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ORIGINAL ARTICLE

A computer-based classifier of three-dimensional spinal scoliosis severity

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Abstract
Objective This article describes a computer-based method for the classification of spine scoliosis severity. This is a first step toward an effective computerized tool to assist general practitioners diagnose spine scoliosis. The method progresses away from Cobb angles toward pattern and magnitude categorization based upon 3D configurations.
Materials and methods The purpose is to classify spine shapes reconstructed from a pair of calibrated X-ray images into one of three categories, namely, normal spine, moderate scoliosis, and severe scoliosis. The spine shape is represented by the three-dimensional coordinates of a sequence of equidistant points sampled by interpolation on the reconstructed spine shape. Classification is carried out using a self-organizing Kohonen neural network trained using this representation.
Results The tests were performed using a database of 174 spine biplane X-rays. The classification accuracy was 97%.
Conclusion The results demonstrate that classification of 3D spine descriptions by a Kohonen neural network affords a solid basis for an effective tool to assist clinicians in assessing scoliosis severity.

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Introduction

The idiopathic scoliosis is the most common form of abnormal spinal deformity in adolescents [19]. It is a three-dimensional (3D) deformation of the natural shape of the spinal column, which includes rotations and vertebral deformations [8]. The treatment of patients with AIS is based on X-ray measurements to identify the coronal and sagittal curves, detect the progression of the deformity and assist in the planning of conservative or surgical management [20]. The Cobb angle measurement is used to quantify the scoliosis curve magnitude and classify the scoliosis severity. In general, patients with curves of less than 10° are considered to be normal. If the curves are between 10° and 40°, the scoliosis severity is categorized as moderate. It is considered severe if the angle is greater than 40°. The Cobb angle is measured from a 2D spine projection (posteroanterior PA view) and, therefore, an indirect indicator which does not carry the full information about the spine 3D shape. Moreover, the Cobb angle reliability was shown to be limited. Its variation inter-observer and intra-observer has been estimated to vary up to 9° and 5°, respectively [1,15] which lead to errors for the classification of spine scoliosis severity.
Recent advances in computing and technology have facilitated the development of computer-aided diagnosis systems and concomitant applications to support the clinicians in their decision making. Automatic classification of pathology from medical images has become an important research area in computer-aided diagnosis. In the area of automatic classification of scoliosis, in its general meaning, little research has been done. The majority of studies have investigated the automatic classification of the scoliotic spines [3,6,12].

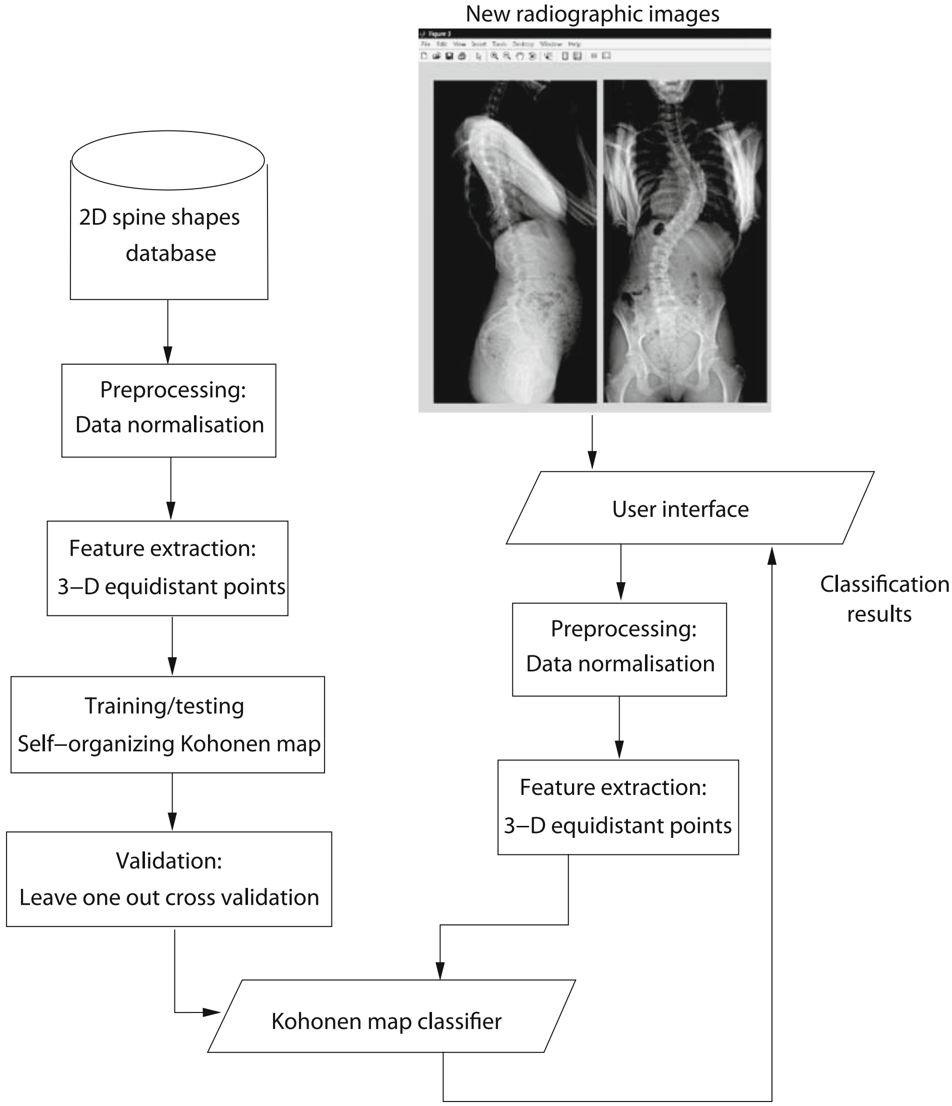

Fig. 1 Block diagram of the proposed classification system

This work deals with the computer classification of scoliosis deformities. The purpose is to automatically classify a spine shape obtained from a pair of calibrated X-ray images into one of three categories, namely, normal spine (NS), moderate scoliosis (MS), and severe scoliosis (SS). Such a system can serve as a basis to build a comprehensive tool to assist internists and general practitioners diagnose spinal conditions. In our method, a spine shape is represented by a sequence of 3D coordinates of equidistant points sampled by interpolation on the reconstructed shape (Sect. Preprocessing and feature extraction). Classification is carried out using a self-organizing Kohonen map trained using this representation (Sect. The Kohonen neural network).

Method

A block diagram of the various modules of the proposed system is shown in Fig. 1.

The modules on the left of this figure are for building the classifier via training of a Kohonen neural network using the spine biplane X-ray database. The modules on the right depict the flow of processing to classify a spine shape of a patient from the pair of calibrated X-ray images.

Database

The database used in this study contains a total of 174 spine models: 91 NS, 47 with MS and 36 with SS. The data collection was done over a few years in the authors laboratories[1] for various research projects [2,4,16], using conventional X-rays and numeric radiographies recorded by the EOS system.[2]

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[2] EOS system (Biospace, Paris, France) includes two X-ray sources with low dose radiation device and two numerical detectors.

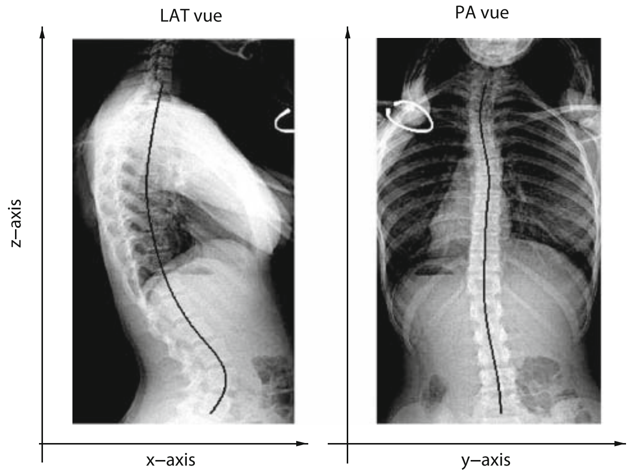

Fig. 2 Reference frame: the x-axis is orthogonal to the frontal plane, the y-axis is orthogonal to the sagittal plane, and the z-axis is orthogonal to the transversal plane

Preprocessing and feature extraction

The database consists of up to 214 parameters of specific anatomical points. In this work, we were interested in the shape of the spine, rather than in the anatomical points of importance. Therefore, we just considered some geometric vertebrae parameters to have the global spine frame. The reference frame is defined as follows (Fig. 2): the x-axis is orthogonal to the frontal plane, the y-axis is orthogonal to the sagittal plane, and the z-axis orthogonal to the transversal plane.

As a preprocessing step, we performed an isotropic scaling to maintain a unit spine in a normalized referential according to the z-axis. This was followed by a smoothing 3D spline that fits on the normalized points. This spline, which describes the overall spinal shape, is used for feature extraction. For the user interface application, we developed an interactive design in which the user can define the spine shape by selecting a few points on the line trough vertebrae centers. In this study, six points where sufficient to perform feature representation and classification.

Feature representation is a crucial step in pattern recognition. It aims at characterizing shapes to be recognized by measurements whose values are similar for shapes in the same category, and different for shapes in different categories [5]. The proposed representation consists of a sequence of 3D coordinates of equidistant points sampled by interpolation on the reconstructed 3D spline shape.

The Kohonen neural network

The Kohonen neural network, also called Self-Organizing Map (SOM or Kohonen Map), was introduced by Teuvo Kohonen [10] and has been widely used in data analysis [9], character recognition [13], and biomedical signal classification [17]. The network is an associative memory, which encodes the input patterns in the form of weight vectors of the same dimension and nature as the input patterns, stored at the nodes of the network (the outputs). The SOM has an attractive characteristic, *self-organizing ordering*, where neighboring nodes encode neighboring input patterns, creating a "topological order" among nodes of the network.

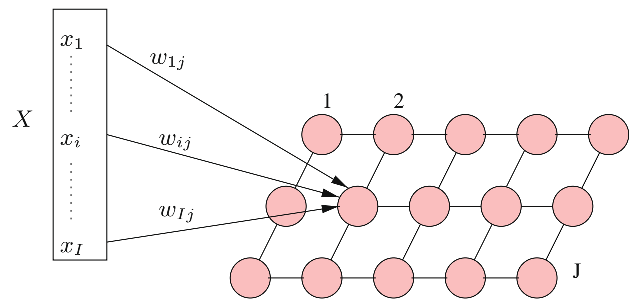

Fig. 3 A two-dimensional Kohonen memory of J nodes

The Kohonen memory training is performed in an unsupervised mode: the input patterns do not need to be labeled. However, with labeled data patterns a pattern category can be assigned to each node once the encoding (called *training* in pattern recognition) is complete, providing the network with a classification function.

Let $\mathbf{X} = (X_1, X_2, \ldots, X_I)$ be an input data vector, and $W_j = (w_{j1}, w_{j2}, \ldots, w_{jI})$ the set of weight vectors of dimension I stored at nodes j, $j = 1, \ldots, J$ (Fig. 3). In this work, an input X is a set of equidistant 3D point coordinates $(x_1, \ldots, x_L, y_1, \ldots, y_L, z_1, \ldots, z_L)$, L being the number of points (as described in Sect. Preprocessing and feature extraction). The Kohonen training algorithm is based on competitive learning [14,18]. After the weights are initialized with small values, the process consists in finding the node, j^*, which contains the weight vector closest to the current input, X. The square of the distance between a memory vector W_j and an input X is, therefore, calculated as follows:

$$d(X, W_j)^2 = \sum_{i=1}^{L} \Big((x_i - w_{ji})^2 + (y_i - w_{j(L+i)})^2 + (z_i - w_{j(2L+i)})^2 \Big). \quad (1)$$

$w_{ji}, i = 1, \ldots, L$ are the weights in node j corresponding to the x-coordinate, $w_{j(L+i)}$, are those which correspond to the y coordinate, and $w_{j(2L+i)}$ are those which correspond to the z coordinate.

At iteration n, the weight vectors at each node j of the memory are updated by an amount that is a function of the grid distance to the node j^* and according to Eq. 2 leading to the topological ordering

$$w_{ji}^{n+1} = w_{ji}^{n} + \epsilon_n h_n^{j,j^*} (x_i^n - w_{ji}^n) \quad (2)$$

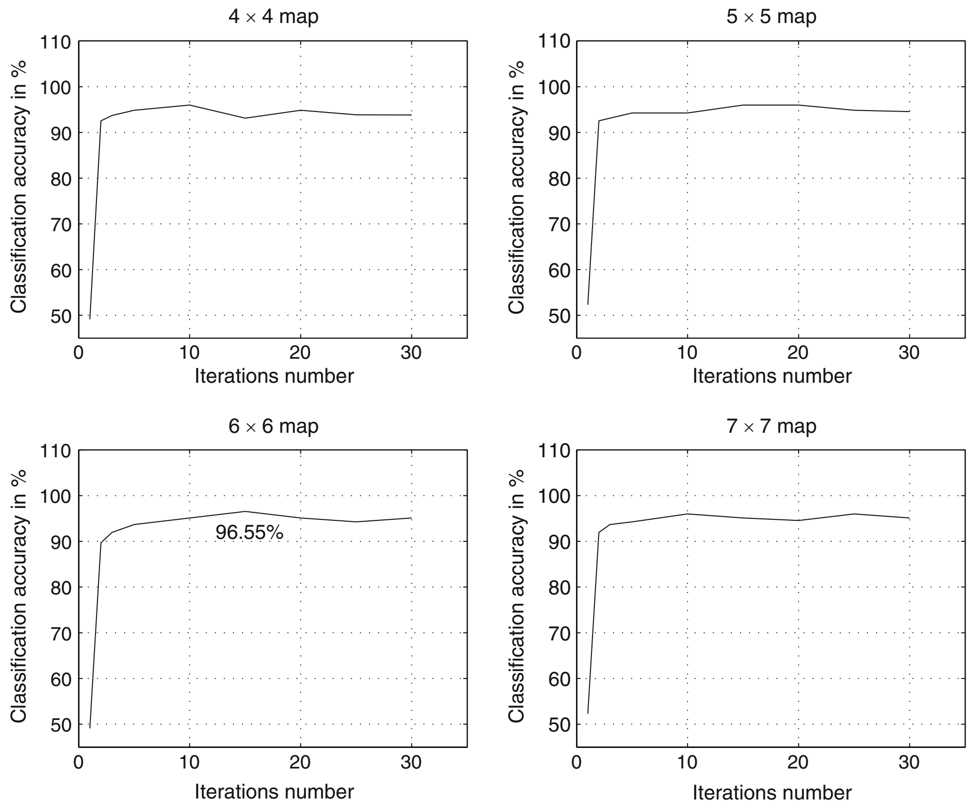

Fig. 4 Classification accuracy versus the iterations number for different map sizes

where

$$\epsilon_n = \epsilon_1 \left(\frac{\epsilon_2}{\epsilon_1}\right)^{\frac{n}{n_{\max}}}, \quad \sigma_n = \sigma_1 \left(\frac{\sigma_2}{\sigma_1}\right)^{\frac{n}{n_{\max}}} \tag{3}$$

$$h_n^{j,j^*} = \exp - \frac{\|j - j^*\|^2}{2\sigma_n^2} \tag{4}$$

The factor h^{j,j^*}, also called the *neighborhood function*, acts as a smoothing kernel and defines the influence of node j^* on node j during update at j. It decreases with increasing grid distance between nodes j^* and j. It depends on a parameter σ which decreases with the number of iterations between values σ_1 and σ_2, respectively, the initial and final values (Eq. 3). The ϵ parameter scales' weight change and varies with the number of iterations from ϵ_1 (initial value) to ϵ_2 (final value) (Eq. 3). The parameters σ_1, σ_2, ϵ_1 and ϵ_2 must be chosen appropriately to ensure algorithm convergence and the network topological ordering. The values of the parameters used in the experiments are: $\sigma_1 = 1$, $\sigma_2 = 0.02$, $\epsilon_1 = 1$ and $\epsilon_2 = 0.0005$.

Validation

We used the leave-one-out cross validation to evaluate the method. The database is divided into $K = N$ subsets, N represents the number of patterns in the database ($N = 174$). Therefore, we performed K experiments. In each experiment all of the patterns are used as reference except one for test. The classification accuracy is computed as the average over all the experiments. Leave-one-out cross validation can be computationally expensive when the database is large.

The leave-one-out cross validation method yields a representative global classification accuracy. To analyze the classification accuracy per class (NS, MS, and SS), the confusion matrix is computed. The confusion matrix is a matrix of the predicted versus the actual classes of the input data. For a given test sample, the entry (i, j) of the confusion matrix is the number of times the classifier identifies an input i as a pattern of class j. Each column of the matrix corresponds to the classifier output, and each row to the input.

Results

We ran experiments to choose the parameters that enter in the Kohonen map classifier design, i.e., the number of iterations and the Kohonen map nodes number.

The graphs of Fig. 4 display the recognition rate as a function of the size of the memory and the number of iterations in the training algorithm. The general tendency of the accuracy is to increase with the number of iterations to attain a maximum, fall slightly and level off. The late decrease of the accuracy is a sign of over learning, a state that has often been observed in practice.

Table 1 Confusion matrix

Actual class	Predicted class		
	NS	MS	SS
NS	90	1	0
MS	0	43	4
SS	1	0	35

(a) 2 iterations

x	x	x	x	x	x
x	x	SS	SS	MS	x
x	x	SS	SS	NS	NS
x	SS	MS	SS	MS	NS
x	SS	SS	SS	SS	MS
x	x	x	SS	SS	x

Training →

(b) 15 iterations

x	x	x	x	x	x
x	x	NS	NS	NS	NS
x	MS	MS	NS	NS	NS
x	SS	MS	MS	NS	NS
x	SS	SS	MS	MS	NS
x	SS	SS	SS	MS	x

Fig. 5 Self organisation of nodes' labels in the Kohonen map after **a** 2 iterations, **b** 15 iterations. *NS* normal spine, *MS* moderate scoliosis, *SS* severe scoliosis, *x* dead node

Table 2 Execution time

Step	Execution time (s)
Training (total time)	4
Classification (time per sample)	1/100

We retained 15 iterations and a 36 nodes (6×6) for the trained map. The corresponding classification accuracy is of 96.55%. Table 1 summarizes the classification accuracy per class: 90/91 for NS class, 43/47 for MS class, and 35/36 for SS class.

Figure 5 shows the Kohonen map after 2 iterations (Fig. 5a) and at the conclusion of training (15 iterations, Fig. 5b). The characters in this map correspond to the nodes labels. The number of nodes assigned to a class varies with the number of iterations. For instance, after 2 iterations the spine patterns are represented by (mapped into) 19 nodes (3 for NS, 4 for MS, and 12 for SS). At the end of the training, the spine patterns are mapped into 23 nodes (10 for NS, 7 for MS, and 5 for SS). Note that the *ordering* property of the Kohonen algorithm yields an ordered map: nodes which encode patterns of the same class (NS, MS, SS) are neighbors. The nodes labelled "x" are *dead nodes*, i.e., nodes which have not been visited by the training algorithm.

Furthermore, we measured the training and classification times in order to compare them. The algorithm was implemented using visual C++ on an Intel pentium 4 computer with a CPU of 3 GHz. Table 2 shows that the classification time is very short which is important in clinical application. Considering the rapidity of the classification decision, this results support the conclusion that the proposed classifier has promising performance to be used in clinical application.

Discussion

In this work, we investigated a computer-based classification method of 3D spinal scoliosis severity. We developed a classifier using a self organizing Kohonen map and a 3D representation of the spinal shape. The proposed representation, based on interpolating 3D equidistant points along the spine shape, has three advantages (1) it provides a 3D representation of the spine using two 2D shapes of biplanar calibrated X-ray radiographic images; such a representation is suitable for the scoliosis deformities as it takes into account the 3D spine deformation, (2) it is independent of specific anatomical points of the vertebrae and it does not require a 3D reconstruction, and (3) it could easily be integrated into a clinical environment. Classification is carried out using a Kohonen neural network, which has attractive proprieties such as self ordering and efficient generalization. At the end of the training, a visual self ordering of the Kohonen map into three classes, namely, NS, MS, and SS is performed. The results demonstrate that classification of 3D spine descriptions by a Kohonen neural network affords a strong basis for an effective tool to assist clinicians in assessing scoliosis severity.

The purpose of this work was to devise a computer classifier of scoliosis severity. In a future work, and using a larger database, we plan to investigate a hierarchical classification of the scoliotic spine curve type. In this case, we will first classify the spines into three classes (NS, MS, and SS), as was performed in this work, and then perform a classification of MS and SS spines into subclasses according to their curve types, to the King model [7] or the Lenke model [11].

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