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Scoliosis screening system based on improved optical photogrammetry using Kinect sensor

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10 Abstract

Background: Scoliosis has become an important factor affecting human health, and there is a trend of younger age, so it is necessary to carry out scoliosis screening in communities and schools. However, common methods of scoliosis screening, such as manual physical examination and X-ray, require the experience of a professional physician and the procedure is complex, so they cannot meet requirements of fast, convenient and low cost. This paper presents a scoliosis screening system based on improved optical photogrammetry using Kinect sensor.

Methods: Color image and depth image collected by Kinect sensor are aligned to generate 3D point cloud. Unnecessary points are removed by filtering and segmentation methods, and the interested back point cloud is obtained. Representative points of two shoulders and anatomical landmarks on the back are extracted, and spine curve is fitted based on the points in the middle of the back derived from depth data. Uneven shoulders, Deep optics-based scoliosis assessment (DOSA) angle, kyphosis index and angle of trunk rotation (ATR) are combined to determine whether the spine is abnormal from three anatomical planes.

Results: Forty subjects with possible scoliosis were tested. Cobb angles were obtained based on X-ray imaging and DOSA angles were obtained by photographic imaging. The mean difference between the two angles mentioned above for all subjects was -0.386° , and the variance was 7.773. 87.5% of the angle difference was between -3° and 3° . When significant level α is 0.05, the critical value $t_{0.05}(39)$ equals ± 2.023 , t value calculated according to the experimental data is -0.877 , Cohen d is 0.138 and r^2 is 0.0193. It can be seen that the difference between the DOSA angle and the traditional standard Cobb angle is small.

Conclusions: For most subjects, measured values of scoliosis using this scoliosis screening system are similar to those obtained by X-ray, and have advantages of no radiation, lower cost, and more convenience.

35 **Keywords:** Scoliosis, point cloud, Kinect, Cobb angle

1. Introduction

Scoliosis is that the spinal segment deviates from the center line of the back on the coronal plane of the human body and bends laterally, usually accompanied by spinal rotation and sagittal kyphosis or lordosis and other symptoms. The International Society for the Study of Scoliosis has given a golden standard definition for scoliosis: take an upright spinal X-ray film, and measure the curvature angle of the spine with the Cobb angle method. If it is greater than 10° , it is called scoliosis [1]. Scoliosis is the most common

spinal disorder among adolescents, with a worldwide prevalence of 0.5-5.2% [2]. In addition to causing back asymmetry, scoliosis can lead to thoracic deformity in severe cases, which in turn can cause visceral dysfunction. Early detection and intervention are crucial to avoid surgery and ensure better recovery. Traditional scoliosis is assessed by manual primary screening and X-ray re-screening [3,4]. However, manual screening is inefficient for large populations, and X-rays involve radiation risks and high costs, making them unsuitable for routine frequent monitoring.

To address these limitations, various non-invasive surface topography methods have been explored. Early approaches primarily utilized Moiré topography [5] and grating stereo photography [6,7] to reconstruct 3D back models. Systems such as the Quantec [8] scanner and DIERS 4D [9] motion system represented significant progress in optical measurement. However, these traditional optical methods often require strict lighting environments, complex calibration procedures, or expensive hardware, which limits their widespread application in community and school screenings.

In recent years, the integration of Artificial Intelligence (AI) has significantly advanced scoliosis screening in the last five years. Unlike traditional geometric methods that rely on manually defined features, deep learning algorithms, such as Convolutional Neural Networks, can automatically learn complex feature representations from back surface images or 3D point clouds. For instance, Yang developed a deep learning algorithm to screen for scoliosis using naked-back images, achieving high diagnostic accuracy [10]. Other studies have employed deep neural networks to directly regress spinal curvature parameters from point cloud data, improving robustness against noise [11,12]. However, strictly data-driven AI methods often require massive annotated datasets which are scarce in medical imaging, and their "black box" nature can lack clinical interpretability compared to geometric feature extraction.

Considering the above situation, turning attention to Kinect, compared to traditional scanners, Kinect sensors are portable, radiation-free, and cost-effective, has provided a new solution for accessible screening. Some researchers demonstrated that Kinect data could automatically extract anatomical landmarks and estimate 3D spinal curves with accuracy comparable to laser systems [13, 14]. Many researchers reconstructed three-dimensional model of the human body using Kinect camera. Ciobanu [15] assessed spinal deformity based on the surface geometry of the trunk. Dejan [16] developed a toolbox for the Azure Kinect COTS device that can be used for automated screening for idiopathic scoliosis. Xu [17] proposed a method which can be used for the assessment of spine deformation. The depth images collected by Kinect sensors were converted into three-dimensional point clouds, anatomical landmarks and spinous process lines were extracted, and then a correlation model between spinous process lines and spinal midline are established. The accuracy of Cobb angles is very close to those using more expensive or complex equipment such as laser imaging or Drerup's moiré imaging [18,19]. Lin [20] researched a Kinect camera-based scoliosis detection system, which got Cobb angles between 0° and 20° within 3 seconds using methods including image grayscale [21], ROI area extraction, depth-first search and contour search. However, since the sample size is not large enough, the measurement error of the Cobb angle and the overall algorithm process needs to be further tested. Castro [22] proposed a method for obtaining a 3D reconstruction model of the skin surface of the subject's back in different postures. The shoulder height difference for each subject was calculated by quantifying the angular slope of the intersection line of two scapulas. The above studies can effectively evaluate scoliosis, but multiple anatomical landmarks are manually labeled or more than one camera are needed, and the number of subjects is relatively small.

In this work, a scoliosis screening system was developed based on improved optical photogrammetry. The image of the back of the human body is obtained via Kinect sensor, the feature points and the midline of the back are extracted using image processing and curve fitting methods, and the DOSA angle, kyphosis

index and ATR are analyzed for all subjects to measure and evaluate the degree of scoliosis.

2. Scoliosis evaluation

2.1. Uneven shoulders

90 Subjects with scoliosis may have uneven shoulders. Therefore, measurements for uneven shoulders can be used to assist in the assessment of the scoliosis. Using representative points of two shoulders, their Y-axis difference is taken as the shoulder height difference, and the angle between the height difference and the X-axis is taken as the shoulder difference angle. These two values can be used to measure whether the subject has uneven shoulders and its severity.

95 2.2. DOSA angle

The severity of scoliosis is often assessed by measuring the curvature angle, and the most commonly used indicator is Cobb angle which is based on the frontal spine X-ray, as shown in Fig 1. The process of Cobb angle measurement is as follows. First, the curved end vertebrae are determined. Upper and lower vertebrae are the one with the largest inclination toward the concave side of the spine. The second step is to draw horizontal lines on the upper edge of the upper vertebra and the lower edge of the lower vertebra, and draw vertical lines for each of these two horizontal lines. And finally, the intersection of these two vertical lines is Cobb angle. Referring to calculation method of Cobb angle, our research group proposed deep optics-based scoliosis assessment angle, namely DOSA angle. Using fitting curve of the spine in the coronal plane, the two places with the largest curvature change are regarded as the upper and lower vertebrae by derivation of the curve, and then DOSA angle is calculated.

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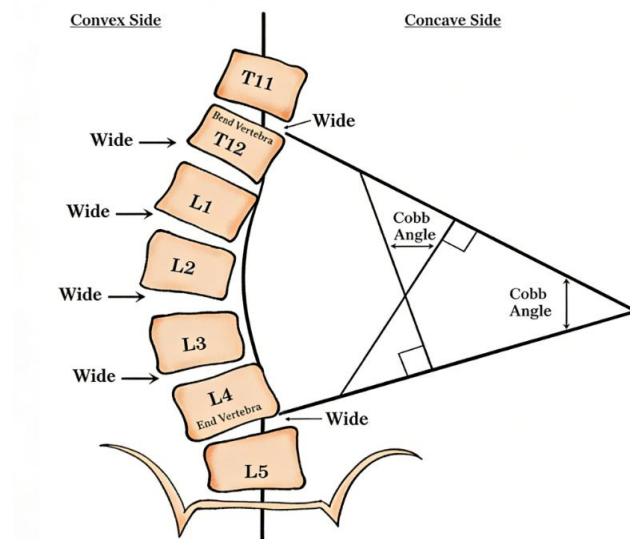
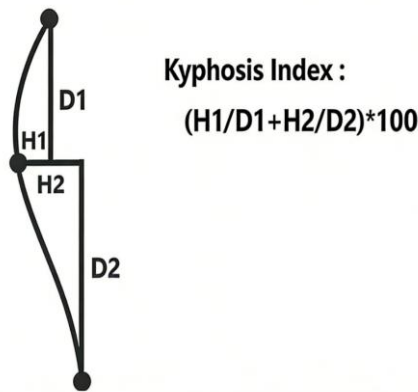


Fig 1. Cobb angle

2.3. Kyphosis index

110 Sinoto value of kyphosis index is used to illustrate lateral deformation of spinal curvature in the sagittal plane, as a supplement to the description of DOSA angle only in the coronal plane, as shown in Fig 2. The Sinoto value indicates the degree of kyphosis by the ratio of hump height to back length. The larger the value, the more serious kyphosis is. Sinoto value is obtained by calculating the hump position, height and corresponding back length using spine fitting curve in the sagittal plane.



115 **Fig 2.** Kyphosis index

2.4. ATR

The ATR value is used to indicate the rotation angle of the spine in the cross-sectional direction, $\alpha = \frac{\arctan(\frac{|D|}{|H|}) \times 180}{\pi}$, where α is the ATR; D and H are the height difference and horizontal distance between selected points A and B respectively, as shown in Fig 3. ATR represents the degree of spinal rotation through the intuitive value of hump height and hump distance. The larger the value, the more severe the spinal rotation.

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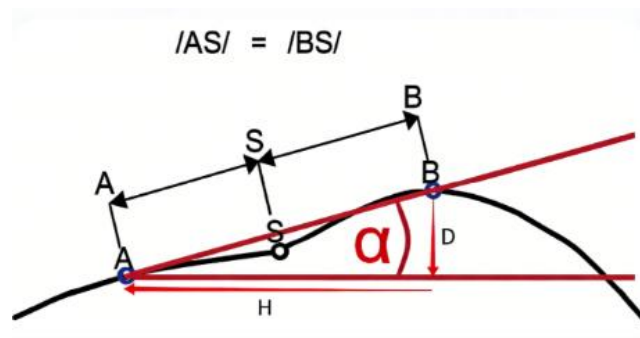


Fig 3 ATR

3. Results

3.1. Uneven shoulders

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Based on Kinect imaging, there were 25 people with shoulder height difference greater than or equal to 1cm, among whom 14 were 1-2cm, 5 were 2-3cm, and 6 were greater than 3cm. Shoulder height difference is not found to be positively associated with the degree of scoliosis because it is associated with age, BMI, and a variety of other factors, and can be affected by the person's posture when measured.

3.2. DOSA angle

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Cobb angles were obtained based on X-ray imaging, among which 10 subjects had Cobb angles less than 10°, 28 subjects greater than or equal to 10° and less than 25°, 2 subjects greater than or equal to 25° and less than 40°. DOSA angles were obtained based on Kinect imaging, 14 subjects had DOSA

angles less than 10° , 25 subjects greater than or equal to 10° and less than 25° , 1 subject greater than or equal to 25° and less than 40° . As shown in the Fig 4, the abscissa is the age and the ordinate is the angle, where the green dot represents DOSA angle and the red square represents Cobb angle. The minimum angle difference of subjects was -3.649° , the maximum was 5.42° , the mean was -0.386° , and the variance was 7.773. 87.5% of the subjects' angle difference was within $\pm 3^\circ$. When significant level α is 0.05, the critical value $t_{0.05}(39)$ equals ± 2.023 , t value calculated according to the experimental data is -0.877, Cohen d is 0.138 and r^2 is 0.0193.

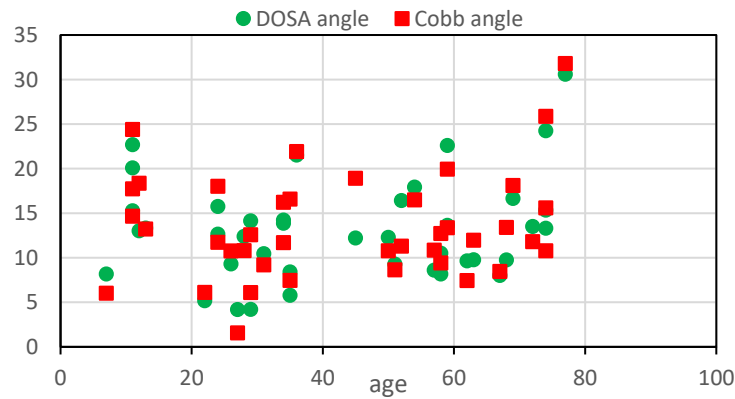


Fig 4. DOSA angle and Cobb angle

To validate the clinical effectiveness of the proposed system, the diagnostic performance was evaluated using the Cobb angle from X-ray as the gold standard. Comparing the two angles, as shown in Table 1, with a threshold of 10° for scoliosis diagnosis, the system correctly identified 25 out of 30 positive cases and 9 out of 10 negative cases. Interestingly, most of the false-negative cases were 'borderline' mild scoliosis, with Cobb angles ranging from 10.74° to 13.39° and corresponding DOSA angles ranging from 8.6° to 9.8° , which are very close to the diagnostic threshold.

Table 1. Comparison of Cobb and DOSA

Index	Cobb	DOSA
angle < 10°	10	14
$10^\circ \leq \text{angle} < 20^\circ$	26	20
$20^\circ \leq \text{angle} < 40^\circ$	4	6
angle $\geq 40^\circ$	0	0

Consequently, the system achieved a sensitivity of 83.33%, a specificity of 90.00%, and an overall accuracy of 85.00%. The Receiver Operating Characteristic (ROC) curve analysis demonstrated excellent classification capability, with an Area Under the Curve (AUC) of 0.967, shown in Fig 5.

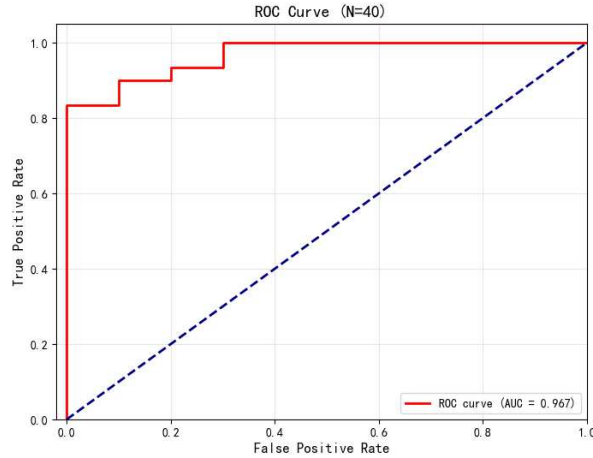


Fig 5. ROC Curve

It can be seen that the difference between the DOSA angle and the traditional standard Cobb angle is small. DOSA angle based on Kinect sensor is a good indicator of scoliosis.

3.3. Kyphosis index

The degree of kyphosis is represented by Sinto value. Based on Kinect imaging, the minimum of Sinto value was 6.37, the maximum was 87.32, the mean was 33.94, and the variance was 313.7404. As shown in the Fig 6, the abscissa is the age, the ordinate of the green dot is DOSA angle, and the ordinate of the blue triangle is Sinto value. Among 20 subjects with age younger than 40, 19 subjects (95.0%) had Sinto values less than 40 and 1 subject (0.5%) greater than or equal to 40 and less than 50. Among 19 subjects with age greater than or equal to 50, 10 subjects (52.6%) had Sinto values less than 40, 3 subjects (15.8%) greater than or equal to 40 and less than 50, and 6 subjects (31.6%) greater than or equal to 50. This suggests that hunchback is more common in older people. DOSA angle has little correlation with Sinto value because scoliosis is a curve of the spine to the left or right side, and kyphosis is a protrusion of the spine to the rear.

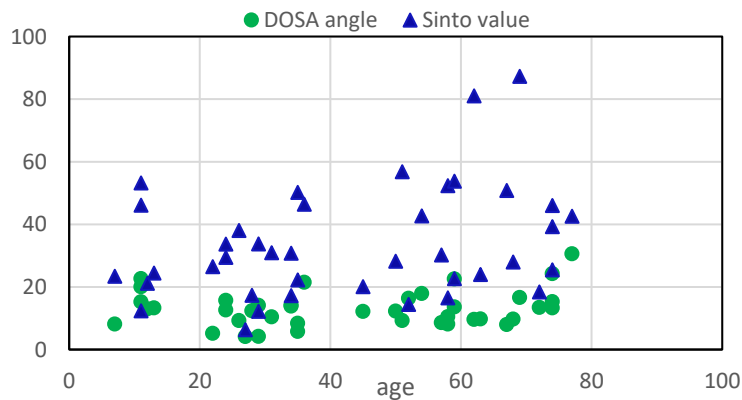


Fig 6. DOSA angle and Sinto value

3.4. ATR

ATR is an important indicator for cross-sectional analysis of the spine, which can analyze the shape of the spine from another dimension. Cobb angle, as an indicator of the coronal plane, cannot explain the whole of the surface deformity, not all patients with radiographic scoliosis have rotation of the trunk, not

all patients with radiographic scoliosis exhibit trunk rotation, and conversely, significant trunk rotation can exist without severe coronal curvature. Therefore, ATR assessment is essential for a comprehensive screening.

Clinically, the normal value of ATR is usually less than 5 degrees, if the ATR is greater than 5 degrees, it indicates that the spine has significant rotation in the lateral direction. In this study, the Kinect-based system identified all subjects with abnormal ATR, showing 100% consistency with the control measurements., and the maximum error between the measured ATR value and the actual ATR value is only 0.408° , which is significantly lower than the intra-observer variability typically observed with a manual Scoliometer (often ranging from 2° to 3°). It can be seen the ATR of Kinect imaging is relatively accurate.

4. Discussion

Compared with the Cobb angle obtained by X-ray imaging, the DOSA angle obtained by improved optical photogrammetry can also reflect the degree of scoliosis. According to the results of this study, there was no significant statistical difference between DOSA angle and Cobb angle, and the diagnostic conclusion of the two methods had a good consistency.

In addition to coronal plane angle, this system can also obtain sagittal kyphosis index, cross-sectional ATR and shoulder height difference, which can infer the degree of kyphosis, the angle of trunk rotation and whether there are uneven shoulders, and then provide multidimensional data to assist the doctor to assess the condition of spine. Scoliosis in the human spine can present as a deformity in three dimensions, therefore, the three-dimensional multi-index data of the human body can more comprehensively and integrally reflect the problems in the body shape and posture, and can serve as an effective supplement to the Cobb angle.

A single Kinect camera is used as a photogrammeter and a portable computer as a data processor. Compared to other photogrammetry methods, the reduction of the number of cameras makes the cost lower, and less manually marked points makes the operation easier. The entire operation is performed within a single software program. The operator's learning time is approximately 5 minutes, and the average measurement time is about 2 minutes. Moreover, the mobility of the device overcomes the shortcomings of traditional X-ray method that cannot be applied in some clinical settings such as school and community screening.

For severely obese people with BMI greater than 28kg/m^2 , or people with excessive loose skin, the back spine line is not obvious. The scoliosis detection based on Kinect sensor may lead to a large measurement error, so other methods should be considered.

In conclusion, the improved optical photogrammetry can be used as a low-cost, low-radiation, high-efficiency, real-time screening method for scoliosis, which can be used in hospitals, communities, schools and other places for primary screening and reexamination, as well as remote online detection.

5. Conclusion

In this work, a system was developed for scoliosis measurement and evaluation using Kinect sensor. The measurement of scoliosis obtained by this system for most subjects is similar to that obtained by X-ray. To further validate our system and evaluate measurement errors, a larger sample size test is needed. In addition, for some obese subjects, the back depression may not be obvious, and more anatomical landmarks or other discriminative methods are needed to evaluate scoliosis.

6. Methods

This study selected the suspected spinal sides that met the inclusion criteria from February to July 2022. The convex subjects were taken as the research subjects. Inclusion criteria: from patients who visited the outpatient department or were hospitalized at Wuchang Hospital; Age < 80 years old; Body Mass Index (BMI) < 28 kg/m². The score of the Mini-Mental State Examination Scale is higher than 23 points. Exclusion criteria: refusal to participate in this research; There is unstable medical care those with certain conditions (such as acute heart failure, acute cerebral infarction, etc.); Lower limbs or those with a history of major spinal trauma or orthopedic diseases, or those who have undergone previous spinal surgeries, or received conservative treatment. Ultimately, 40 subjects were included, among whom 19 were male and 21 were female. The age ranged from 7 to 77 years old, six of them were less than 18 years old. The height was 1.20-1.80m and the weight was 23-86kg. Information about individual participants can be identified by authors during or after data collection. All participants provide informed consent in writing, and for minors, guardian consent is obtained. This study was approved by the Ethics Committee of Wuhan Wuchang Hospital and complied with the Declaration of Helsinki. (Batch number: 2022001)

6.1. Scoliosis screening system

Scoliosis screening system consists of subject, Kinect sensor and computer [23]. The Kinect sensor obtains color and depth image of the subject and surroundings, and then they are transmitted to the computer. Main functions of the computer are as follows. (1) Point cloud generation. By coordinate transformation, color image and depth image are aligned to generate 3D point cloud including color and position information. (2) Point cloud processing. Unnecessary points are removed by point cloud filtering and segmentation, and the interested back point cloud is obtained. Also, the effect of measurement error can be reduced using point cloud smoothing. (3) Feature extraction. Representative points of two shoulders and artificial identification points on the back are extracted, and spine curve is fitted based on the points in the middle of the back derived from depth data. (4) Scoliosis evaluation. Uneven shoulders, DOSA angle, kyphosis index and ATR are combined to determine whether the spine is abnormal from three anatomical planes.

As shown in Fig 7, Kinect sensor, subject and background wall are placed in sequence. The distance between the two is kept within the effective range of Kinect, which can be set to 0.8-2.5m. In Fig 7(a), the subject is required to stand vertically, with arms hanging down naturally, back bare, and wearing dark pants. In Fig 7(b), the subject is required to sit in a 90° forward bend position, back bare, and wearing dark pants. The background wall is monochrome, and there should be a certain gap between the subject and background wall. Posture (a) is used to calculate Uneven shoulders, DOSA angle and Kyphosis index, and posture (b) is used to calculate ATR.



(a) Stand vertically position



(b) 90° forward bend position

Fig 7. Experimental scene

6.2. Point cloud generation

The Kinect sensor has a color camera and a depth camera that can collect a 1920 by 1080 color image and a 512 by 424 depth image respectively. Points in the depth pixel map are transformed into the depth camera space, the color camera space, and the color pixel map, then the depth pixel map is aligned with the color pixel map, and finally point cloud including 3D position and RGB color is generated. Fig 8 shows the basic idea of point cloud generation.

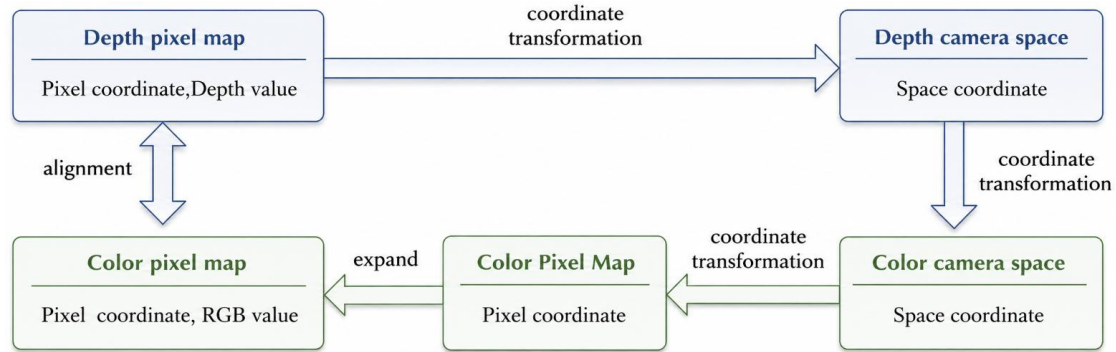


Fig 8. Alignment of depth image and color image

6.3. Point cloud processing

6.3.1. Filtering

The initial point cloud includes points of the subject, background wall, surroundings and noise. In order to get the point cloud mainly composed of the back of the subject, filtering methods are adopted to remove most of uninterested points. Considering there is space between the subject and surroundings, pass-through filtering is used by limiting the values of X, Y and Z axes for all points, so as to remove irrelevant points and keep only points of the subject. In addition, outlier filtering is used to remove noise points that deviate from the region of interest. Point cloud after filtering is shown in Fig 9.



Fig 9. Point cloud after filtering

6.3.2. Segmentation

Human skin is different from hair and clothes in color, so color-based region growing segmentation algorithm is used to cluster point cloud. By this way, points composed of the back and upper limbs of the subject are kept, and others points such as hair and clothes are removed. Color-based region growing

segmentation algorithm consists of two key steps. The first is segmentation. If the color distance between a point and one of its neighbors is smaller than a given threshold, then the two points are grouped in the same cluster. The second is merging. If the color distance between two clusters is less than a given threshold, the two clusters will be merged into one. In addition, if the number of points in a cluster is less than the minimum number of points to become a cluster, the cluster will be combined with its nearest cluster.

The neighborhood color distance threshold and inter-cluster color distance threshold have non-negligible influence on the effect and efficiency of segmentation. Two parameters are set to the same value, respectively 3, 5, 7 and 9. After running the color-based segmentation algorithm for 10 times, the number of clusters and the average running time are shown in Table 2, and the results are shown in Fig 10.

Table 2. Data results for different color thresholds

neighborhood color distance threshold	inter-cluster color distance threshold	the number of clusters	average running time(ms)
3	3	21	12432
5	5	4	10178
7	7	4	9822
9	9	3	9564

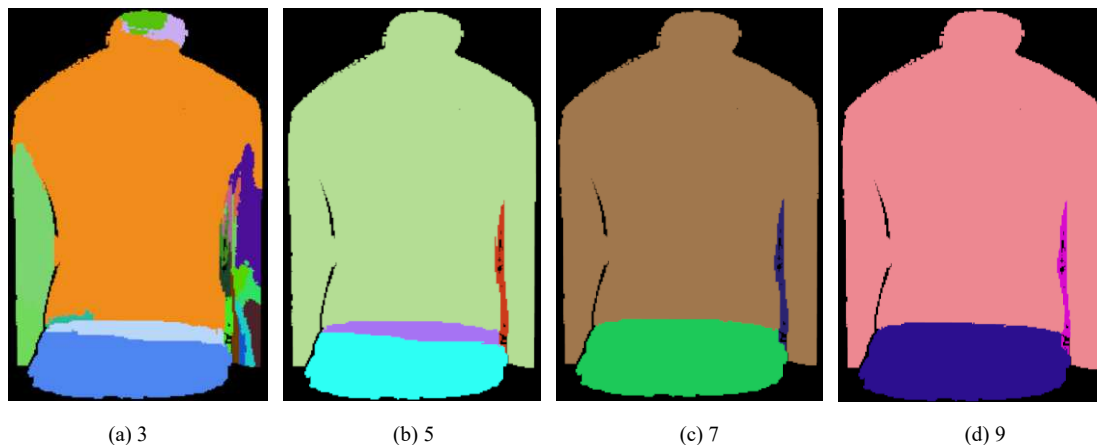


Fig 10. Segmentation for different color thresholds

According to Table 1, when two color distance thresholds are set to 3, the number of clusters is 21 and the average running time of the segmentation algorithm is 12432ms. It shows that the color difference between neighboring clusters is small, the number of clusters is large, and the algorithm takes a long time to run. If the color distance threshold is 5, the number of clusters is 4, and the average running time is 10178ms. It indicates that when the color distance threshold increases, the color segmentation is rough, the number of clusters decreases, and the average running time decreases. If the color distance threshold is 7 and 9, the number of clusters is both 3, and the average running time is 9822ms and 10023ms, respectively. The results show that when the color distance threshold increases, the number of clusters and the running time decrease accordingly. In this case, similar colors are difficult to distinguish. Based on the above analysis, both color distance thresholds are set to 5.

Of all the clustering blocks, the one consisting of the back and upper limbs is the largest. The interested point cloud can be obtained by extracting the block with the largest number of points, as shown in Fig 11.



Fig 11. The interested point cloud

6.3.3. Smoothing

Using Kinect sensor to collect data, there will be measurement errors. For better feature extraction, the moving least square method is used to smooth the point cloud. Point cloud smoothing helps to reduce the impact of measurement errors, but it also increases running time of the program. The order of polynomial fitting curve was set as 2 and 3, and the radius of sub-region was set as 0.005, 0.01, 0.02, 0.03 and 0.04m, respectively. The average running time of point cloud smoothing was obtained as shown in the Fig 12. With the increase of polynomial order, the running time increases slightly. With the increase of sub-region radius, the running time increases rapidly. Considering the balance between smoothing effect and operation efficiency, the order is set to 2 and the sub-area radius 0.02.

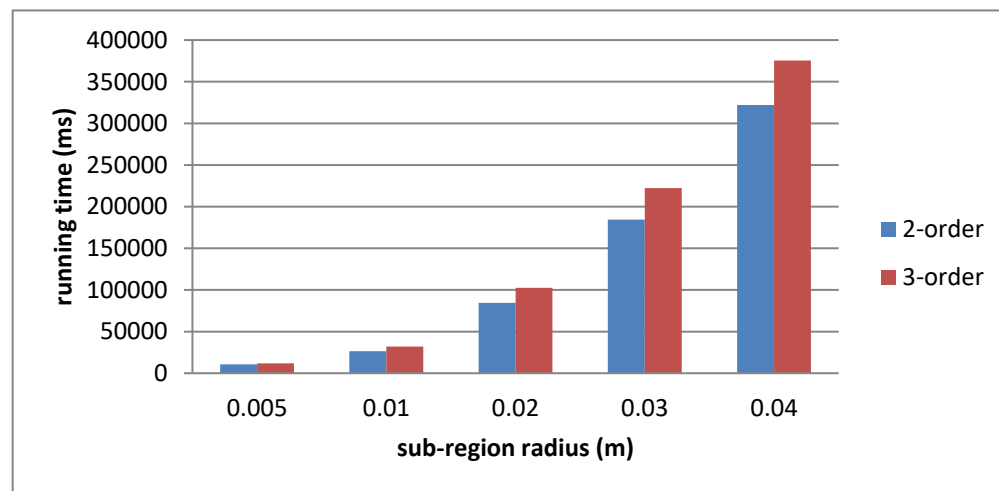


Fig 12. Running time for different smoothing parameters

6.4. Feature extraction

6.4.1. Height of shoulders

Edge points of the left and right shoulder are extracted from the point cloud and projected onto the two-dimensional coronal plane, and then two cubic polynomial curves are used to fit them. As shown in the

Fig 13(a), red points are edge points of two shoulders. In Fig 13(b) the two blue curves are fitting curves of shoulders, two green points with curvature peak in two curves are taken as the representatives of the left and right shoulder, then the height of two shoulders can be obtained.

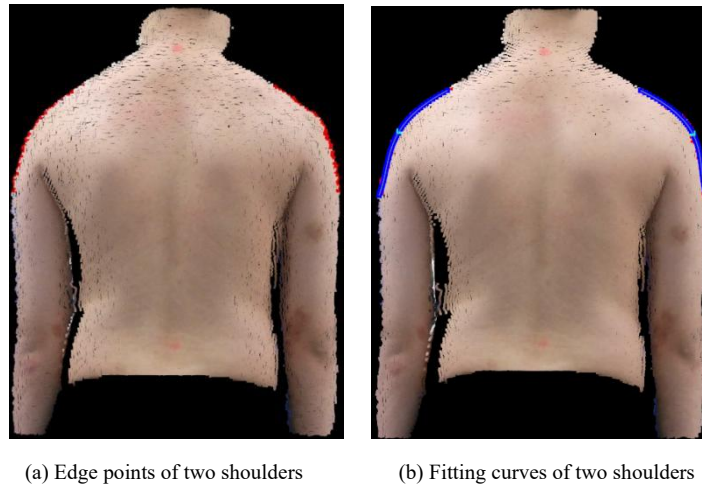


Fig 13. Representative points of shoulders

6.4.2. Anatomical landmarks

In order to improve the availability of spinal feature, anatomical landmarks C7 and L5 are indicated on the back of the subject as the start and end of the spinal, and A and B as the measurement points for ATR by an experienced physician in this study. If RGB is used to represent the color of point cloud, it is sometimes difficult to distinguish anatomical landmarks from the skin, so landmarks may not be recognized or misrecognized. Therefore, the color is converted from RGB to HSV, and then anatomical landmarks C7 and L5, A and B can be clearly extracted by hue H, as shown in Fig 14.

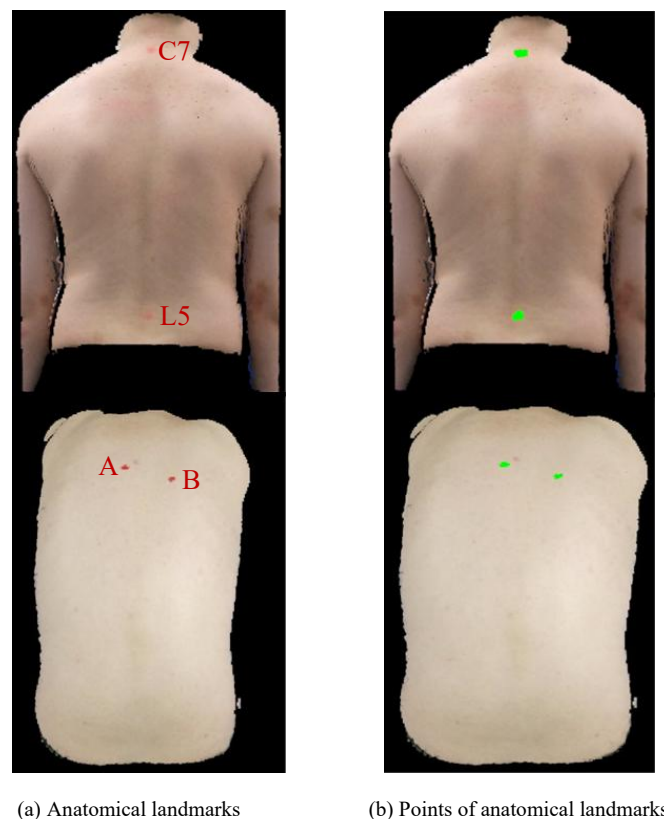


Fig 14. Anatomical landmarks

6.4.3. Points on the spine

Usually on the surface of the back, the spine is concave relative to its surroundings. Specifically, the Z-axis value of the point on the spine is smaller than that of its surroundings, so the concave point in the middle of the back can be regarded as a point on the spine. However, due to age, body size, obesity, and muscle slack, some people have lateral or oblique concave surface in their backs that can interfere with the recognition of the spine. In order to eliminate interference, the point cloud is segmented into many small fragments along the Y-axis. The Z-value of each point and the one of its neighboring points are compared on each fragment. For a point, if the ratio of the number of neighboring points with lower Z value to the number of all neighboring points reaches a certain threshold, the point is regarded as a concave point. Here the threshold is called the concave coefficient. By this way, concave points in the middle of the back are obtained.

Two parameters are critical in the extraction of concave points on the back, one is Y-axis fragment length and the other is concave coefficient. The fragment length was set to 0.001, 0.002, and 0.008(unit: m) respectively, and concave points on the back of the subject were obtained, as shown in Fig 15.

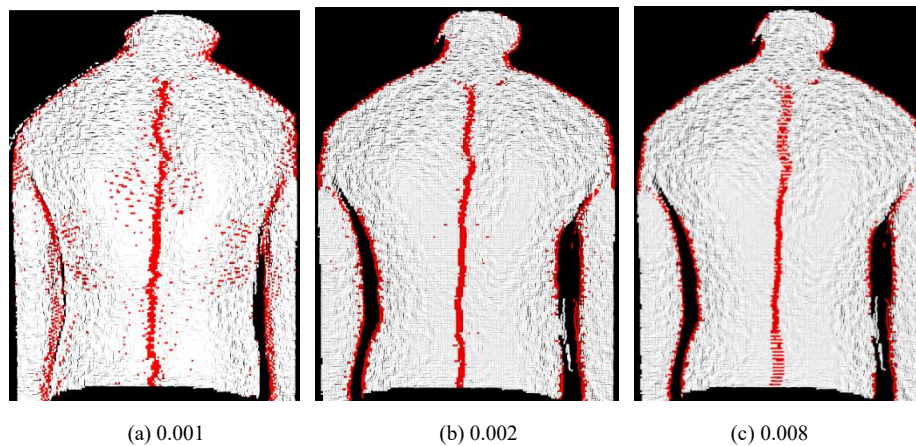
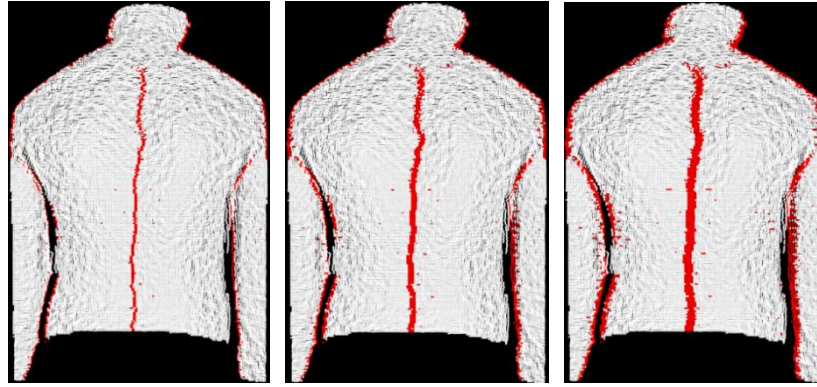


Fig 15. Concave points on the back for different fragment length

When the fragment length is 0.001m, there are many concave points meeting given conditions, and concave points are relatively messy, as shown in Fig 15(a). When the fragment length is increased to 0.002m, concave points of the spine are more obvious, as shown in Fig 15(b). When the fragment length is increased to 0.008m, the shape of the point cloud of the spine shows a zigzag, as shown in Fig 15(c). In this study, the length of Y-axis fragment is selected as 0.002m.

The concave coefficient was set to 0.95, 0.9, and 0.85 respectively, and concave points on the back of the subject were obtained, as shown in Fig 16.



(a) 0.95

(b) 0.9

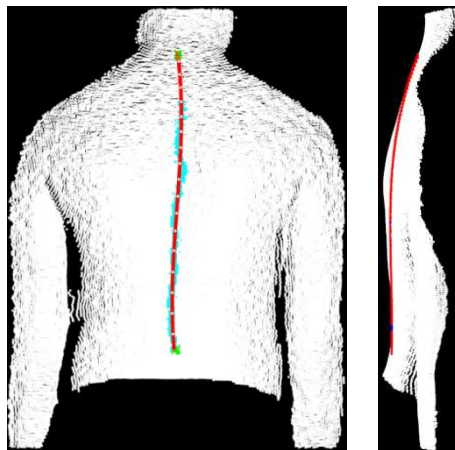
(c) 0.85

Fig 16. Concave points on the back for different concave coefficient

As shown in Fig 16, points around the spine are obvious and the overall shape is clear in four cases. When the concave coefficient is 0.95, the point cloud around the spine is obvious, but the number of points is relatively small, and it is more susceptible to the interference of surrounding noise points, as shown in Fig 16(a). When the concave coefficient is 0.9, the number of point cloud around the spine increases, as shown in Fig 16(b). When the concave coefficients are 0.85, the number of point cloud around the spine further increases and the transverse width increases, as shown in Fig 16(c). Considering the actual spinal morphology and subsequent curve fitting, the concave coefficient is selected as 0.9.

6.4.4. Spine line

Concave points in the middle of the back and points of anatomical landmarks are projected onto the two-dimensional coronal plane and sagittal plane, and the least square method is used for polynomial fitting to generate two spine lines. spinal curves fitted in the coronal plane and sagittal plane are shown in red, respectively, as shown in Fig 17(a) and (b).



(a) coronal plane

(b) sagittal plane

Fig 17. Spinal fitting curve

7. Declarations

Ethics approval and consent to participate

This study was approved by the Ethics Committee of Wuhan Wuchang Hospital and complied with the Declaration of Helsinki. Participants involved in this research were informed of the research procedures and signed an informed consent before participation.

Consent for publication

The authors have confirmed that any identifiable participants in this study have given their consent for publication.

Availability of data and materials

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Competing interests

The authors declare that they have no competing interests

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Author contributions

XL designed this study. ZL and XW analyzed the data. TY recruited subjects and performed the measurements. YZ debugged equipment and collected data. All authors read and approved the final manuscript.

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