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A Mobile Sensing and Imaging System for Real-Time Monitoring of Spine Health

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Poor posture or extra stress on the spine has been shown to lead to a variety of spinal disorders including chronic back pain, and to incur numerous health costs to society. For this reason, workplace ergonomics is rapidly becoming indispensable in all major corporations. Making the individual continuously aware of poor posture may reduce out-of-posture tendencies and encourage healthy spinal habits. Spine stress can also worsen existing structural deformities in the spine such as adolescent idiopathic scoliosis (AIS). In this work we developed a system to monitor spine health through both dynamic monitoring and structural imaging. The dynamic sensing method monitors spine stress in real-time by detecting poor back posture and strain on the back due to prolonged sitting or standing, and provides real-time user feedback when poor posture is sustained. The imaging method extracts the structural curvature of the spine and is used for the diagnosis of AIS in a non-invasive and inexpensive manner. Namely, the image is obtained using a photograph where the spinous processes have been marked to trace the shape of the spine. The spine curvature is then extracted automatically and modeled by a curve-fitting polynomial. The approach is simple and practical and allows scoliosis patients to monitor their curvature progress from home while minimizing the use of X-rays. The theme of our work is spine health, which we monitor through the wireless sensing system and the orthopedic imaging system. The two are complementary: the mobile wireless system assesses spine health during daily activity while the imaging system can assess the progression of a patient's structural spine curvature. We demonstrate effectiveness of our sensing system in simultaneously monitoring posture and position by testing in numerous situations. Furthermore, experiments show that our imaging method is accurate and robust under different brightness conditions. X-ray data used for this study was obtained from the international, electronic database of surgical cases of AIS, Scolisoft®.

Keywords: Spine Health, Complete Assessment, Dynamic Monitoring, Structural Imaging, Non-Invasive.

1. INTRODUCTION

Spine stress caused by poor back posture or extensive standing or sitting in fixed positions can result in pain and discomfort, and may lead to unpleasant changes to soft tissue and bone, resulting in bone spurs and intervertebral disc damage, and other spinal musculoskeletal disorders.[1] The resulting back pain can eventually become chronic. These spinal problems are a burden to society because of the high costs of health care incurred as well as the negative repercussions as to employee disablement, absence from work, and the individual's overall life quality. Poor posture is common among adolescents as well as employees who work for prolonged hours. It is estimated that about 80% of adults will experience back pain at some point in life, and roughly 10% of those will suffer a relapse.[2] Moreover, spinal injuries are second only to the common cold as a cause of absence from work, with many of these problems emerging from poor posture habits. Since more spinal problems will inevitably lead to higher health costs and lower productivity, helping people maintain healthy spinal habits and reduce spine stress during daily activity is of considerable benefit. In particular, we found that making the user continuously aware of poor posture will reduce out-of-posture tendencies and encourage healthy spinal habits.[3] Increasing patient awareness of poor posture means that the patient can use her own back muscles to correct the spinal curvature, instead of using external support devices which could cause physical and psychological discomfort.[3]

Poor posture and spine stress can also worsen existing spinal deformities such as adolescent idiopathic scoliosis (AIS). Scoliosis is a spinal deformity characterized by lateral curvature of the spine. Serious cases of scoliosis affect the digestive,

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cardiovascular, and nervous systems,[4] and can cause distressing symptoms of pain and result in cosmetic deformities.[5] Scoliosis at early stages remains undetected for many patients because of their lack of awareness of the existence of the condition. In a significant number of patients, early stages of scoliosis are progressive, usually increasing in symptoms as the patients grow older.[6]

For a complete assessment of spine health, we have developed a mobile sensing system which monitors spine stress in real-time, and an imaging method that allows simple, inexpensive, and non-invasive diagnosis of scoliosis that can be used for initial screening and tracking of curvature progression. The mobile sensing system monitors the patient through daily activity, while the imaging method can provide an approximation of the patient's structural curvature. This approximation can help the patient monitor her condition on her own when a physician is not available, but it should not replace or eliminate the need for expert medical diagnosis by physicians.

The mobile sensing system simultaneously monitors back posture and patient position (sitting, standing, and walking). For poor posture, the system provides feedback to the patient in the form of a text message when the time spent out-of-posture exceeds a threshold that can be specified by the doctor. For patient position, the system monitors increased pressure on the back due to undesirable positions such as standing or sitting in a fixed position for a long period of time. The system measures the weight at the user's feet and detects whether he or she is standing, sitting, or walking at any given time. Furthermore, a daily summary report is automatically generated and provides an account of the amount of time during the day that the patient is standing, sitting, or walking, as well as daily information related to posture angle and severity of poor posture. We used an inclinometer to measure posture and load cells, positioned at the soles of the feet, to measure weight. Data from the sensors is acquired and transmitted wirelessly to a central processor, allowing storage of data for tracking of the patient's progress. Furthermore, a graphical animation of the patient that mirrors her posture and position is displayed in real-time on the central processor. Finally, all sensor data is stored in a database that can be used for post-processing analysis to track the patient's spine stress progression over time.

The imaging method, on the other hand, allows the extraction and measurement of a patient's scoliosis curvature by using a photograph of the back, after the spinous processes have been marked. The figure of merit used for this diagnosis is the 'Cobb Angle', described in Section 4. A sequence of image processing steps are applied to segment the image and extract the spine curvature leading to the calculation of the Cobb angle.

The rest of this paper is organized as follows: Section II presents existing techniques which measure posture in real time as well as imaging techniques that have been developed for structural assessment of spine health. Section III describes the mobile sensing system including approach, device design, and the algorithms we implemented, and presents experiments verifying the effectiveness of the system. Section IV describes the imaging system for scoliosis diagnosis, including image acquisition, feature extraction, and curvature measurement, and presents results verifying accuracy and robustness. Finally, Section V concludes with a summary of our findings and future work.

2. RELATED WORK

The use of sensor technology for dynamic monitoring of spine health has generally been limited. Some of the existing systems for monitoring spine health typically include X-rays and photogrammetric systems. However, these systems cannot monitor spine during daily activity and thus cannot provide the awareness that comes with monitoring and user feedback. Some systems that can be used for dynamic monitoring of spine health include electromagnetic tracking systems and potentiometric goniometers, and are discussed in Ref. [7] along with their limitations. Another system, designed specifically for posture monitoring, was proposed in Ref. [3]. The system uses accelerometers and gyroscopes. It is a smart garment that monitors poor posture of the spine during daily activities and provides corresponding feedback signals to the user through a buzzer. The system was able to prove the effectiveness of user feedback in correcting posture. Data processing was local using microcontrollers. Other related work for dynamic activity monitoring, but unrelated to spine health, includes 'The Mobile Sensing Platform',[8] which describes a small wearable device that uses multimodal sensors to monitor physical activity to encourage physical exercise and healthy habits. There have also been studies to monitor the posture habits of patients and provide corresponding feedback, as in Refs. [7, 9].

For structural assessment, traditional and popular techniques to diagnose the scoliosis curvature of the spine include analysis of radiographic images, which subjects patients to harmful radiation. More modern techniques in the literature include electromagnetic, photogrammetric and ultrasonic means of image acquisition, although these are not yet widely used and rely in most cases on complex medical equipment such as scanners, optical machines, and high resolution equipment. Some of the most recent techniques or machines found are summarized in Table I.

3. MOBILE SENSING SYSTEM

In this section we describe the mobile wireless sensing system for dynamic monitoring of spine stress.

3.1. Wearable Device Components

We used an inclinometer (Digi-key; part# 551-1017-ND) (1), a device which measures the positive and negative angles in a given plane, to measure the forward bending angle of a person's back. As for the weight, we used load cells fixed inside one's shoes (2). The load cells (measurement specialities; part# MSP6954-ND), measure the strain placed by each foot. As for the wireless link between the sensors and the base station, we used a Wi-Fi data acquisition device (National Instruments; NI-WLS 9215) (3) which wirelessly transmits the sensor data it receives to the base station. (4) is the battery used to power the sensors and DAQ module. The components are shown in Figure 1. The system when worn by the patient, with a comfortable attach and pocket for inclinometer, is shown in Figure 2.

3.2. Measuring Inclination

In order to measure the forward bending angle of the user's upper back, and thus determine to what extent the user is bending down, we fixed the inclinometer at the neck, at the intersection of the shoulders and the spinal cord. We experimented with placing it at different positions and found.

Table I. Some techniques to measure structural curvature.

	Type	Advantages	Disadvantages
Ortelius 800[10,11]	Electromagnetic	High correlation with Cobb angle measurements, intra and inter examiner reliability	Expensive, not portable, Not suitable for patients with metallic implants
ISIS2[12,13]	Photogrammetric	Radiation free, fast	Complex equipment
ISIS1[12]	Photogrammetric	Radiation free, no palpation required, fast, generally less expensive than other techniques	Complex equipment, patient's build or position may cause erroneous results, not portable
Zebris[14]	Ultrasonic	Radiation free, high measurement accuracy	Expensive, complex ultrasound equipment, not portable, uncomfortable
CA 6000[15]	Mechanical	Radiation free	Complex equipment, may be uncomfortable

The requirement of the inclination algorithm is to detect when the angle made by a person's back exceeds the angle threshold for a sustained period of time. The two parameters of the algorithm are the angle threshold T_p and the time threshold T_t, which can both be specified by the doctor or user. The algorithm starts by reading streaming posture angles continuously. To perform the analysis, it averages the values coming in every stream and continuously compares each average to the angle threshold. If the stream average exceeds the angle threshold, a timer starts. If the user adjusts his or her posture within the time, then no warning message is sent and the algorithm restarts. If the user does not correct his posture within the time threshold T_t, a message is automatically sent to the user's mobile device (e.g., cell phone) warning him/her to correct his/her posture. Every time the average of a stream is calculated, the angle and the corresponding timestamp are saved. The timestamp corresponds to the time at which the last value in the stream was sampled. A pseudocode of this algorithm can be found in Figure 3.

The reason that average values of a certain number of the inclination angles are considered rather than individual values is to render the algorithm more robust to temporary variations. In this way, if a user bends down for an insignificant period of time, the timer is not triggered. Similarly, if a user only temporarily straightens his or her back and then returns to an incorrect position, the timer is not reset and the user will be judged to have remained the whole period of time in an incorrect posture situation.

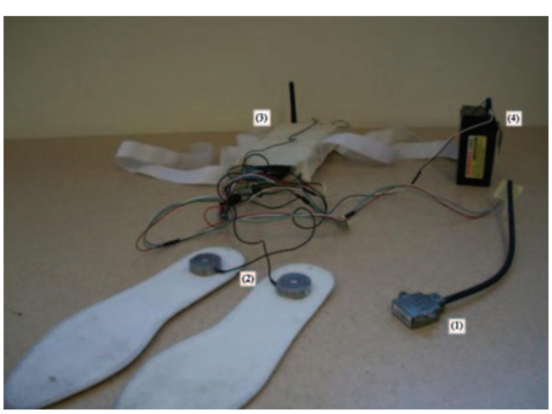

Fig. 1. Wearable components of spine stress monitoring system: Inclinometer (1), Load cells (2), Wireless DAQ (3), and battery (4).

3.3. Measuring Strain and Position

Load cells placed in the user's shoes are used to measure the stress exerted on the spine during the day. This allows the patient to determine how much strain was placed on the spine over the course of a day due to prolonged standing or sitting in fixed positions. Such analysis can be useful not only for spine health but also for improving the user's fitness if it is found that the user does not engage in sufficient physical activity. Different activities and positions may be preferable for different users, depending on that person's age and health condition. Note that the use of strain data is not limited to monitoring patient position, which we have demonstrated as an example application, but it can also be used to monitor increased pressure on the back due to continuous lifting of heavy items, or to detect imbalance in walking resulting from structural spinal conditions such as adolescent idiopathic scoliosis. The requirement of the strain detection algorithm is to determine the position of the user at every sampled period of time. Position takes on categorical values: 'walk', 'sit' or 'stand'. Then analysis can be performed to determine for how long the user was standing, sitting, or walking. As before, we based our analysis on the averages of streams of data rather than on individual values. For every stream, the output of the

Fig. 2. Spine stress monitoring system worn by patient.

```
Ak: an input stream array of posture angles of size k, from DAQ analog
output
Tt: threshold for time, user-defined
Tp: threshold for posture angle, user-defined

while(system is running) do begin:

     boolean bad_posture = true;

     read values in Ak
     find average_angles = average of the values in Ak;
     find timestamp = time of recording of last value in Ak;

     writeToCSVFile(average_angles, timestamp);

     if (average_angles > Tp) do:
          start timer;

          while (timer < Tt) do begin:
               Ak = next array of angles of size k;
               average_angles = average of the values in Ak;

               if (average_angles < Tp) do:
                    break;
                    bad_posture = false;
               end
          end //end while, time up

          if (bad_posture = true) do
               sendSMS(user);
          end
     end
end
```

Fig. 3. Inclination algorithm.

algorithm is 'sit', 'stand', or 'walk'. The data of both load cells, one in the left foot and one in the right, is collected and analyzed as follows:

(1) If the difference between the weight values of the two load cells in each foot is "large", then the person is walking at that particular instant of time

(2) If the difference is "small", then the person is either standing or sitting.

(3) If the difference is "small" and the average of the actual values are "small" then the person is sitting; otherwise, the person is standing.

The definitions of "large" and "small" are also parameters that are user-defined and that are usually dependent on the weight and build of the person. For example, less heavy people will need a lower threshold to be judged as standing. As before the output for every stream is saved and the values and corresponding timestamps are then stored in the database.

3.4. User Interface

The user interface allows the user or doctor to specify the preferences for a number of parameters and thresholds. Moreover, it allows real-time monitoring of both numerical and graphical data related to the user's activity. The doctor can use the graphical display to monitor the distant patient using Wi-Fi to visually and easily track the patient's status. The graphical display is in the form of an animation figure that mirrors the posture and position of the user in real time (shown in Fig. 4). This display serves not only for monitoring but also as a test for accuracy by comparing the display with the user's actual position. The graphical display indicates whether the user is sitting, standing or walking. In case the user is sitting, the graphical display changes according to his or her back posture.

3.5. User Feedback

User feedback is implemented in two forms: a real-time text message when sustained bad posture is detected, and a summary report of the day's activities that is sent by email to the user at the end of the session. The SMS message is received by the user when incorrect posture is detected. The summary report, which is sent by email, is generated at the end of the day from the

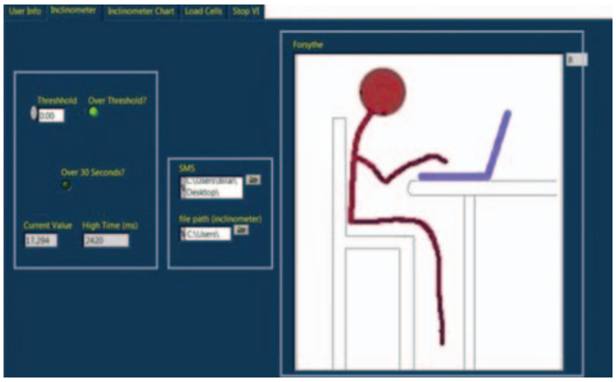

Fig. 4. User interface.

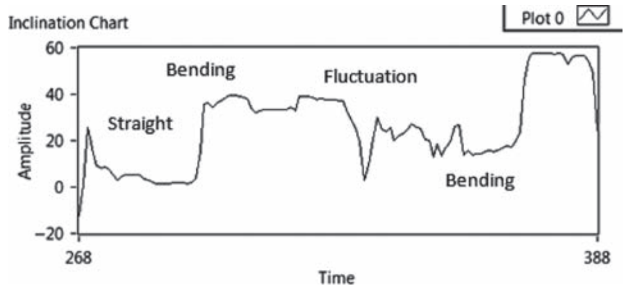

Fig. 5. Inclination chart.

database where the data is stored. The report contains information such as the average posture angle per day, the number of text notifications sent per day, the percentage of time during the day spent sitting, standing or walking, and other relevant information.

3.6. Experiments and Results

3.6.1. Inclination

We tested the inclinometer in a variety of scenarios. Figure 6 shows one of the tests, where the user was first in a correct posture position, then bent over, and then briefly straightened up before going through a period of fluctuation. We verified that after the user bent down below the threshold, the timer started. If the user spends the specified amount of time in an incorrect position, a message is sent to her cell phone in real-time with minimal delay. And as the user bent down, the animation figure in the interface mimicked the user's actions, and bent down its back in proportion to the user's bending.

3.6.2. Strain and Position

Similarly, we tested the load cells in several different scenarios comprising walking, sitting, and standing. Figure 7 shows the results of one such test case. As can be seen from the figure, when the user was sitting, the mean of load cells was low and the mean of difference was low. When she was standing, the mean of load cells was high and the mean of difference was low. When she was walking, both were high. Furthermore, the animation figure in the graphical display was able to successfully mimic the user in real-time; he stood when the user stood, walked when she walked, and sat down when the user sat down.

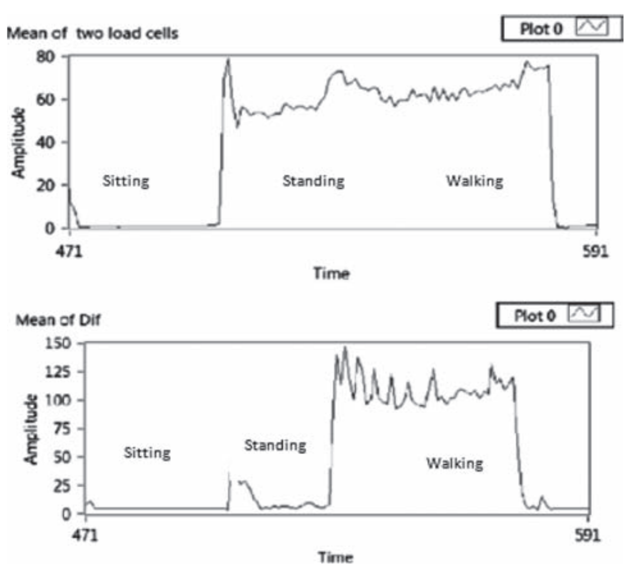

Fig. 6. Strain chart.

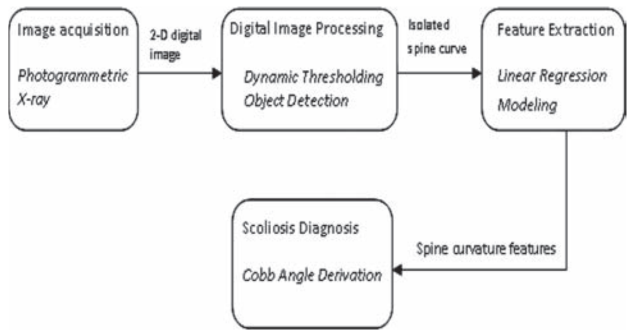

Fig. 7. Approach employed for cobb angle derivation.

4. IMAGING SYSTEM

Here we describe a simple, inexpensive and noninvasive method to automate the assessment of the degree of a user's scoliosis condition using a photograph of her back. The figure of merit that we use to determine the degree of severity of a patient's condition is the Cobb angle, described and shown in Ref. [5]. Several image features need to be identified for the derivation of the Cobb angle, which is defined as the angle made by the two lines perpendicular to the most deviated vertebrae on either side of the apex of the curve, and is considered the "golden standard" for scoliosis diagnosis.[5] The apex of a curve is the farthest position from the cranial (neck) vertebrae. Thus, to evaluate the Cobb angle, it is required to identify first the apex, and then the most deviated vertebrae on either side of the apex-also known as the upper and lower-end vertebrae,[5] and then the lines perpendicular to the curve at these vertebrae. The procedure is usually done manually by a medical examiner using an X-ray image of the patient's spine. Naturally, as the Cobb angle increases, the severity of the curve increases.

The approach comprises four stages. The first stage involves acquiring the 2-D image by taking a photograph or tracing an X-ray. The second stage comprises image segmentation and object detection using digital image processing and by applying a dynamic thresholding algorithm. The third stage involves feature includes the Cobb angle derivation and diagnosis using the output of the previous stages. Figure 7 shows a block diagram of the approach employed to calculate the Cobb angle. The steps are described in the subsequent sections. Note that all stages, except for image acquisition, are automated in software.

4.1. Image Acquisition

To obtain the image, we start by tracing the spinous processes on the back of the patient and marking them with adhesive markers. The inherent assumption is that the lateral curve obtained by tracing the spinous processes corresponds to the scoliosis curve, an assumption which is shared by several techniques in the literature such as the Ortelius800,[10,11] ISIS[12,13] and Zebris.[14] We then take a photograph of the patient's back and run the sequence of automated image processing steps on the photograph. A simple camera of average resolution quality will suffice, and no other equipment is required.

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4.2. Image Segmentation

The goal of this stage is to isolate the spine curve from image noise, image background, and other image objects, for further processing and feature extraction. We had to account for the fact that different objects in the photograph other than the spine trace may be detected. Moreover, we had to account for conditions such as varying brightness and lighting of the photograph and varying skin color. We start segmenting the image by converting the RGB color image into a grayscale image and then dynamically assigning a threshold that converts the grayscale image into a binary image. Pixels that fall below the threshold are part of the background and not the spine curve, and are hence rejected from the image. This step is the first step in isolating the spine and is a preprocessing step for object detection. Since objects other than the spine-such as back contour or light from the camera-may also be identified as part of the foreground, the next step is to label the image to detect its different objects or 'blobs'. We then find the areas of all detected objects. We assume that the object of interest, namely the spine, is the object with the largest area, and hence we reject all other objects from the image by setting their pixel values to zero. Finally, we proceed to "skeletonizing" the spine image to transform it into a single-pixel-thin line. This step is required for feature extraction in the next stage. The photograph at the different processing stages is shown in Figure 8.

Depending on the amount of light, the color of the person's skin, the colors of the background, and other such factors, the threshold could be different for each image. To account for this we opted for dynamic threshold selection based on the brightness content of the image. We used an iterative segmenting algorithm based on image histogram analysis that finds the optimal middle threshold. The histogram shows the frequency content or number of pixels for each of the 256 levels in the grayscale image, as shown below in Figure 9 for the same photograph where the brightness level has been changed from dark to bright.

4.3. Feature Extraction Using Non-Linear Regression Modeling

Once the spine curve has been isolated, the next step is to use the resulting image to obtain a mathematical model of the curvature. This model is used to extract the features that are needed for the Cobb angle derivation and that are described at the beginning of the section: the apex of the curve, the upper and lower-end vertebrae, and the lines perpendicular to the curve at these vertebrae. We use the model to approximate these features by characterizing mathematical points of interest on the curve. Namely, given an image we apply a transformation T:

$$T(I): I(p_x, p_y) \rightarrow P(x)$$

where p_x and p_y are 2-D pixel values, and $P(x)$ is a non-linear polynomial representing the scoliosis curvature of the spine. The curvature patterns of the polynomial can be determined by solving the equation $P''(x) = 0$, which yields the inflection points. The position of the apex (usually turning out to be the global maximum or minimum of the curve) is approximated by the point whose y-value is the farthest from the cervical end of the curve, and the positions of the upper and lower-end vertebrae are approximated by the closest inflection points on either side of the apex. Note that in choosing the inflection points we take only real roots and reject any complex solutions. The perpendicular lines are the tangents at the inflection points.

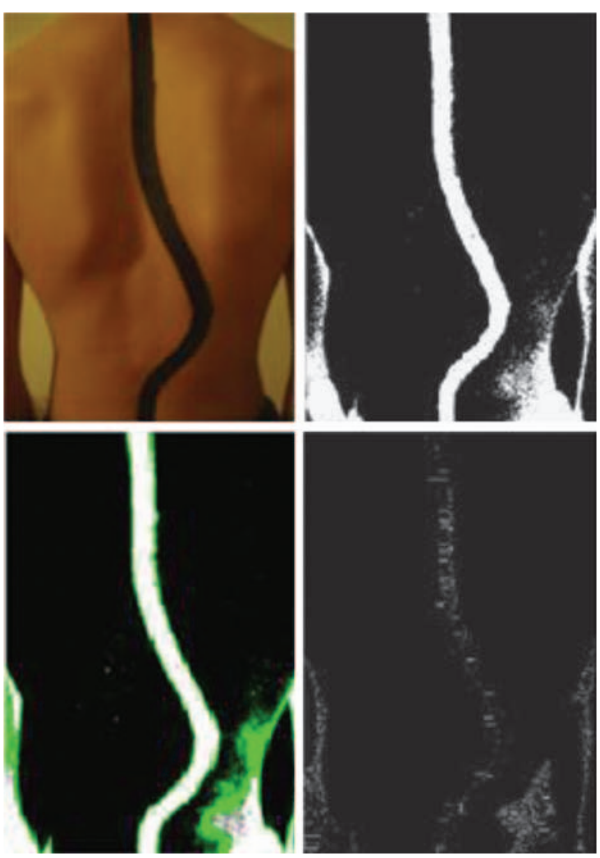

Fig. 8. Spine curve using spine isolation steps.

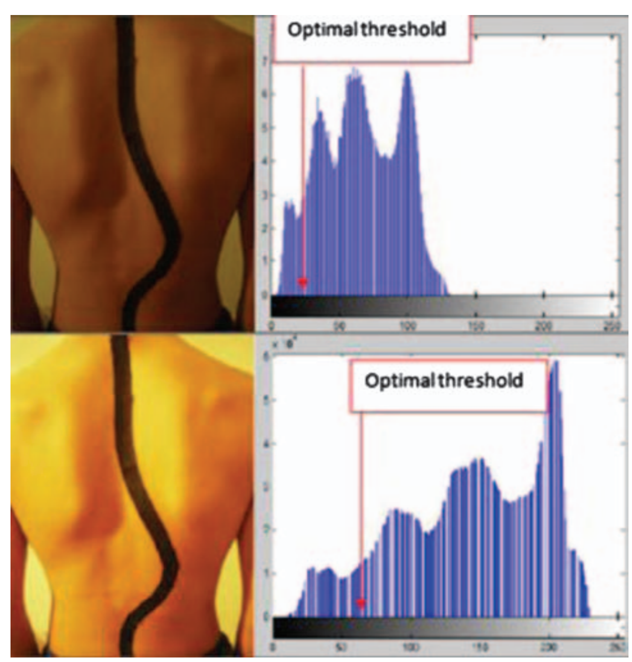

Fig. 9. Histogram content and optimal threshold for bright and dark image.

To obtain the model, we use the pixel-thin and isolated spine produced by the previous stage. We first rotate the spine, originally oriented in the vertical direction, in the counter-clockwise direction such that it becomes horizontally oriented. The purpose of this step to allow for the transformation of the image into a function. We then extract the spatial coordinates of the pixels of the spine and use a least-squares non-linear regression function to fit the coordinates to a polynomial curve. We experimented with polynomials of different degrees and found that a polynomial of degree seven gives the best combination of accuracy and robustness. Once the polynomial model is obtained, we extract the required apex, inflection points, and tangents.

4.4. Cobb Angle Derivation and Diagnosis

The final stage is the Cobb angle calculation based on the identified features of the curve. We use the tangents constructed at the inflection points of the obtained polynomial and find the angles of each of the tangents with the horizontal. The sum of the two angles is the Cobb angle of the curve, as can be seen in Figure 10. The fitted plot is superimposed over the pixel plot and the inflection points are marked with stars on the figure. The tangents are drawn passing through the points and the Cobb angle is the acute angle of the curve. Note that according to the scoliosis condition of the patient, the spine may have a minor (much smaller) curve-also known as a compensatory curve-alongside the major curve. It may also have two major curves, the resulting condition known as a 'double major curve'. In all such cases, our method would ideally extract the Cobb angle of the largest curve, i.e., with the apex of largest magnitude.

4.5. Experiments and Results

We had two experimental setups to test our method:

Setup 1: System accuracy: This tests the mathematical accuracy of our method. We used X-rays of scoliosis patients from the electronic database Scolisoft,® that have already been diagnosed by orthopedic surgeons. Cobb angle measurements from our system are compared with these X-rays.

Setup 2: Robustness: This setup tests the digital image processing aspect of our method, mainly the spine isolation and object detection approach. The purpose is to evaluate the validity of image analysis using a photograph. We used photographs taken of the back of a healthy volunteer. We varied several parameters while taking the photographs to ensure a variety of different scenarios.

4.5.1. System Accuracy

We evaluated the results of our implementation against 31 cases picked randomly from the Scolisoft database. We traced the database X-rays on a white background and used them as an input to our program. Note that for this setup we used a simplified version of our image processing method whereby object detection is not needed as edge detection will suffice for extracting a black spine on a white background. We compared the resulting Cobb angle measurement with the actual doctor's diagnosis of the major Cobb angle. Out of the 31 cases, 27 runs were able to pick out the major Cobb angle while in the other 4, the angle of a minor curve was extracted. Of the 27 successful runs, we obtained an average relative error of 6.01% with 14 cases below 6% and 9 cases below 3%. Moreover, we obtained an average error in degrees of 3.6 with 14 cases below 3 and 6 cases below 2. It is important to note, however, that this test does not fully test our photogrammetric technique; it tests the validity of our curve representation and linear regression modeling method. Tests on photogrammetric robustness are presented in the next section.

Fig. 10. Input photographs simulating different skin color.

Table II. Relative error for the same photograph under different brightness conditions.

Brightness (in increasing levels)	Cobb angle (in degrees)	Relative error compared to actual (%)
Level 1 (darkest)	72	2.8
Level 2	70	0
Level 3	69	1.4
Level 4 (brightest)	69	1.4

Table III. Reliability test for different photographs of the same back.

Photographs	Cobb angle (in degrees)	Relative error compared to actual (%)
Image 1	72	2.8
Image 2	72	2.8
Image 3	69	1.4
Image 4 (brightest)	67	4.3

4.5.2. Robustness of Image Segmentation

We tested the photogrammetric technique using photographs of a healthy volunteer whose back was marked so as to simulate a scoliosis spine. Our manual estimate of the Cobb angle was 70 degrees. First we used one photograph and varied the brightness to obtain quasi-different scenarios that simulate different skin color.

The input photographs are shown in Figure 10 and the results are shown in Table II. Note how the four photographs, despite the difference in brightness, yielded approximately the same result, which shows that our dynamic segmentation approach is robust enough to withstand changes in the brightness of the photograph.

Then we compared the results of different photographs taken of the same back with the same curve of 70 degrees. The results are shown in Table III. The different photographs gave very similar results, once more demonstrating the robustness of our image segmentation method under different conditions.

Note that we also took a photograph of this curve when flash was on. Flash proved to be problematic because it caused a bright spot to fall on the marked 'dark' spine and thus the corresponding region was identified by the thresholding algorithm as part of the background pixels rather than the foreground.

5. CONCLUSIONS AND FUTURE WORK

We have developed a mobile sensing and imaging system for complete assessment of spine health from both a dynamic and structural perspective. The wireless mobile sensing system monitors spine stress during daily activity while the imaging system provides a simple, inexpensive, and portable means of identifying and monitoring the progress of a patient's scoliosis condition, and this can be carried out by the patient at any time while minimizing exposure to X-rays.

The sensing system can achieve real-time monitoring of both poor back posture and stress on the spine deduced through measurements at the feet. It ensures patient awareness of poor posture in real-time through user feedback by SMS, encouraging the persistence of healthy spinal habits and reducing poor posture tendencies. For our given experiments, the system demonstrates high accuracy in identifying posture and position combined with a relatively inexpensive cost.

The imaging system is able to find the Cobb angle in an automated, non-invasive and simple fashion. We introduced a photogrammetric digital image processing approach based on dynamic thresholding and object detection for isolation of the spine object, and an automated approach for Cobb angle feature extraction using a non-linear regression model of the spine. Results, based on comparison with X-ray images, verified the accuracy of the mathematical method, and robustness of the photogrammetric method was shown under different brightness conditions that simulate different skin color. Compared to past techniques, this imaging technique approach is inexpensive, simple, portable, and requires no complex equipment. Note, however that this system is to be used by the patient as an initial screening or for regular progression monitoring from home. It should not replace or eliminate the need for professional medical diagnosis by expert physicians.

To fully verify the accuracy and reliability of the imaging method, further experiments are needed where the full approach is tested by taking photographs of real scoliosis patients whose curvature angles are known. Moreover, the mobile system can be further productized for mass consumption by using smaller sensors and acquisition device. Finally, the goal is to have the two systems fully integrated whereby the database for each patient contains both dynamic and structural spine health data that can be mined to find patterns and correlations between the two subsystem outputs and generate user recommendations and notifications accordingly. Such a system can then- with use of appropriate interfaces to the sensors and data transmission- enable the development of a mobile phone application that helps users continuously and easily track and monitor their spinal health.

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