Linear Fuzzy Space Based Scoliosis Screening

Marko Jocić*, Dejan Dimitrijević*, Milan Pantović**, Dejan Madić**, Zora Konjović*
* University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia
** University of Novi Sad, Faculty of Sport and Physical Education, Novi Sad, Serbia
{m.jocic, dimitrijevic}@uns.ac.rs, milan.pantovic@yahoo.com, dekimadic@gmail.com, ftn_zora@uns.ac.rs

Abstract — In this paper we propose a method for scoliosis screening based on mathematical model of linear fuzzy space and image processing using self-organizing maps. Taking into account that the number of school age children with some sort of a spine deformity in Serbia exceeds 27%, this paper's research came out of a need to develop and implement some novel, effective and primarily economical methods for automated diagnostics of some spine disorders. The ultimate goal however is to produce a suite of mobile applications capable of automated diagnostic of some spine disorders, which could be used by non-medically educated school personal for the purpose of early diagnosis i.e. screening for those spine disorders within adolescents (when the early physical therapy and scoliotic bracing proves to be most effective, and thus least monetary demanding compared to some other invasive means of clinical therapy).

I. INTRODUCTION

The main subject of research presented in this paper is an evaluation of some novel noninvasive spine disorders diagnostic methods and implementations realized with limitations by price and precision. Automated diagnostic solutions for spine disorders currently come in various shapes and sizes, using various diagnostic methods. Some of the methods i.e. techniques used today for diagnosing spine disorders are based on manual deformity testing, topographic visualizations, other sensory inputs (such as laser, infrared, ultrasound scanners, etc.), magnetic resonance imaging (MRI) and/or radiographic imaging i.e. ionizing radiation. Beside deformity tests which can be conducted, with or without additional aids (scoliometers), by sufficiently medically trained personal only [1], second most used method for spine deformity disorder diagnostic is via radiographic imaging. However, since the recommended age for scoliosis testing is between ages 10 and 14, and even twice with the same period for female adolescents [2] with a positive diagnosis rate of about 5%, it is of no surprise that radiographic imaging is avoided. Also, since the number of recommended scoliosis tests does not include the number of post-diagnostic follow-ups for positively diagnosed adolescents, and thus the potential number of needed additional radiographic images taken, it is even more so obvious that the development of alternative noninvasive methods and techniques came from a *de facto* need for reduction of negative cumulative effects of ionizing radiation on adolescents [3].

The first noninvasive methods for diagnosing scoliosis without the use of ionizing radiation or deformity tests came about after 1970, with the so-called *Moiré topography* [4]. Moiré topography represents a method of morphometrics in which a three dimensional contour maps are produced using the interference of coherent light, as the observed object gets flooded with parallel light projected from two or more light sources (waves). Depending on the light wave amplitudes, phase difference and its frequencies, the interferences can cause the light to either grow or dim, which in turn produces darker or lighter lit zones. During the 70-ies and early 80-ies of the last century new methods were developed for diagnostics and follow-ups of some spine deformity disorders sing the aforementioned Moiré topography contour maps [5–7]. That had also triggered a rise in the research of modelling a human spine and its potential deformities [8–10] predominantly based on visual data. However, since the 80-ies and the early 90-ies of the previous century, along with the advances in development and greater accessibility of other sensory technologies and more precise devices, such as laser scanners, the interference images, silk fabric blinds and models produced through regular optical means were mostly substituted by more precise three dimensional models of human back surfaces and spines produced using more advanced measuring methods [11].

The "golden" standard in the scoliosis diagnostics is known as the *Cobb's angle* [12] and is the best method for measuring of scoliotic curvatures used today. It equals the angle formed by the intersection of the two lines drawn perpendicularly to the end plates of the superior and inferior spinal vertebrae which form the scoliotic curves. However, since that requires the spinal anterior-posterior projection first (not easily attainable without radiography), a number of other measuring methods have been formed as an alternative which don't require radiography, among them a couple named *Posterior Trunk Symmetry Index* (POTSI) and *Deformity in the Axial Plane Index* (DAPI), both of which will be further reviewed later on.

This paper is laid out in the following chapters: the first chapter gives an introduction into the research we are conducting, as well as the personal and historical motives driving such and similar research. Chapter II gives an overview of some related work done previously that has been identified by us both in academic paper and practical both commercial and academic solution terms. Chapter III gives preliminaries, providing some basic facts about self-organizing maps and linear fuzzy space. Chapter IV shows the proposed algorithm, and Chapter V shows the results of the proposed algorithm, concluding with directions of future research.

II. RELATED WORK

As noted, this section deals with existing automated spine disorder diagnostics related work. Subsection A lists some of the methods deduced in the academic literature, and subsection B surveys some of the solutions currently available for automated scoliosis spine disorder diagnostic.

A. Current academic literature and given guidelines

Even though the *Moiré topography* contour maps could provide immediate visual feedback into potential spinal deformities, such feedback was only crudely quantifiable without such advances as POTSI or DAPI, explained now:

Posterior Trunk Symmetry Index (POTSI) is a parameter of assessment of the surface trunk deformity in scoliosis, first described by Suzuki et al. back in 1999 [13], and it is a key parameter to assess deformity in the coronal plane. Eight specific points at the surface of the patient's back are required, and those are: the natural cleft, C7 vertebra, most indented point of the trunk side line on both sides, the axilla fold on both sides and the shoulder points which are cross points of the shoulder level lines (Figure 1 left) and the lines drawn vertically from each axilla fold (Figure 1 right). The center line is drawn from the natal cleft. POTSI is relatively simple to measure, even on regular photography of the back. Ideal POTSI is zero, meaning full symmetry of the back surface. Normal values were reported to be below 27 [13, 14]. POTSI is very sensitive in revealing any frontal plane asymmetry. To measure it *Frontal Asymmetry Index* (FAI) values for the axillar, trunk and C7 spinal vertebra must be determined, respectfully as $\mathbf{FAI\text{-}A}=\frac{|\mathbf{c}-\mathbf{d}|}{\mathbf{c}+\mathbf{d}}\times\mathbf{100}$, $\mathbf{FAI\text{-}T}=\frac{|\mathbf{a}-\mathbf{b}|}{\mathbf{a}+\mathbf{b}}\times\mathbf{100}$, $\mathbf{FAI\text{-}C7}=\frac{\mathbf{i}}{\mathbf{c}+\mathbf{d}}\times\mathbf{100}$, where **a** and **b** are distances measured from the center line to waist points, **c** and **d** are lengths from center lines to axilla fold points and **i** equals center line distance to C7 vertebra position. *Height Difference Index* (HDI) values of the shoulders, underarm (axilla) and trunk must also be determined, respectfully as $\mathbf{HDI\text{-}S}=\frac{\mathbf{h}}{\mathbf{e}}\times\mathbf{100}$, $\mathbf{HDI\text{-}A}=\frac{\mathbf{g}}{\mathbf{e}}\times\mathbf{100}$, $\mathbf{HDI\text{-}T}=\frac{\mathbf{f}}{\mathbf{e}}\times\mathbf{100}$, where **e** equals height offset from natal cleft to C7 vertebra points, and **f, g** and **h** equal the height offsets of left and right most indented waist, axilla fold and shoulder level points. The total sum of all the listed index values represents the *Posterior Trunk Symmetry Index* (POTSI).

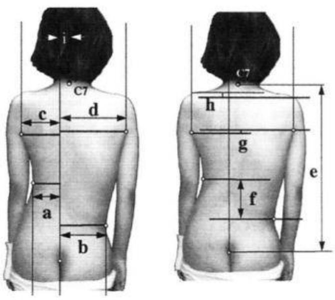

Figure 1 - Schematic of POTSI FAI (left) and HDI (right) parameter points and measurement lines

As for the other parameter of spinal deformity mentioned which is named *Deformity in the Axial Plane Index* (DAPI), it represents a topographic variable which quantifies the spinal deformity in another plane different from POSTI. Its value is measured mostly based on depth distances of most and least prominent points on the human back surface, making it a complementary value for a combined more accurate diagnostic criterion [15]: subjects with normal DAPI and POTSI values (DAPI ≤ 3.9% i POTSI ≤ 27.5%) are classified as non-pathological, but subjects with high DAPI or either POTSI are diagnosed as pathological.

B. Current spine disorder diagnostic solutions

Because the number of school age children in Serbia [16] with some sort of a spinal disorder rose above 27% of which on scoliosis accounts more than 19%, there is a significant motivation for seeking out improved solutions used in early screenings for various spinal disorders. However, the economic costs for screening of an individual child for scoliosis also seems to increase with greater solution's complexity, compared to use of simple aids such as scoliometers [17]. Thus, our systematic research of publicly available PhD papers produced within the last decade identified two papers dealing with the solutions for automated diagnostics of scoliosis [18, 19]. But, both solutions were considerably more complex and expensive, requiring highly computationally and measurably capable resources (i.e. laser scanners) for analysis and diagnostics.

III. PRELIMINARIES

Approach proposed in this paper consists of using self-organizing maps and fuzzy sets theory to determine scoliosis by digital image analysis. Our previous work [22-25] in mathematical models for describing imprecise data image and medical analysis [26,27] has shown that this approach based on fuzzy points and fuzzy lines in linear fuzzy space is simple, yet can be very effective. Another motivation for this alternative approach is because of the inherent properties of digital images which are vagueness and imprecision, which are caused by image resolution, bad contrast, noise, etc.

A. Self-organizing map

Self-organizing map, also called Kohonen map, is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a map. Self-organizing maps are different from other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space. Unsupervised learning algorithm is based on competitive learning, in which the output neurons compete amongst themselves to be activated, with the result that only one is activated at any one time. This activated neuron is called the winning neuron. Such competition can be induced/implemented by having lateral inhibition connections (negative feedback paths) between neurons. The result is that neurons are forced to organize themselves.

B. Linear fuzzy space

Definition. *Fuzzy point* $P \in \mathbb{R}^2$, denoted by $\tilde{P}$ is defined by its membership function $\mu_{\tilde{P}} \in \mathcal{F}^2$, where the set $\mathcal{F}^2$ contains all membership functions $u: \mathbb{R}^2 \to [0,1]$ satisfying following conditions:

i) $(\forall u \in \mathcal{F}^2)(\exists_1 P \in \mathbb{R}^2)\, u(P) = 1,$

ii) $(\forall X_1, X_2 \in \mathbb{R}^2)(\lambda \in [0,1])\ u(\lambda X_1 + (1-\lambda)X_2) \geq \min\big(u(X_1), u(X_2)\big)$,
iii) function u is upper semi continuous,
iv) $[u]^\alpha = \{X | X \in \mathbb{R}^2, u(X) \geq \alpha\}$ α-cut of function u is convex.

The point from $\mathbb{R}^2$, with membership function $\mu_{\tilde{P}}(P) = 1$, will be denoted by P (P is the core of the fuzzy point $\tilde{P}$), and the membership function of the point $\tilde{P}$ will be denoted by $\mu_{\tilde{P}}$. By $[P]^\alpha$ we denote the α-cut of the fuzzy point (this is a set from $\mathbb{R}^2$).

Definition. $\mathbb{R}^2$ *Linear fuzzy space* is the set $\mathcal{H}^2 \subset \mathcal{F}^2$ of all functions which, in addition to the properties given in Definition 2.1, are:

i) Symmetric against the core $S \in \mathbb{R}^2$ ($\mu(S) = 1$),
$\mu(V) = \mu(M) \wedge \mu(M) \neq 0 \Rightarrow d(S,V) = d(S,M)$,
where $d(S,M)$ is the distance in $\mathbb{R}^2$.
ii) Inverse-linear decreasing w.r.t. points' distance from the core according to:

$$if\ r \neq 0\ \mu_{\tilde{S}}(V) = \max\left(0, 1 - \frac{d(S,V)}{|r_S|}\right)$$

$$if\ r = 0\ \mu_{\tilde{S}}(V) = \begin{cases} 1 & if\ \ S = V \\ 0 & if\ \ S \neq V \end{cases}$$

where $d(S,V)$ is the distance between the point V and the core S ($V, S \in R^n$) and $r \in \mathbb{R}$ is constant. Elements of that space are represented as ordered pairs $\tilde{S} = (S, r_S)$ where $S \in \mathbb{R}^2$ is the core of $\tilde{S}$, and $r_S \in \mathbb{R}$ is the distance from the core for which the function value becomes 0; in the sequel parameter r_S will be denoted as *fuzzy support radius*.

Definition. Let $\mathcal{H}^2$ be a linear fuzzy space. Then a function $f: \mathcal{H}^2 \times \mathcal{H}^2 \times [0,1] \to \mathcal{H}^2$ is called *linear combination* of the fuzzy points $\tilde{A}, \tilde{B} \in \mathcal{H}^2$ given by

$$f(\tilde{A}, \tilde{B}, u) = \tilde{A} + u \cdot (\tilde{B} - \tilde{A}),$$

where $u \in [0,1]$ and operator $\cdot$ is a scalar multiplication of fuzzy point.

Definition 3.3 Let $\tilde{A}, \tilde{B} \in \mathcal{H}^2$ and $\tilde{A} \neq \tilde{B}$. Then a point $T_{AB} \in \mathbb{R}^2$ is called *internal homothetic center* if the following holds

$$T_{AB} = A + \frac{a_r}{a_r + b_r}(B - A),$$

where $\tilde{A} = (A, a_r)$ and $\tilde{B} = (B, b_r)$.

Definition 3.5 Let $\widetilde{AB}$ be *fuzzy line* defined on linear fuzzy space $\mathcal{H}^2$ and $X \in \mathbb{R}^2$. Then a fuzzy point $\widetilde{X'} \subset \widetilde{AB}$ is called *fuzzy image of point X on fuzzy line* $\widetilde{AB}$, and a real number $u \in [0,1]$ is called *eigenvalue of the fuzzy image X* on fuzzy line $\widetilde{AB}$ if following hold

(i) $\widetilde{X'} = \tilde{A} + u(\tilde{B} - \tilde{A})$,
(ii) $d\left(X, \left[\widetilde{X'}\right]^1\right) = \min\left\{d(X,Y) | \forall Y \in \left[\widetilde{AB}\right]^1\right\}$,
(iii) $u = \min\left(1, max\left(0, \frac{(x_1-a_1)(b_1-a_1)+(x_2-a_2)(b_2-a_2)}{(b_1-a_1)^2+(b_2-a_2)^2}\right)\right)$

where $X = (x_1, x_2)$, $\tilde{A} = ((a_1, a_2), a_r)$ i $\tilde{B} = ((b_1, b_2), b_r)$.

C. Spatial relations in $\boldsymbol{R^2}$ *linear fuzzy space*

Spatial relations (predicates) are functions that are used to establish mutual relations between the fuzzy geometric objects. The basic spatial relations are *coincide*, *between* and *collinear*. In this section we will give their definitions and basic properties.
Fuzzy relation *coincidence* expresses the degree of truth that two fuzzy points are on the same place.

Definition 4.1 Let λ be the Lebesgue measure on the set $[0,1]$ and $\mathcal{H}^2$ is a linear fuzzy space. The fuzzy relation $coin: \mathcal{H}^2 \times \mathcal{H}^2 \to [0,1]$ is *fuzzy coincidence* represented by the following membership function

$$\mu_{coin}(\tilde{A}, \tilde{B}) = \lambda(\{\alpha \mid [\tilde{A}]^\alpha \cap [\tilde{B}]^\alpha \neq \emptyset\}).$$

Remark. Since the lowest α is always 0, then a membership function of the *fuzzy coincidence* is given by

$$\mu_{coin}(\tilde{A}, \tilde{B}) = max\{\alpha \mid [\tilde{A}]^\alpha \cap [\tilde{B}]^\alpha \neq \emptyset\}.$$

Proposition "*Fuzzy point $\tilde{A}$ is coincident to fuzzy point $\tilde{B}$*" is partially true with the truth degree $\mu_{coin}(\tilde{A}, \tilde{B})$; in the Theorem 4.1 we present method for its calculation.

Theorem 4.1 Let the fuzzy relation *coin* be a fuzzy coincidence. Then the membership function of the fuzzy relation *fuzzy coincidence* is determined according to the following formula

$$\mu_{coin}(\tilde{A}, \tilde{B}) = \begin{cases} 0 & if\ \ |a_r| + |b_r| = 0\ \wedge d(A,B) \neq 0, \\ \max\left(0, 1 - \dfrac{d(A,B)}{|a_r| + |b_r|}\right) & if\ \ |a_r| + |b_r| \neq 0, \\ 1 & if\ \ |a_r| + |b_r| = 0\ \wedge d(A,B) = 0\,. \end{cases}$$

Fuzzy relation *contains* or *between* is a measure that fuzzy point belongs to fuzzy line or fuzzy line contains fuzzy point.

Definition 4.2 Let λ be Lebesgue measure on the set $[0,1]$, $\mathcal{H}^2$ linear fuzzy space and $\mathcal{L}^2$ be set of all fuzzy lines defined on $\mathcal{H}^2$. Then fuzzy relation $contain: \mathcal{H}^2 \times \mathcal{L}^2 \to [0,1]$ is *fuzzy contain* represented by following membership function

$$\mu_{contain}(\tilde{A}, \widetilde{BC}) = \lambda(\{\alpha \mid [\tilde{A}]^\alpha \cap [\widetilde{BC}]^\alpha \neq \emptyset\}).$$

Remark. Its membership function could be also represented as

$$\mu_{contain}(\tilde{A}, \widetilde{BC}) = \lambda(\{\alpha | \exists u \in [0,1] \wedge \exists X \in [\tilde{A}]^{\alpha} \wedge \exists Y, Z \in [\widetilde{BC}]^{\alpha} \wedge X = Y + u(Z - Y)\}).$$

Proposition "*Fuzzy line* $\widetilde{BC}$ *contain fuzzy point* $\tilde{A}$" is partially true with the truth degree $\mu_{contain}(\tilde{A}, \widetilde{BC})$; in the Theorem 4.2 we present method for its efficient calculation.

Theorem 4.2 Let $\tilde{A}, \tilde{B}, \tilde{C} \in \mathcal{H}^2$ be fuzzy points defined on $\mathcal{H}^2$ linear fuzzy space, $u \in [0,1]$ and $\widetilde{A'}$ be *fuzzy image of point* A *on fuzzy line* $\widetilde{BC}$. Points T_{AB} and T_{AC} are *internal homothetic center* fuzzy points for fuzzy points $\tilde{A}$ and $\tilde{B}$ and $\tilde{A}$ and $\tilde{C}$ respectively. Then the membership function of the fuzzy relation *fuzzy contain* is determined according to the following formula

$$\mu_{contain}(\tilde{A}, \widetilde{BC}) = \begin{cases} \mu_{coin}(\tilde{A}, \tilde{A}') \; if \;\; u \in \{0,1\} \\ \mu_{\tilde{A}}(A^*) \; if \;\; u \in (0,1) \end{cases},$$

where point A^* is a projection of core of $\tilde{A}$ on the line passing through the points T_{AB} and T_{AC}.

Definition 4.3 Let $\tilde{A}, \tilde{B}, \tilde{C} \in \mathcal{H}^2$ be a fuzzy points defined on $\mathcal{H}^2$ linear fuzzy space and λ be Lebesgue measure on the set [0,1]. The fuzzy relation $coli: \mathcal{H}^2 \times \mathcal{H}^2 \times \mathcal{H}^2 \to [0,1]$ is *fuzzy collinearity* between three fuzzy points and it is represented by following membership function

$$\mu_{coli}(\tilde{A}, \tilde{B}, \tilde{C}) = \lambda\{\alpha | \exists u \in R \wedge \exists X \in [\tilde{A}]^{\alpha} \wedge \exists Y \in [\tilde{B}]^{\alpha} \wedge \exists Z \in [\tilde{C}]^{\alpha} \wedge \;\; A = B + u(C - B)\}.$$

Proposition *"Fuzzy points* $\tilde{A}, \tilde{B}$ *and* $\tilde{C}$ *are collinear"* is partially true with the truth degree $\mu_{coli}(\tilde{A}, \tilde{B}, \tilde{C})$; in the Theorem 4.3 we present method for its calculation.

Theorem 4.3 Let $\tilde{A}, \tilde{B}, \tilde{C} \in \mathcal{H}^2$, fuzzy relation $contain$ be *fuzzy contain*. Then a membership function of the fuzzy relation *fuzzy collinearity* is determined according to the following formula

$$\mu_{coli}(\tilde{A}, \tilde{B}, \tilde{C}) = \max\left(\mu_{contain}(\tilde{A}, \widetilde{BC}), \mu_{contain}(\tilde{B}, \widetilde{AC}), \mu_{contain}(\tilde{C}, \widetilde{AB})\right).$$

This definition of fuzzy collinearity for three points is easily extended to arbitrary number of fuzzy points.

IV. PROPOSED ALGORITHM

First step in our algorithm is image segmentation by using self-organizing map (SOM). SOM is used to reduce the number of colors of the digital image that is analyzed. More precisely, after providing SOM with training data (colors on the image), 16 million possible colors are quantized to only 4 colors, and then trained SOM is applied to the original image to get much more simplified image. This allows easier extraction of edge points. These edge points are extracted in a simple way – every horizontal line on the image is scanned in order to find transitions between colors, and each of these color transitions is considered an edge points. After that, for each horizontal line, a mean point, or a center of symmetry for found edge points on that horizontal line is calculated. At this point, we calculate an angle that these centers form, and this is done by using linear regression. This angle can be another useful indicator for determining scoliosis.

Because the image processed with SOM is simplified, inherently a certain amount of imprecision is introduced to the image. So, we decided to model this imprecision by using fuzzy points for previously calculated points that represent centers of symmetry. The amount of uncertainty for these fuzzy points is inversely proportional to size of SOM that was used to segment the image – the smaller the SOM used the more imprecise these points are. Following this, a measure of fuzzy collinearity for these fuzzy points is calculated and this value can be used with as an input for some machine learning algorithms to infer whether scoliosis is present in the analyzed image or not. Complete algorithm is shown as flowchart in Figure 2.

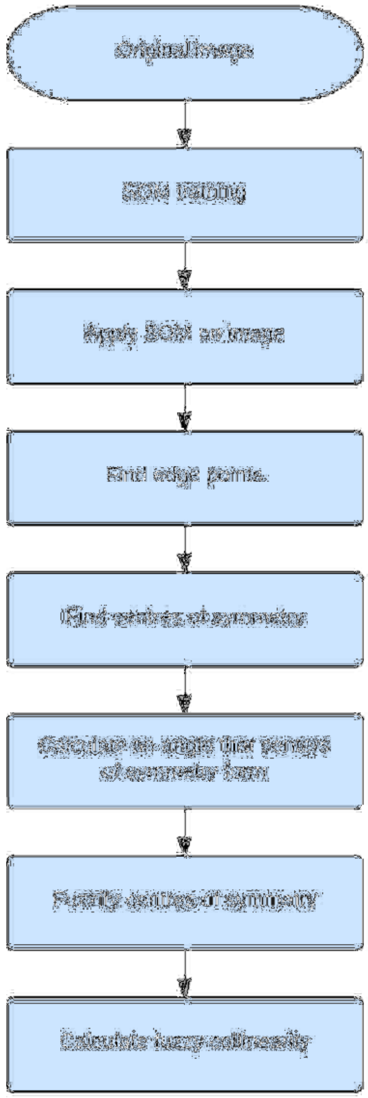

Figure 2 – The proposed algorithm flowchart

V. RESULTS

In this chapter we show the results of applying the proposed algorithm to image shown in Figure 3. On the left side of this figure, a healthy spine is shown, while the right side shows a scoliotic spine. As previously described, SOM with dimensions 2x2 is used to reduce the number of colors from 16 million to only 4. The results of image segmentation are shown in Figure 4.

Figure 3 – Image of spine without (left) and with scoliosis (right)

Following the image segmentation, edge points are found and after that their corresponding centers of symmetry. With available centers of symmetry, the angles that these points form are calculated by using linear regression (blue lines). Fuzzified centers of symmetry, along with calculated angles and extracted edge points are shown in Figure 5. Calculated angles that centers of symmetry form are 4° on the left image, and 17° on the right image. Also, calculated measure of fuzzy collinearity between fuzzy points is 0.8 on the left image, and 0 on the right image.

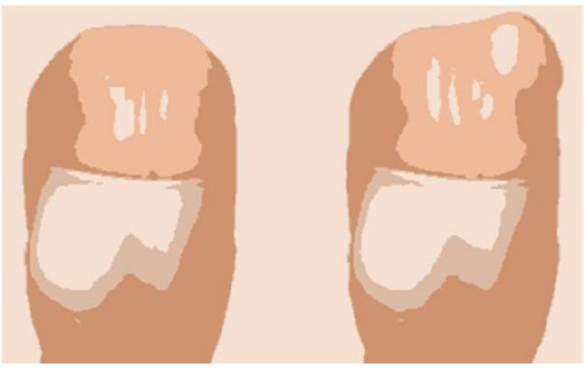

Figure 4 – Image segmentation with self-organizing map

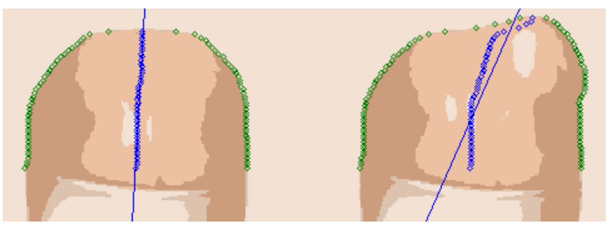

Figure 5 – Result image

VI. CONCLUSION

In this paper we proposed a novel method for scoliosis screening based on mathematical model of linear fuzzy space and image processing using self-organizing maps. Proposed algorithm results in two values: angle formed by calculated centers of symmetry and fuzzy collinearity. Future research would provide the proposed algorithm with many real-world images of patients with and without scoliosis, and certain number of these images could be taken as a training set for some supervised machine learning algorithm which would later be used to infer the presence of scoliosis. As inputs for this training set, calculated measures of fuzzy collinearity and calculated angles which centers of symmetry form could be used along with indicator if scoliosis is present.

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