# Automatic Classification of Spinal Deformity by using Four Symmetrical Features on the Moire Images

Hyoungseop Kim [1], Satoshi Nakano [1], Joo Kooi Tan [1], Seiji Ishikawa [1]
Yoshinori Otsuka [2], Hisashi Shimizu [3] and Takashi Shinomiya [4]

[1] Department of Control Engineering, Kyushu Institute of Technology
1-1, Sensui-cho, Tobata, Kitakyushu, Japan
Kim@cntl.kyutech.ac.jp
[2] National Sanatorium Chiba Higashi Hospital, Japan
[3] Chiba Foundation for Health Promotion & Disease Prevention, Japan
[4] Nikon Co. LTD., Japan

**Abstract.** Spinal deformity is a disease mainly suffered by teenagers during their growth stage particularly from element school to middle school. There are many different causes of abnormal spinal curves, but all of them are unknown. The most common type is termed “idiopathic” that show 80% of the spinal deformity. Spinal deformity is a serious disease, mainly suffered by teenagers, especially girl’s student, during their growth stage.To find the spinal deformity in early stage, orthopedists have traditionally performed on children a painless examination called a forward bending test in mass screening of school. But this test is neither objective nor reproductive, and the inspection takes much time when applied to medical examination in schools. To solve this problem, a moire method has been proposed which takes moire topographic images of human subject backs and checks symmetry/asymmetry of the moire patterns in a two-dimensional way. In this paper, we propose a method for automatic classification of spinal deformity from moire topographic images by extracting four symmetrical features of the left-hand and right-hand side on the moire image. Feature of asymmetry degrees are applied to train employing the classifier such as Artificial Neural Network, Support Vector Machine, Self-Organization Map and AdaBoost.

## 1 Introduction

Spinal deformity is one of the serious diseases, mainly suffered by teenagers. It is tends to run in families and is more common in females than males during their growth stage. There are many different causes of spinal deformity such as congenital, kyphosis (curvature of the spine with the convexity pointing toward the back), but in the vast majority of cases there is no known cause. Although the spine does curve from front to back side it should not curve lateral. A side-to-side called scoliosis and it may take the shape of an ‘S’ or ‘C’ character. The difficulty because of not accompanied by the subjective symptom such as pains the early stage detect and the early treatment becomes a problem. When one suffers from a spinal deformity, in severe case, it is associated with pain and it requires surgical treatment. The treatment of spinal deformity depends on the location and degree of curvature. Slight curves usually require no treatment, but as the curve progresses the treatment is required because the size of chest cavity diminish, it causes pain and decrease in lung.

To find the spinal deformity in early stage, orthopedists have traditionally performed a painless examination which called the forward bending test in mass screening of school. In the forward bending test, mainly medical doctor checks 5 points such as rib hump, lumbar hump, and asymmetric degree on the shoulder and west line. But this test is neither objective nor reproductive, and the inspection takes much time when applied to medical examination in school screening. To solve such various problems, a moire method [1-2] has been proposed which takes moire topographic images of human subject backs and checks symmetry/asymmetry of the moire patterns in a two-dimensional way. The moire topographic image represented stripe pattern as one of the three dimension information. Moire stripes appear as symmetry the subject is classified as normal.

By using the moire image, the diagnosis efficiency of spinal deformity in the mass screening improved. However, the burden of the doctor who diagnoses a large amount of moire image is still remained. Then, the necessity of the image diagnosis support by using a computer is requested from the medical site. To detect the spinal deformity, some algorithms are proposed [3-4]. In this paper, we propose a technique for automatic classification of spinal deformity from moire topographic images by extracting four symmetrical features of the left-hand and right-hand side on the moire image. In the first step, once the original moire images is fed into computer, the middle line of the subject's back is extracted on the moire image employing the approximate symmetry analysis[5]. Regions of interest (ROIs) are automatically selected on the moire image from its upper part to the lower part and the middle line of the subject's back. Then the four asymmetry degrees are calculated from obtained ROIs. Numerical representation of the degree of asymmetry, displacement of local centroids and difference of gray value, are calculated between the right-hand side and the left-hand side regions of the moire images with respect to the extracted middle line. Feature of four asymmetry degrees (mean value and standard deviation from the each displacement) from the right-hand side and left-hand side rectangle areas apply to train the Artificial Neural Network (ANN), Support Vector Machine (SVM), Self-Organization Map (SOM) and AdaBoost.

## 2 Extraction of the Middle Line

Moire photography uses light projected through a grid and then photographed to record the 3-D shape of the subject's back. Generally, the moire stripes show symmetric patterns on the normal subject's backs. But when one becomes spinal deformity, an asymmetric moire pattern appears on the moire image of the subject's back. In the diagnostic of imaging by using the moire method, asymmetry degree are evaluated on the moire images, so it is effective to make the asymmetry degree on the moire image in the visual screening.

To analyze the asymmetric of moire pattern, the middle line is extracted based on approximately symmetry analysis technique [5]. The approximate symmetric axis can be found by superposing the original and the reflected original image (mirror image). The best position of the superposing is determined, by evaluating the difference image which is overlapped the original and the mirror image. We adjusted to the position in which the difference of the density of a pixel values are minimized. The approximate symmetric axis is represented by the perpendicular bisector of the center of gravity of the original and the mirror image.

We assume an original moire image is $f(x,y),(x,y)\in R$, and its reflected image is represented by $f'(x,y)\ ,(x,y)\in R^r$. The $f'(x,y)$ is superposed onto the $f(x,y)$ by parallel translation $c=(c_x,c_y)$, $T$ is a rotation transform and rotation $\theta$ to find the best match in eq.(1). In this paper, we assume that $\theta$=0 in eq.(2), because the moire images are captured normally straight using position-supporter so that their middle lines remain vertical.

$$D_{axis} = \min_T \sum_{(x,y)\in R\cup R^r} \left| f(x,y) - Tf'(x,y) \right| \tag{1}$$

$$T = \begin{pmatrix} \cos\theta & \sin\theta & c_x \\ -\sin\theta & \cos\theta & c_y \\ 0 & 0 & 1 \end{pmatrix} \tag{2}$$

## 3 Extraction the Four Asymmetrical Features on the ROIs

The ROIs are selected by using pre-processing technique, the asymmetrical features are calculated by the following way.

Within the region $R$ and at a certain position $y=j$, two rectangle areas are defined, as shown in Fig.1, at symmetric locations with respect to the middle line $x=m$. The width $R_x$ of the rectangle area is defined by,

$$R_x = \min(m-l, r-m)\,. \tag{3}$$

Here $m$ is the middle line which is extracted above mentioned, $l$ is minimum frequency of the left-hand side $r$ is minimum frequency of the right-hand side on the histogram. On the other hand, height of the area is defined empirically.

Let us denote the rectangle areas of the left-hand side and right-hand side at $y=i$ by $A_i^l$ and $A_i^r$, respectively. Here $i$=1,2,…,$N$. The centroids of $A_i^l$ and $A_i^r$ are denoted by $G_l(x_l,y_l)$ and $G_r(x_r,y_r)$, respectively. The centroid $G_l(x_l,y_l)$ is reflected with respect to the middle line $x=m$ into the region $A_i^r$ and denoted by $G_l^*(x_l^*,y_l^*)$. The distance $G$ between $G'_l(x'_l,y'_l)$ and $G_r(x_r,y_r)$ is calculated by,

$$E = \sqrt{(x'_l - x_r)^2 + (y'_l - y_r)^2} \tag{4}$$

The mean $\mu_E$ and standard deviation $\sigma_E$ of the values $E$ ($i$=1,2,…,$N$) are employed as the features representing the degree of asymmetry of the moire image in calculation rectangle area. The expressions are shown as follows.

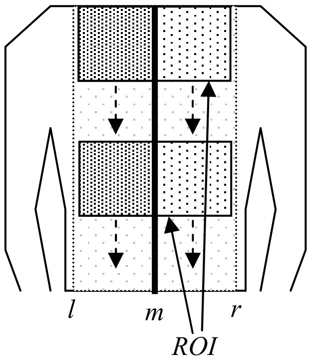



**Fig. 1.** Rectangle areas in the region of interest.

$$\begin{cases} \mu_E = \dfrac{1}{N}\sum_{i=1}^{N} E \\ \sigma_E = \sqrt{\dfrac{1}{N}\sum_{i=1}^{N}\left(E-\mu_E\right)^2} \end{cases} \tag{5}$$

Furthermore, in the same rectangle area, the difference of gray value $D$ is calculated by,

$$D = \left| r_d - l_d \right| \tag{6}$$

Here, $r_d$ and $l_d$ are shown the mean value of the gray value on the right-hand and left-hand side in the ROIs, respectively. The mean $\mu_D$ and standard deviation $\sigma_D$ of the difference of gray values $D$ $(i=1,2,\ldots,N)$ are employed as the features representing the degree of asymmetry of the moire image in calculation rectangle area. The expressions are shown as follows.

$$\begin{cases} \mu_D = \dfrac{1}{N}\sum_{i=1}^{N} D \\ \sigma_D = \sqrt{\dfrac{1}{N}\sum_{i=1}^{N}\left(D-\mu_D\right)^2} \end{cases} \tag{7}$$

## 4 Classification Methods

The mean value and the standard deviation of the difference of the center of gravity and difference of gray value on the right-hand and left-hand side area are obtained as the feature, respectively. To classify the unknown moire image, we have tried the ANN, SVM, SOM and AdaBoost techniques employing four asymmetrical features.

ANN is used a useful technique for the pattern classification. This technique provided a method for the automatic spinal deformity. It is necessary for input layers, which extracted numerical feature. To classifying the unknown moire image, the four features (mean values and standard deviation in eq.(5), (7)) are used for training by using the back propagation in ANN. Our ANN is consist of three layers, which include four inputs neurons, three hidden neurons and two output neurons for training. Finally, unknown moire images are discriminated as normal or abnormal case automatically.

A SVM [6, 7] is a supervised learning technique from the field of machine learning applicable to both classification and regression. SVM is a set of related supervised learning methods used for classification. It is an optimization algorithm for the problem of pattern recognition. Some free software also provided methods for assessing the generalization performance efficiently. It was worked out for linear two-class classification with margin, which has the minimal distance from the separating hyperplane to the closest data points. SVM learning machine seeks for an optimal separating hyper plane, where the margin is maximal. In this method, to classify the unknown moire images, we implement the SVM technique employing four feature vectors from the left-hand side and right-hand side of rectangle areas (in eq.(5) and eq.(7)).

SOM [8] is a data visualization technique invented by T. Kohonen which reduces the dimensions of data through the use of self-organizing neural networks. In this study, we applied our method to the SOM for clustering the normal and abnormal moire image.

AdaBoost [9] is the useful technique of the Boosting technique. Boosting makes a learning machine different as the weight of the exercise is changed one after another, the technique which composes the learning machine that these are combined and accuracy is high. In AdaBoost when the weight of the learning machine is updated, weight to the training sample misclassified with the learning machine increases, and weight to the training sample correctly classified decreases. Therefore, it might become difficult to see the whole image because data with a difficult distinction is emphatically learned.

## 5 Experimental Results

Experiment was done employing 1200 real moire images which is 600 of abnormal and normal, respectively. The employed moire images are separated into two groups such as training and test data sets. As a training data for this study, we have selected randomly 400 (200 normal and abnormal cases, respectively) moire images which is called $G_1$, $G_2$, and $G_3$. The leave-one out method is applied onto three data groups, and the average recognition rate is calculated. The leave-one out is a method of applying the obtained criteria to the data group of the remainder for two data groups, doing the evaluation to which data is not biased.

The employed moire topographic image size is 256X256 pixels with 256 gray levels. Fig.2 illustrates experimental results. In Fig.2, (a) shows a normal moire image and (b) shows an abnormal moire image. Table 1 shows obtained classification rates. In the table, $G_i$ ($i$=1,2,3) shows data sets, "*Normal*" shows classification rates which normal cases were classified correctly, and "*Abnormal*" shows classification rates which abnormal cases were classified correctly. Finally, "*Average*" shows the average classification rate obtained from each data group, "***Ave***." shows the entire average classification rate. That is, the paragraph of $G_1$ shows the identification rate when $G_2$ and $G_3$ are learned as learning data, and the result of obtaining is applied to $G_1$. As a result, on the total average, classification rate of 85.2%, 85.3%, 71.8%, and 85.6% were achieved in the ANN, SVM, SOM, and AdaBoost, respectively.

## 6 Discussion and Conclusions

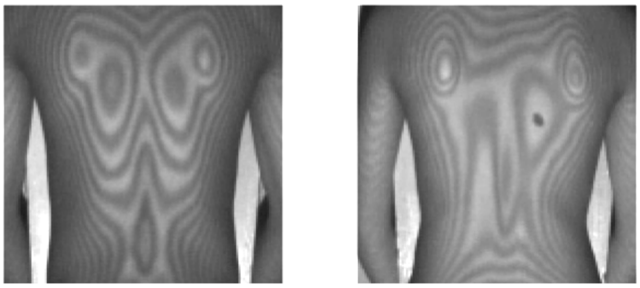
In this paper, we proposed a new automatic classification method for the spinal deformity detection by using ANN, SVM, SOM, and AdaBoost method which is extracted asymmetry degree. The middle line of the subject's back is extracted on moire image employing the approximate symmetry analysis, and ROIs are automatically selected, then the asymmetry degree is calculated. Four asymmetry degrees from the right-hand and left-hand side rectangle areas which is selected as ROIs apply to train the ANN, SVM, SOM, and AdaBoost. The total average shows the classification rate of 85.2%, 85.3%, 71.8%, and 85.6% in the ANN, SVM, SOM, and AdaBoost respectively in the experiment employing 1200 moire image. In the experimental results, the average classification rate of spinal deformity by ANN and AdaBoost was slightly higher than the other classifier.

Fig.3 illustrates examples of misclassification result. In Fig.3, a normal case is classified into abnormal in (a), whereas an abnormal case is classified into normal in (b). In figure 3, sunburn trace appears on the waist part in (a). In Fig. 3 (b), gray values subtly differ in the vicinity of an edge particularly on the shoulder part. All of the misclassified normal cases are found asymmetry of moiré patterns. This is because gray values distribution in the rectangle regions unfortunately affected symmetrically when the features were calculated. To escape from this difficulty, some other asymmetry features such as asymmetric of shoulders line or asymmetric of angle on a waist line might be taken into account in conjunction with it. These issues remain for further study.

In the experimental results, the classification rates which normal cases were classified correctly are higher than the classification rates which abnormal cases were classified correctly. Generally, medical doctor checks the symmetric shape of right-hand and left-hand side such as waist line and shoulder line of human back. In the normal case, waist line shows almost symmetric shapes. On the other hand, in the abnormal case, asymmetric moire patterns are appeared on the waist line. To improve the classification rate in the future, we introduce a new feature such as waist line and shoulder line for the new features. That still remained as a future works.

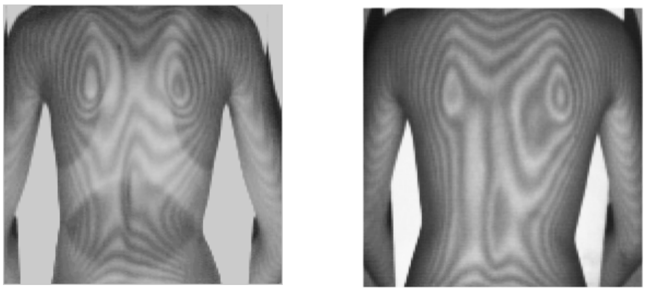
## Acknowledgements

This work was supported by a Grant-In-Aid for Scientific Research on Priority Areas (18560414) from the Ministry of Education, Culture, Sports, Science and Technology, Japan.



(a)normal (b)abnormal

**Fig. 2.** Experimental results.



(a) (b)

**Fig. 3.** Examples of misclassification: (a) Classified normal to abnormal; and (b) Classified abnormal to normal.

**Table 1.** Classification rates [%].

| | $G_1$ | $G_2$ | $G_3$ | *Ave.* |
|---|---|---|---|---|
| **ANN** | | | | |
| *Normal* | 75 | 79.5 | 76 | 75 |
| *Abnormal* | 96.5 | 90 | 94 | 94 |
| *Average* | 85.8 | 84.8 | 85 | 85.2 |
| **SVM** | | | | |
| *Normal* | 76 | 78.5 | 73 | 75.8 |
| *Abnormal* | 98 | 91 | 79.5 | 94.8 |
| *Average* | 87 | 84.8 | 84.3 | 85.3 |
| **SOM** | | | | |
| *Normal* | 68 | 74.5 | 74 | 72.2 |
| *Abnormal* | 75 | 67.5 | 71.5 | 72.9 |
| *Average* | 71.5 | 71 | 72.8 | 71.8 |
| **AdaBoost** | | | | |
| *Normal* | 75.5 | 81 | 80 | 78.8 |
| *Abnormal* | 95.5 | 90 | 91.5 | 92.3 |
| *Average* | 85.5 | 85.5 | 85.8 | 85.6 |

## References

1. Y. Ohtsuka, A. Shinoto, and S. Inoue, "Mass school screening for early detection of scoliosis by use of moire topography camera and low dose X-ray imageing", *Clinical Orthopaedic Surgery*, 14, 10, pp.973-984, 1979. (in Japanese).
2. H. Takasaki, "Moire topography from its birth to practical application", *Optics and Lasers in Engineering*, 3, pp.3-14, 1982.
3. Kim, H.S., Ishikawa, S., Ohtsuka, Y., Shimizu, H., Sinomiya, T., Viergever, M.A. "Automatic scoliosis detection based on local centroids evaluation on moire topographic images of human backs", *IEEE Transaction on Medical Imag*ing, Vol.20, No.12, pp.1314-1320, 2001.
4. Batouche, M. "A knowledge based system for diagnosing spinal deformations Moire pattern analysis and interpretation", *International Conference of Pattern Recognition*, pp.591-594, 1992.
5. Minovic, P., Ishikawa, S., Kato, K. "Symmetry identification of a 3-D object represented by octree", *IEEE Trans. Patt. Anal. Machine Intell.*, PAMI-15, 5, 507-514, 1993.
6. V. Vapnic: The nature of statistical learning theory, Springer-Verlag, New York, 1995.
7. Christopher J. C. Burges "A Tutorial on Support Vector Machines for Pattern Recognition", Data Mining and Knowledge Discovery 2, pp.121 - 167, 1998.
8. T. Kohonen Self-organizing maps, Springer-Verlag New York, Inc., Secaucus, NJ, 1997.
9. Y. Freund, R. E. Schapire, "Experiments with a New Boosting Algorithm", *International Conference on Machine Learning*, pp.148-156, 1996.