points.

Fig. 8 Trendlines illustrating the distribution of geometrical indices such as the Main Thoracic (MT) Cobb angle, kyphosis, MT plane of maximum curvature and MT apex apical rotation for all 170 patients when analyzing the **a** 1st dimension, **b** 2nd dimension and **c** 3rd dimension of the low-dimensional manifold

Manifold embedding techniques were chosen for their proven ability to accomplish data reduction from complex patterns and distributions, as well as provide a quantitative approach to solve the basic limitations of current classification systems based on visual curve pattern identification on radiographs. The embedding of a 3D reconstructed population using locally linear mappings allowed significantly reducing the number of inputs from the 3D reconstructions, while still offering a good performance from the clustering which offers coherent distributions of the sample population. Unsupervised learning techniques have the ability to provide insight into data distribution and deliver an automated approach that can reduce the intra and inter-

observer variability associated with current visual classification systems.

Quantitative evaluation illustrates that the complex space of spine variability can be modeled by a low-dimensional manifold which detected four statistically different subgroups. We showed the existence of an additional subgroup with thoracic hyper-kyphosis from the cohort of 3D spine reconstructions of Lenke Type-1 patients when compared with a previous study by Sangole et al. [14]. Indeed, the authors had shown subgroups with thoracic spine deformities demonstrating only hypo-kyphotic or moderate kyphosis profiles, which limited the comparison only to thoracic indices. The findings in [14] suggested that Lenke Type-1 curves are not always hypo-kyphotic as it was often hypothesized based on the analysis of 2D measurements. Still, while it showed some tendency in higher kyphosis angles, it could not prove the existence of hyper-kyphosis within this cohort. The embedding algorithm presented here was able to detect a statistically significant subgroup showing hyper-kyphotic spines, based on an alternative approach using intrinsic features which analyzed the entire spine geometry, including the lumbar region. The manifold representation can potentially be useful for classification of 3D spinal pathologies such as AIS and serve as a tool for understanding the progression of deformities in longitudinal studies. Analyzing each dimension of the manifold, it shows the PMC is a consistent factor in all principal vectors of variability unlike coronal Cobb angles or kyphosis measures, demonstrating the importance of such index in assessing the 3D deformity. Axial rotation of the apical vertebra was also found to be a statistically significant discriminating factor in all groups.

This study involved patients with single-type thoracic structural curves. Further investigation of this manifold tool measuring the extent of variations within a sub-population of spine deformations is necessary to fully assess its potential by considering other types of scoliotic curves. For instance, subtle changes in the spine geometry within a particular class of deformity can be accurately discerned within the manifold. On the other hand, the behavior of the algorithm can drastically change with out-of-sample problems when significantly different topologies (e.g. double thoracic curves) are introduced in the data set for classification. This aspect will have to be considered when using such a classification scheme for surgical procedures, for example. Still, the study adds evidence that 3D characterization of the scoliotic curve reveals inherent structural differences that are not apparent in single planar radiographic assessments and further illustrates the influence of the measure on curve classification.

Conflict of interest None.

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