IIEEJ Paper -- Special Issue on Image Processing for Life and Its Applications --

CNN-based Spine and Cobb Angle Estimator Using Moire Images

Ran CHOI†, Kota WATANABE‡, Hiroaki JINGUJI‡†, Nobuyuki FUJITA‡, Yoji OGURA‡, Satoru DEMURA‡‡, Toshiaki KOTANI*, Kanichiro WADA⁑, Masashi MIYAZAKI⁂, Hideki SHIGEMATSU⁑⁑, Yoshimitsu AOKI† (*Member*)

†Keio Univ. School of Science and Technology, ‡Keio Univ. School of medicine, ‡†Tokyo Health Service Association, ‡‡Kanazawa Univ, Graduate School of Medical Science, ∗Seirei Sakura Citizen Hospital, ⁑ Hirosaki Univ. Graduate School of Medicine, ⁂Oita Univ. School of Medicine, ⁑⁑ Nara Medical University

<Summary> Adolescent idiopathic scoliosis (AIS) causes serious health problems when left untreated after onset. In Japan, moire images obtained from moire screening systems have been widely used for early stage detection of AIS. However, the problems of this system are the need for manual diagnosis after screening and the result classifying only two classes, normal or abnormal, which cannot provide diagnostic information essential for treating AIS. Therefore, we propose a screening system that can estimate spinal positions from a moire image using a convolutional neural network (CNN) and then automatically screening the spinal deformity from the estimated spine. For this, training dataset is generated by merging a moire image and spine positions on a radiograph. The estimated spine by CNN is evaluated for scoliosis by the proposed measuring method, which calculates the Cobb angle, a standard for scoliosis diagnosis. Results show that the proposed system has low error when compared with the published results of similar systems and the observer error of manual diagnosis. The proposed system is not only able to screen the spine as an alternative to radiography using only the moire image but also provides detailed spinal information for treatment.

Keywords: deep learning, measurement of Cobb angle, moire imaging, spine estimation

1. Introduction

In Japan, a moire screening system is used for the medical examination of a patient's spine. This device is used to capture moire images for spinal deformity screening based on the symmetry level of the moire patterns in the moire image. The moire system is used because Adolescent Idiopathic Scoliosis (AIS) may cause serious health problems if left untreated[1). Therefore, monitoring and early detection are essential for preventing this problem. Furthermore, the moire system is easy to use and does not carry the risk of irradiation despite the fact that it requires manual diagnosis.

Several other studies have focused on spinal screening. Most developed systems are based on photography and measure the back of the body to reconstruct a three dimensional (3D) surface to estimate the spine. However, markers on anatomical landmarks are required to estimate the spine[2,3)]. Formetric, which is one of the developed techniques, can detect spinal deformity using both the rotation and curvature of the spine even without markers[4-6)]. Nevertheless, the moire system remains in use because it is cost effective.

Reference[7)] used a moire image to detect deformity. The depth of the back surface is shown in the moire image. Four vectors representing the complexity level of the moire pattern are extracted; then, these vectors are classified into two levels, normal and abnormal, by a support vector machine (SVM) and neural network [8)]. Even though this is sufficient as a screening system, a radiograph is necessary for treatment after screening because the spinal information necessary for treatment cannot be obtained.

As machine learning continues to develop, its applications have also expanded. Machine learning has also been applied to detect spinal deformity, mainly for classification[8,9)]. An SVM was used to classify the severity of spinal deformity based on a surface image that was obtained by a scanner[9)]. Furthermore, an SVM was used to classify a 3D surface into three types of spinal curves: thoracic major, thoracolumbar major, and double major[8)]. Hence, there is a close relationship between the surface of the back and spinal curvature.

In addition, image recognition in machine learning, especially Convolutional Neural Network(CNN)s, has obtained remarkable achievements in the past few years. A CNN consists of convolution layers that extract obvious features, pooling layers that reduce the feature complexity, and fully connected layers to classify the feature[10-12)]. Any object with features can be detected from an image by a CNN. The moire image represents depth, and the surface of a back

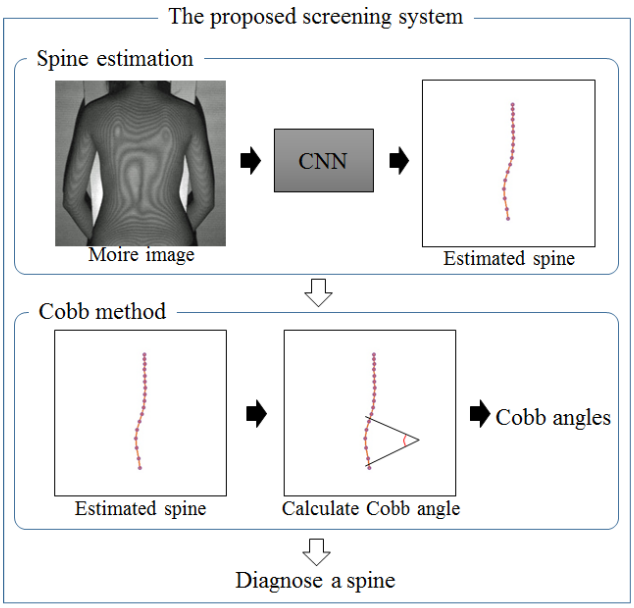


Fig. 1 Process of the proposed system

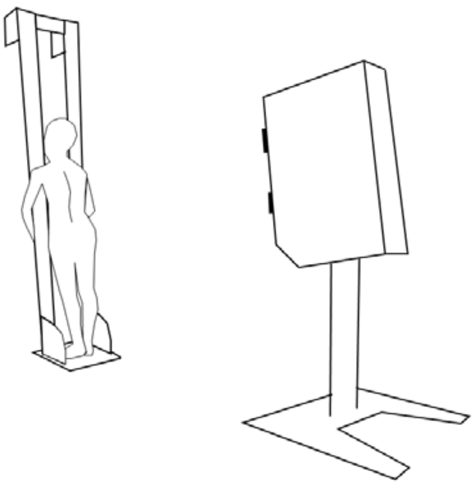


Fig. 2 Moire screening system consisting of a moire machine and a support for the patient

is influenced by the spine. Hence, the spine curvature could be extracted from the moire patterns in the image.

Therefore, in this paper, we propose an automatic screening system that uses a CNN to estimate the gravity centers of 17 vertebrae including the dorsal and lumbar vertebrae from a moire image. In order to screen scoliosis based on the estimated spine, we also propose a measuring method that calculates the bending angle of the spine. The proposed process is shown in **Fig. 1**.

In Section 2, we introduce the moire screening system in use. Section 3 explains how we generated the dataset for spine estimation. Sections 4 and 5 show methods of spine estimation and evaluation of the estimated spine. Section 6 presents the experiment results, the accuracy of the spinal

Normal　　Mild deformity　　Severe deformity

Fig. 3 Moire patterns and radiographs showing spine shape in accordance with each deformity level

evaluation method, and the evaluations of the estimated spines. Section 7 concludes the paper.

2. Conventional Moire Screening System

The conventional moire screening system in **Fig. 2** is able to check for spinal deformity using the moire image of a back by projecting a moire pattern onto the back of a human. Moire machine is consisted of the moire machine and a support for the patient. The support and the moire machine are tilted by 10°. The moire machine incorporates a camera and projector. The moire pattern of the moire image shows contour lines representing the depth of the object surface[1,13].

In addition to the moire pattern, structured light is used for 3D reconstruction of the back in screening machine[4-6]. The moire pattern is used to easily recognize the symmetry level, and the structured light is used to measure the back accurately. Both methods can be used in the proposed system as a method to represent the surface shape of objects[14]. The reason we chose the moire pattern is that there are many accumulated data owing to the long period of use.

The Cobb angle is a descriptor of the severity of scoliosis[9,15]. **Figure 3** shows moire images with radiographs for three cases: normal, with a Cobb angle below 10°, mild deformity, with a Cobb angle of 10°-20°, and severe deformity, with a Cobb angle above 20°. The general moire patterns on the back are “M”, “O”, and “W” patterns as in the normal case of Fig. 3[2] but they are affected by bone, fat, and

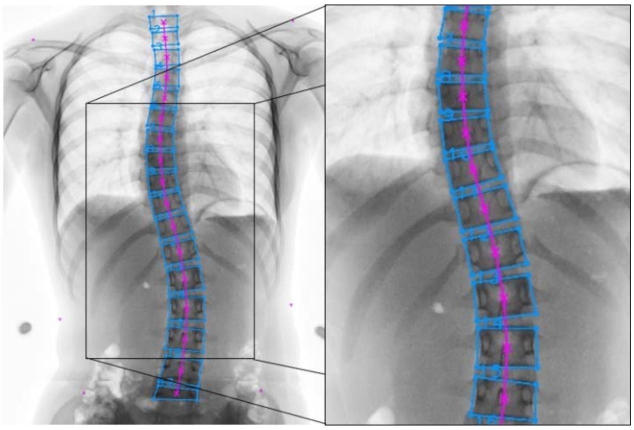


Fig. 4 Moire patterns and radiographs showing spine shape in accordance with each deformity level

muscle. The pattern has bilateral symmetry in an upright spine but has a complex pattern if there is a spinal deformity, as in the case of the severe deformity in Fig. 3. Hence, spinal screening using moire pattern analysis is a practical approach.

The conventional moire screening system has been used for a long period of time[1,2,13] because it is simple, cost effective, and can screen many patients rapidly. However, the moire image only classifies two intensities of spinal deformity, normal or abnormal, using a manual score of the symmetry level that checks equal depths on the moire image. Therefore, although a patient can be screening by the moire system, a radiograph is required to obtain precise treatment.

3. Dataset for Spine Estimation

To estimate the spinal position from the moire image, numerous moire images with spine information are needed as a dataset for machine learning. However, the spinal positions cannot be detected if the moire image is used alone. Therefore, we collected two types of data from the same person, a moire image and a radiographic image that includes manually detected spinal positions. **Figure 4** shows the detected spine information, which consists of the four corners and computed gravity center. The detected spine includes twelve dorsal vertebra blocks (= thoracic vertebrae) and five lumbar vertebra blocks.

To merge the two data sets, i.e., the moire image and spine information on the radiograph, the radiograph should be superimposed on the moire image based on the silhouettes of the body by scaling and translation because there is not an anatomical landmark in common on both the moire image and radiograph. In this case, merging the two images can be a problem regardless of the differences of the poses on the images and viewpoints of the two cameras. In **Fig. 5**, Two images are poorly fitted because of the differences of the camera's viewpoints and the poses of the patient.

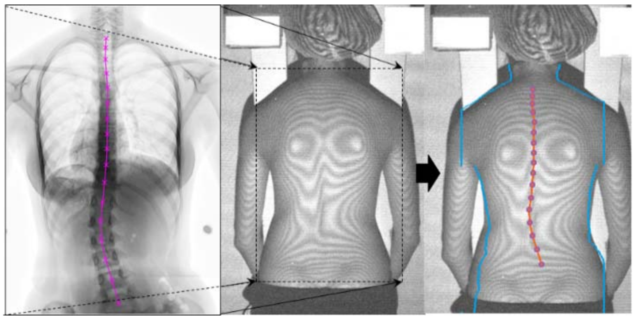


Fig. 5 Result merged by translation and scaling transforms

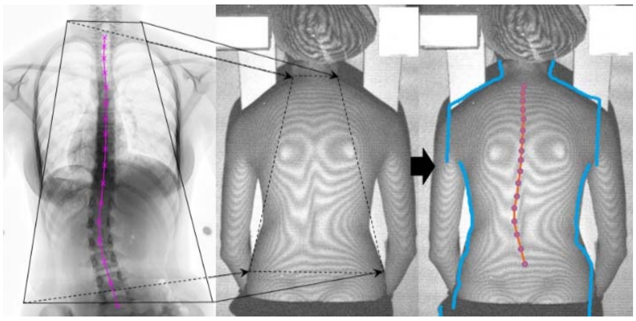


Fig. 6 Result merged by a perspective projection

To merge the two images accurately, they should be calibrated to have the same coordinate system and one pose should be transformed into the other pose. This is difficult not only because of its complexity but also because of the limited information of the camera viewpoints in the data set, which was collected under dozens of different environments. For more accurate fitting using a simpler procedure, we applied a perspective projection under the hypothesis that the surface of the back on the moire image and radiograph are an identical plane viewed from different viewpoints.

Perspective projection represents an object as seen from the viewpoint of the observer. It is used for mapping 3D points onto a two dimensional (2D) plane in the field of computer graphics. This projection is expressible as the relationship of the same object from different viewpoints[16,17]. If locations of feature on 2D plane from two different viewpoints are known, a shape/image at one viewpoint can be transformed to that at another viewpoint. Thus, perspective projection is able to generate a more fitted result using feature points than simple translation and scaling to merge different viewpoints and small movements of the subject between images.

The algorithm to merge the two images uses strong curve features on the neck, waist, and pelvis. Using these features on the corresponding parts in both images, the reference

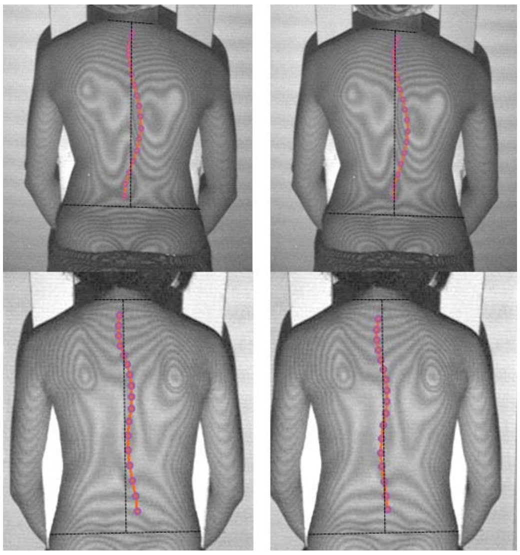


Fig. 7 The merged images by translation and scaling (left), and the merged images by perspective projection (right)

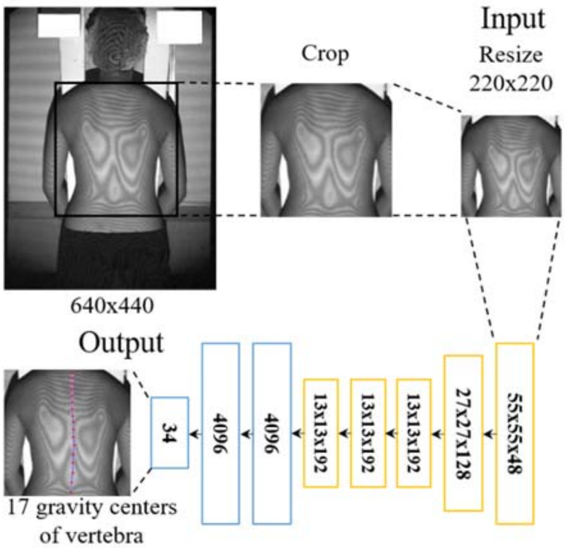


Fig. 8 Architecture of CNN

planes for projection are generated and combined by perspective projection for merging. The strong features consist of four positions: both sides of the neck and both sides of the waist, or both sides of the neck and both sides of the pelvis. After the four features on both images have been located manually, the plane in the radiograph is projected to the other plane in the moire image, as shown in **Fig. 6**. Typically, the spine is located at the center of the neck and pelvis. In **Fig. 7**, both ends of the vertebrae on the spine are located at the center of the neck and pelvis on the image merged by perspective projection but not on the image merged by translation and scaling Formulae using four feature points are shown below (1,2). In (1), neck points are $(x_1, y_1), (x_2, y_2)$, and waist points are $(x_3, y_3), (x_4, y_4)$. (x', y') is a point on moire image and (x, y) is point on radiograph. First, a homography matrix is created by (1). h_{33} of the homography is 1. Then, the transformed image is created by (2). In (2), (x_I, y_I) is input position and (x_o, y_o) is output position.

$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x_1x'_1 & -y_1x'_1 \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -x_1y'_1 & -y_1y'_1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 & -x_2x'_2 & -y_2x'_2 \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -x_2y'_2 & -y_2y'_2 \\ x_3 & y_3 & 1 & 0 & 0 & 0 & -x_3x'_3 & -y_3x'_3 \\ 0 & 0 & 0 & x_3 & y_3 & 1 & -x_3y'_3 & -y_3y'_3 \\ x_4 & y_4 & 1 & 0 & 0 & 0 & -x_4x'_4 & -y_4x'_4 \\ 0 & 0 & 0 & x_4 & y_4 & 1 & -x_4y'_4 & -y_4y'_4 \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \end{bmatrix} = \begin{bmatrix} x'_1 \\ y'_1 \\ x'_2 \\ y'_2 \\ x'_3 \\ y'_3 \\ x'_4 \\ y'_4 \end{bmatrix} \quad (1)$$

$$\begin{aligned} w &= x_I h_{31} + y_I h_{32} + h_{33} \\ x_o &= x_I h_{11} + y_I h_{12} + h_{13}/w \\ y_o &= x_I h_{21} + y_I h_{22} + h_{23}/\mathrm{w} \end{aligned} \quad (2)$$

4. Spine Estimation

To estimate a spine on the moire image, a CNN is used. The network structure of CNN is Alexnet and its architecture is based on the reference[11]. The different point from the reference[11] is that the last layer of Alexnet is 34 dimensions. **Figure 8** shows a network architecture, pre-processing of input image, input and output for the estimation.

An original moire image is 640×480 size and the back of human on the moire image is about 300×240 size that is less half size of the original. Since the pattern shape of moire is important information and input size is limited for training, using cropped image is better than using whole image. A size of copped image is determined by y length of spine. A center of the spine positions is centered on the cropped image and cut to the size, spine length + padding, and then resized to a suitable size for the network.

The input image is a moire image and the output vector comprises the 17 gravity centers of the vertebrae. The moire image is cropped around the spine positions and resized to 220×220 pixels. The Alexnet is comprised of five convolution layers and two fully connected layers to obtain the output, which consists of 17 (x, y) coordinates.

A CNN requires a large amount of data for accurate estimation. The dataset collected for this study consists of 1,996 pairs of moire and spinal information. The patients for the dataset are teenagers from 10 to 16 years old.

To avoid overfitting during the training, the dimensions of output can be reduced. Otherwise, increasing the amount of

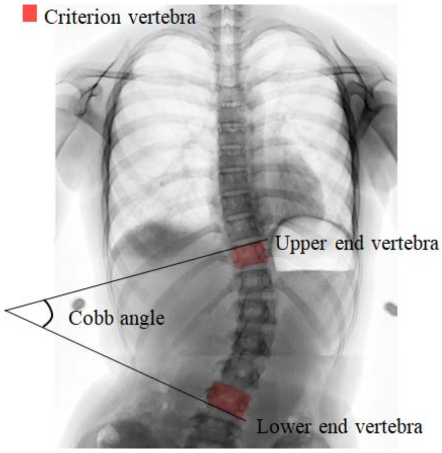


Fig. 9 Cobb angles using the original measure

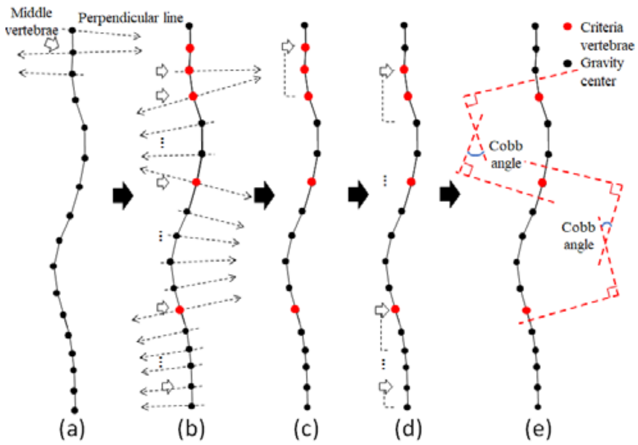


Fig. 10 Proposed measuring method

data is also able to overcome this problem[13]. Therefore, rotation (3° clockwise and anti-clockwise) and mirroring was used for data augmentation of training dataset after dividing dataset into two datasets.

Consequently, we used 10,788 image-radiograph pairs, which included images with 0° to 55° Cobb angles as the training dataset, and 198 image-radiograph pairs, including images with 0° to 45° Cobb angles, as the test dataset. The training data consisted of 50% normal spine images, 30% spine images with mild deformity, and 20% spine images with severe deformity. The test data consisted of 33% normal spine images, 33% spine images with mild deformity, and 34% spine images with severe deformity.

5. Evaluation Method for Spine Estimation

To screen scoliosis from the estimated spine that comprises 17 points, a new method for measuring the Cobb angle is required that is different from the conventional methods using a shape of vertebral block on radiography. The Cobb angle is defined as the bending angle of the spine and is a standard for scoliosis classification[18]. The conventional methods for the Cobb angle measure the difference in the angles between the upper-end and lower end vertebrae of the criterion vertebrae, which is the most tilted vertebrae on the concavity of the curve, as shown in Fig. 9[8,15]. While measuring the difference in the angles for the Cobb angle, the reference lines are the upper and lower lines of vertebral block connecting corners of vertebrae. In a conventional manual method[15], doctors need to decide the shapes of vertebral blocks and criterion vertebrae. Conventional auto methods[18,19] automatically define criterion vertebrae, and calculate Cobb angles from the criterion vertebrae; however, it is necessary to manually design the shapes of vertebral blocks.

Therefore, we propose new measuring method to calculate Cobb angle from the only estimated spine including only point data. The measuring method (Fig. 10) proceeds as follows:

1) Fit a curve to the 17 positions using cubic B-spline.
2) Calculate the two contact points of three lines perpendicular to the curve at three sequential vertebrae: upper, middle, and bottom (Fig.10, (a)).
3) Define the middle vertebra as the criterion vertebra where the side of the point of contact changes (Fig.10, (b)).
4) Structurally, the concavity of the spinal curve is composed of more than four vertebrae including two criterion vertebrae at the both ends of curve. However, the curve using cubic B-spline is slightly anfractuous because the spine is the estimated result (Fig.10, (c)). The criterion vertebra is redefined as a normal vertebra when other criterion vertebrae located on the lower level are located closer than the three vertebrae at the location of the criteria vertebrae. This step is implemented from T1 (the highest level) to L5 (the lowest level) in order of the vertebral level (Fig.10, (d)).
5) Calculate the angles between the two lines perpendicular to the curve at the midpoint between the top criterion vertebra and the vertebra above it, and at the mid-point between the bottom criterion vertebra and the vertebra below it (Fig. 10, (e)).

Steps 1–3 are for finding the inflection points. We used the contact points of the perpendicular lines to find the inflection points fast only using 17 points. In, step 4, the error is removed. Occasionally, the spine curve has a zigzag shape, particularly when the spine has a small curve. This step removes the criterion vertebrae located consecutively on

Table 1 Comparison of datasets

	MAE	Standard deviation
Translated dataset	4.7°	3.5°
projected dataset	4.3°	3.3°

Table 2 Error of the proposed Cobb method and comparison

	MAE	Standard deviation
All	2.9°	2.54°
Normal	3.13°	2.76°
Mild deformity	2.98°	2.51°
Severe deformity	2.78°	2.47°
Sardjono et al. [19]	3.91°	3.6°

vertebral level. In step 5, we used the midpoint, which is equidistant from the upper and the lower side of vertebral block, instead of the criterion point located on the gravity center. Thus, the angle obtained using this measuring method was more similar than that found in the doctor's result.

6. Experiment

6.1 Comparison the generating methods of perspective projection and scaling/translation for dataset

To ascertain if the perspective projection is an effective method to merge two images, we compared the estimation results using two datasets applied for each method, the scaling/translation (non-perspective projection) and the perspective projection. As numbers of the training data and the test data, the translated dataset are (800,75) and the projected dataset are (899,80). These datasets are for the category of teenagers, 10–16 years old having (0 < Cobb angle ≤ 50). The training process is equal to the description in section 4.

As shown **Table 1**, The mean absolute error (MAE) and standard deviation were 4.7° and 3.5°, respectively, in the translated dataset and 4.3° and 3.3°, respectively, in projected dataset. The error was calculated by comparing the result of collected spine positions with two results, the translated and the projected datasets, by the proposed measuring method. The MAE of projected dataset has a small error. Therefore, the dataset applied the perspective projection has high accuracy.

6.2 Evaluation of proposed measuring method

To verify the accuracy of the proposed measuring method, the Cobb angle measured by a doctor was used as ground truth and compared with the Cobb angle calculated by the proposed method.

Table 3 Error of estimated positions

MAE	Standard deviation
3.6 pixel (about 5.4 mm)	2.5 pixel (3.5 mm)

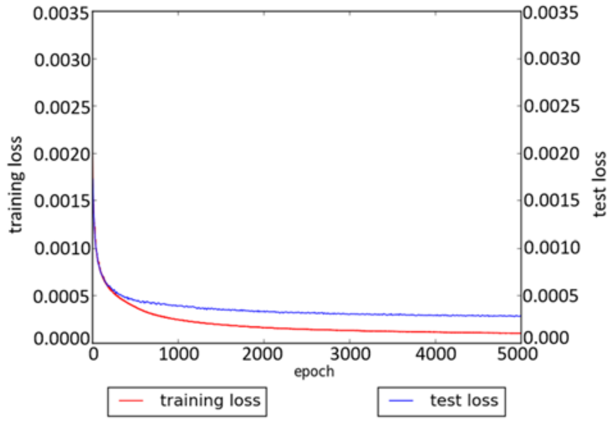


Fig. 11 Loss graph of training

The Cobb angle measured by a doctor, in many cases, was marked as 0° if the spine was normal. However, sometimes it was not 0° but lower than 10°. This angle is measured only for the large angles, and small Cobb angles tend to be ignored if the spine is abnormal because the spinal deformity is diagnosed by the largest angle. For this reason, Cobb angles are compared only for the biggest angle per data pair.

As shown **Table 2**, the MAE of the Cobb angles was 2.9°, and the standard deviation was 2.54°. The data set used for these results consisted of 1,687 radiograph-image pairs, including data for spines of 10 to 16 years old, having Cobb angles from 1° to 55°. In this data, normal spines (Cobb angle ≤ 10°) are 175, mild deformities (10° < Cobb angle ≤ 20°) are 890, severe deformities (20° < Cobb angle) are 622. In this result, the MAE of a normal spine was 3.13°, the MAE of a spine with mild deformity was 2.98° and the MAE of a spine with severe deformity was 2.78°. The correlation infers that the MAE increases when the angle obtained by the doctor is smaller. Similarly, the spines with larger deformities had lower MAEs because of the clear criteria. This is owing to the observer variability of the Cobb angle measurement. It is harder to measure the Cobb angle on a straighter spine. The Accuracy of the angle is also influenced by the experience of the doctor, quality of the radiograph, and judgment of the observer. Observer error has been reported to vary from 3° to 10°[18,19].

The results of the automatic measurement of Cobb angle from the radiograph in other research[19] has reported a MAE of 3.91° with a standard deviation of 3.60° as shown in Table

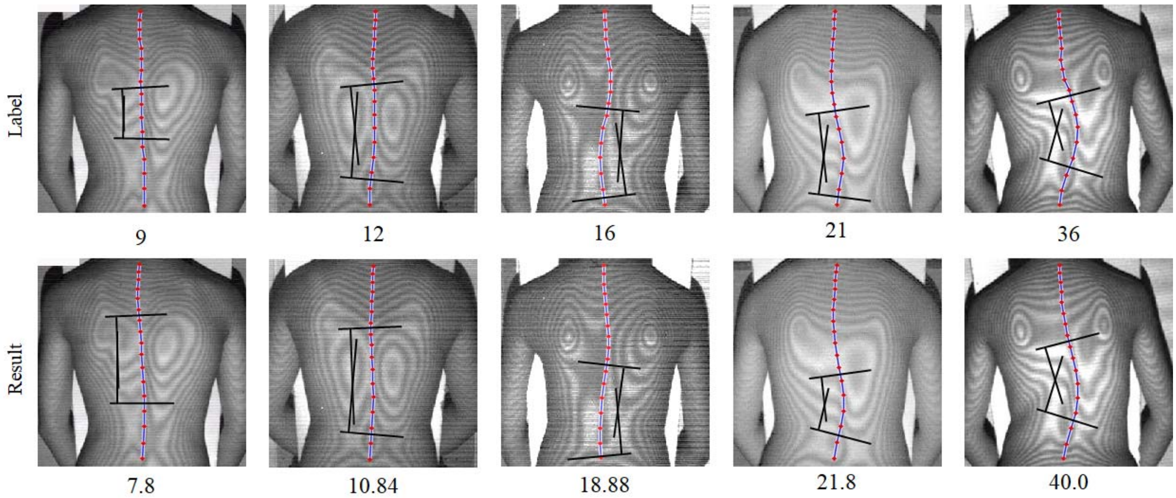


Fig.12 Label images (top row) and images estimated using the proposed method (bottom row)

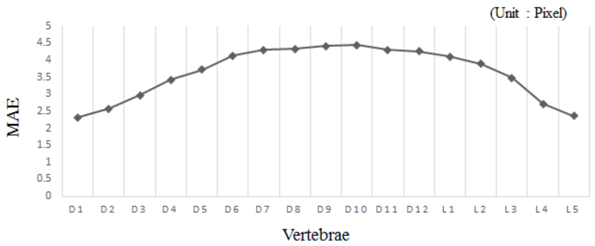


Fig.13 MAE of each vertebra

Table 4 Error of Cobb angle of estimated position

	MAE	Standard deviation
All	3.42°	2.64°
Normal	4.38°	3.11°
Mild deformity	3.13°	2.22°
Severe deformity	2.74°	2.37°

Table 5 Result comparison

	RMSE
Proposed method	4.37°, 5.86 mm
Hackenberg et al.[4]	4.4°, 5.8 mm

2. In comparison with these results, the proposed method has small error.

6.3 Evaluation of the estimated spine

Figure 11 shows a training performance by loss values of each dataset. The loss is calculated using mean square error. If there is overfitting problem, the loss of test dataset increases in the following echo. The shape of loss graph in Fig.11 means it has high learning rate.

Figure 12 shows the label images (top row) and corresponding estimated results (bottom row). The numbers under the label images are Cobb angles obtained by doctors based on the original spine, and the numbers under the results estimated by CNN are the Cobb angles obtained by the proposed measuring method and estimated spine. The locations of the measured angle are also show on the moire images.

The spinal curves connecting the gravity centers on the results have similar curve shapes on the labels. Furthermore, the curves on the results show more natural curves than the spinal curves on the labels, as shown in Fig. 12.

MAE, the spinal positions and estimated spinal positions, was 3.6 pixels (~5.4 mm) per person as shown in **Table 3**. **Figure 13** shows the MAE of each vertebra. Here, labels D1 to D12 are the dorsal vertebra from the first to twelfth vertebra and L1 to L5 indicate the lumber vertebra from the first to fifth vertebra. D1 and L5 have smaller MAEs than the others because it is easy to estimate the positions using locations that are at the center of the neck and pelvis, respectively.

In addition, we calculated the Cobb angles based on the estimated spine and compared it with the Cobb angles obtained by doctors. The MAE per person between the ground truth and estimated spine was 3.42°, as shown in **Table 4**. In this result, the MAE for each category was 4.38° for normal spines, 3.13° for spines with mild deformity, and 2.74° for spines with severe deformity.

In another study[4] that reconstructed the 3D body for spine estimation and was also a previous paper for the current developed product, the root mean square error (RMSE) was 4.4° or 5.8 mm. They evaluated the result of their system with real data, that condition was same as proposed method, therefore we chose to compare. In comparison with this, angle estimation error was smaller in the proposed system as shown in **Table 5**.

7. Conclusion

We proposed a system for spinal screening based on the positions of 17 vertebrae estimated only from a moire image of the back.

To develop this system, a moire image and radiograph of the same person were collected to create dataset. On the radiographs, 17 gravity centers including 12 dorsal and 5 lumbar vertebrae were detected to define the spine position on the moire image.

The dataset for training was generated by merging the moire image and radiograph, calculating the spine position by perspective projection to reduce the error caused by merging two images taken from different camera viewpoints. As a method for transforming a shape observed at a different viewpoint, the perspective projection cannot merge two images properly in the cases of changes in posture.

A CNN was used to estimate the accurate spine positions of 12 dorsal and 5 lumbar vertebrae. In addition, the measuring method for calculating the Cobb angle is proposed to screen the spine from the 17 gravity centers of the vertebra block. As a result of the screening, a spinal shape and Cobb angles are obtained. These are essential values for cure which cannot obtain from the conventional moire machine. Thus, the result of screening can be used directly for the cure. It is different point from the conventional moire machine that require an additional diagnosis for the cure by radiograph.

Instead of the spinal process that other conventional methods[2-5] used, we estimated the location of gravity center (of vertebral body) a part used in hospitals. The spinal process is easily observed on the surface of back, other conventional methods detected the location of it from a 3D reconstructed back. However, if the spinal process is a measuring reference for the bent angle, the bent angle can be larger than the actual Cobb angle by the structure of twisted spine or can be a different angle by a transmutable shape of spinal process. Thus, the results obtained from conventional methods are clinical values that are different from the Cobb angle. Therefore, the proposed system is a meaningful method that can be used as a screening system to obtain the Cobb angle that is a standard value. By using the proposed system, the diagnosed result from a clinic is able to refer in the hospital as well.

In comparison with the Cobb angle measured by doctors on the same radiographs, the Cobb angle obtained by the proposed measuring method has a smaller difference in angle than the error among observers in the manually measured Cobb angles. However, it tends to obtain a bigger angle when the Cobb angle is calculated from criterion vertebrae that include the first dorsal vertebra or last lumbar vertebra. The curvature of the line becomes straight at the connected part of the neck and pelvis by the tendency to keep balance of these parts. The proposed method used the vertebral center of the first dorsal and last lumbar since there is no consecutive spinal line to neck and pelvis, while doctors used these connected parts.

In comparison with a study screening the spine by measuring the back, the estimated spinal position and resulting Cobb angle have smaller error.

With respect to other studies and the observer error of the manual Cobb angle, the proposed system is reliable. Furthermore, the result of the estimated spine screened by our proposed measuring method can be used for spinal screening.

The proposed system is able to used not only for screening but also as a healthcare machine for the spine. The general screening machine functions to send the student at risk to the hospital, which actually includes many students just needs a little care like exercise. Since the proposed system provides a spine shape and a bent angle of the spine as results, the proposed system is able to function as screening machine to send student only at high risk who needs a hospital treatment as well as function as a healthcare machine to care the students at risk.

In conclusion, the proposed screening system is able to screen the spine by using only a moire image without markers on the landmarks or the risk of cancer, but with the advantages of a moire screening machine. It can be used in schools as well as health centers or industrial complexes where spinal screening and checks are conducted.

References

1) M. Batouche: “A Knowledge Based System for Diagnosing Spinal Deformations: Moire Pattern Analysis and Interpretation”, in Proc. of the 11th International Conference on Pattern Recognition, pp.591-594 (1992).
2) X.C. Liu, J.G. Thometz, J.C. Tassone, L.C. Paulsen, R.M. Lyon: “Historical Review and Experience with the Use of Surface Topographic Systems in Children with Idiopathic Scoliosis”, Integrated Shape Imaging System, Vol.2, No.8, pp.1-8 (2013).
3) L. Rankine, X.C. Liu, C. Tassone, R. Lyon, S. Tarima, J. Thometz: “Reproducibility of Newly Developed Spinal Topography Measurements for Scoliosis”, The Open Orthopedics Journal, Vol. 6, No. 226, pp.226-230 (2012).
4) L. Hackenberg, E. Hierholzer: “3-D Back Surface Analysis of Severe Idiopathic Scoliosis by Rasterstereography: Comparison of Rasterstereographic and Digitized Radiometric Data”, Studies in Health

technology and informatics, Vol. 88, No.1, pp.86-89 (2002).
5) Diers, Formetric, http://www.diers.de/ (2017).
6) P. Knott, S. Mardjetko, S. Thompson: "A Comparison of Authomatic vs. Manual Detection of Anatomical Landmarks during Surface Topography Evaluation Using the Formtric 4D System", Scoliosis, Vol.7, Suppl.1, O19 (2012).
7) H.S Kim, S. Ishikawa, Y. Ohtuka, H Shimizu, T. Shinomiya, M.A. Viergever: "Automatic Scoliosis Detection Based on Local Centroids Evaluation on Moire Topographic Images of Human Backs", IEEE Trans. on Medical Imaging, Vol.20, No.12, pp.1314-1320 (2001).
8) H. Kim, H. Ushijima, J.K. Tan, S. Ishikawa, Y. Otsuka, H. Shimizu, T. Shinomiya: "Spinal Deformity Detection from Moire Topographic Image Based on Evaluating Asymmetric Degree", World Congress on Medical Physics and Biomedical Engineering, pp.2308-2311 (2006).
9) L. Ramirez, N.G. Durdle, J. Raso, D. Hill: "A Support Vector Machines Classifier to Assess the Severity of Idiopathic Scoliosis from Surface Topography", IEEE Trans. on Information Technolgy in Biomedicine, Vol.10, No.1, pp.84-91 (2006).
10) A. Krizhevsky, I. Sutskever, G.E. Hinton: "ImageNet Classification with Deep Convolutional Neural Networks", Advances in neural information processing system, pp.1106-1114 (2012).
11) A. Toshev, C. Szegedy: "DeepPose: Human Pose Estimation via Deep Neural Networks", in The 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp.1654-1660 (2014).
12) I. Goodfellow, Y. Bengio, A. Courville: Deep Learning, online, pp.330-372 (2016). Available: http://www.deeplearningbook.org/
13) H. Takasaki: "Moire Topography", Applied Optics, Vol.9 No.6, pp.1467-1472 (1970).
14) P. X. Neto, G. C. Coelho: "The Shadow Moire Method using the Phase Shifting Technique and Digital Image Processing: Computational Implementation and Application to the 3D-Reconstruction of a Buckled plate", Journal of the Brazilian Society of Mechanical Sciences, Vol.22, No.3, pp.399-409 (2000).
15) J.R. Cobb: "Outline for the Study of Scoliosis" The American Academy of Orthopedic Surgeons Instructional Course Lectures, Vol.5, pp.261-275 (1948).
16) E. Dubrofsky: "Homograph Estimation", Ph.D. dissertation, Computer Science, University of British Columbia, Vancouver, (2009).
17) I. Carlbom, J. Paciorek: "Planar Geometric Projections and Viewing Transformations", Computing surveys, Vol.10, No.4, pp.465-502 (1978).
18) J. Zhang, E. Lou, D.L. Hill, J.V. Raso, Y. Wang, L.H. Le, X. Shi: "Computer-aided Assessment of Scoliosis on Posteroanterior Radiographs", Medical and biological engineering and computing, Vol.48, No.2, pp.185-195 (2010).
19) T.A. Sardjono, M.H.F. Wilkinson, A. G. Veldhuizen, P.M.A.V. Ooijen, K.E. Purname, G.J. Verkerke: "Automatic Cobb Angle Determination from Radiographic Images", Spine, Vol.38, No.20, pp.E1256-E1262, (2013).

(Received Apr. 30, 2017)
(Revised Sept. 30, 2017)

Ran CHOI

She received her M.S in Information Science and Telecommunication from Hanshin University, Korea, in 2014. She is currently pursuing the Ph.D. degree in engineering at Keio University. Her research interests include medical imaging and computer vision.

Kota WATANABE

He received M.D and Ph.D. from Keio University School of Medicine, Japan. He was an assistant professor with Department of Advanced Therapy for Spine and Spinal Cord Disorders, Keio University School of Medicine, Japan, from 2008 to 2015. Since 2015, He has been an assistant professor, with Department of Orthopedic Surgery, Keio University school of Medicine, Japan. He has received many awards including the 35th Japanese Society for Spine Surgery and Related Research Taisho-Toyama Award, the 13th International Phillip Zorab Symposium Best Paper Award, and the 22nd International Meeting on Advanced Spine Techniques Whitecloud Award.

Hiroaki JINGUJI

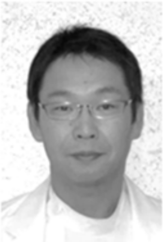
He is a deputy director with Department of Medical Examination, Tokyo Health Service Association, Japan. He is a clinical laboratory technologist and a medical sonographer of the digestive system and the circulatory system who is registered The Japan Society of Ultrasonics in Medicine.

Nobuyuki FUJITA

He received M.D and Ph.D. from Keio University School of Medicine, Japan. He is a board-certified orthopedic and spinal surgeon in Japan. Since 2013, he has been a research associate with Department of Orthopedic Surgery, Keio University school of Medicine. He performs basic and clinical researches on spine.

Yoji OGURA

He received M.D and Ph.D. from Keio University School of Medicine, Japan. He finished orthopaedic residency and spine surgery fellowship in Department of Orthopedic Surgery, Keio University school of Medicine, Japan. He had been a research fellow in RIKEN from 2012 to 2014. Since 2015, He has been an attending surgeon in Shizuoka Red Cross Hospital. He has received many awards including the 50th Scoliosis Research Society John H Moe Award, 29th Annual Research Meeting of Japanese Orthopaedic Association Best Presentation Award (second place) and 31st Annual Research Meeting of Japanese Orthopaedic Association Best Poster Award.



Satoru DEMURA

He received M.D and Ph.D. from Kanazawa University School of Medicine, Japan. He is an assistant professor, in the Department of Orthopedic Surgery, Kanazawa University, Japan. His main research includes treatment of spinal deformity, spine tumor and biomechanics of the spine.

Toshiaki KOTANI

He received M.D. and Ph.D. from Chiba University, School of Medicine, Japan. From 2010 to 2015, he was a director of spine center, Seirei Sakura Citizen Hospital, Japan. Since 2015, he has been a deputy director of Seirei Sakura Citizen Hospital, Japan. He has received many awards including Spinal Deformity Awards in 2003, 2004 and 2007.

Kanichiro WADA

He received M.D from Hirosaki University Graduate School of Medicine, Japan. He was an assistant professor with Department of Orthopaedic Surgery, Hirosaki University Graduate School of Medicine, Japan, From 2010 to 2013. Since 2014, he has been a lecturer, with Department of Orthopaedic Surgery, Hirosaki University Graduate School of Medicine, Japan. He performs researches in the clinical and epidemiological areas of spinal disorders.

Masashi MIYAZAKI

He received M.D and Ph.D. from Oita University, School of Medicine, Japan. He is an assistant professor in Orthopaedic Surgery, Oita University Hospital, Oita, Japan. He has received many awards including 2008 North American Spine Society Outstanding Paper Award Runner-up and the 2nd Best Musculoskeletal Disease Paper Award.

Hideki SHIGEMATSU

He received M.D and Ph.D. from Nara Medical University, Japan. He was a resident with Department of Orthopaedic Surgery, Todabayashi Hospital, Japan, in 2000. In Japan, he was a medical staff with Department of Orthopaedic Surgery, at Tondabayashi Hospital from 2001 to 2003, Matsusakatyuuou Hospital from 2003 to 2005, and Yamatotakada municipal Hospital from 2009 to 2011. He finished Fellowship in Hong Kong University. Since 2012, he has been an assistant professor with Department of Orthopaedic Surgery, Nara Medical University, Japan. Dr. Shigematsu is a member of Japanese Orthopaedic Association and Japanese Society for Spine Surgery and Related Research.

Yoshimitsu AOKI (*Member*)

He received his Ph.D. in Engineering from Waseda University in 2001. From 2002 to 2008, he was an associate professor in Shibaura Institute of Technology, Department of Information Engineering. He is a Professor, Department of Electronics & Electrical Engineering, Keio University. He performs researches in the areas of computer vision, pattern recognition, and media understanding.