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CT Posture Detection Base on Random Forest

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Abstract: In order to realize the body posture recognition automatically in CT scanning and provides an automatic operational reference system for training students, a method of automatic posture recognition for CT scanning is studied in this paper. Firstly, a Random Forest model is used to detect the joint points of the human body parts and extracts the datum line. Then we use the relative position between the datum line and the laser positioning line to judge whether the body position is correct. The experiment shows that the proposed method can accurately detect the body postures with an accuracy rate up to 91.2%, which meets the requirements of accuracy and real-time in CT detection.

Key words: *CT scanning; posture recognition; joints detection; HOG feature; Random Forest*

I. INTRODUCTIONS

In the CT detection, the doctor need to guide the patient lying on the CT bed in a specific posture and judge whether the posture is correct through the laser positioning line that projected by the CT bed firstly, which is the key to obtain high quality and clear CT images. In this paper, an automatic detection system for CT posture detection is designed. In this system, the body image of the patient is collected by the camera firstly, and then it is identify the human joint and extract the datum line (some specific ligature between the joints) of the human body and the location of laser positioning line to do the comparison and judgment. In the detection system of this paper, the detection effect of the human joint is the key factor that affects the automatic recognition system of CT posture detection.

II. METHOD

2.1 Method and procedure

In this paper, we constructed a color CT posture sample library that including training set and test set based on the random forest method to identify the human joints and then according the relative position of datum line and datum line to judge whether the patient's position is correct or not. The flow block diagram of position shown in Fig. 1.

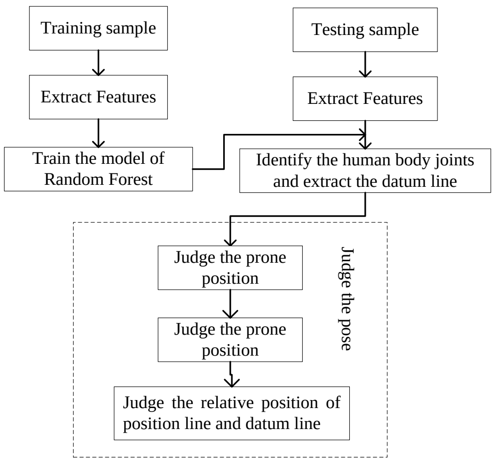


Figure 1 Procedure of method

2.2 CT posture image acquisition

Because there is no public database of CT posture, so in this paper we got the homemade sample library through camera. Fig. 2 is for the part of collection of the CT pose image. In actual clinical procedures, CT scan can require the patient to wear a specific garment for the detection.

Figure 2 CT posture images

There are three common postures use in CT detection, including lateral, supine and prone position. In this paper, 40 different videos were recorded for 40 different people and 800 images were sampled (The resolution ratio is 480x320). Among them, 650 images were used as training samples and 150 images were used as test samples. We divided the human joints into 14 parts, which respectively are the head, neck, left/right shoulder, left/right elbow, left/right wrist, left/right haunch, left/right knee, left/right ankle, and marked them.

III. FEATURE EXTRACTION JOINTS RECOGNITION

3.1 Feature extraction

Feature extraction refers to transform the original features (such as images) into features that are easier to handle via computers by means of map (or transform) methods. Point features and gradient characteristics are two commonly used characteristics of visible light recognition on human body. Point features such as angular point [1] and SIFT feature [2]. They are low dimensionality, small amount of calculation. But it is difficult to adapt to detect the human joints. The gradient features, like HOG features [3, 4], has advantages of high precision, good distinguish performance and strong robustness, but high dimensionality costs large amount of calculation. Therefore, we adopted the method of visual dimension reduction to improve the original HOG features [5-7], namely we obtained the new HOG feature--the 14 dimension HOG feature. This feature reduces the computational complexity by reducing the dimension under the premise of ensuring the accuracy, which makes the algorithm satisfy the real time requirement in this article.

3.2 Joints recognition

Joints recognition is a challenging subject in the field of machine vision and it has important application in the fields of human-computer interaction, behavior judgment and so on. Random forest [3,8,9] is a classifier that uses multiple trees to train and predict samples, which has a good performance on joints recognition.

The random forest training process is as follows:

(1) Suppose that there are t trees in the forest, the maximum depth is *Depth*, it can classify maximum for C class. Each tree has split nodes and leaf nodes. The splitting node has the threshold value τ, the training set S, the test set T and the sample feature is F.

For tree i = 1: t

(2) S_i is the same size with S, which come from S. Using S_i to tart the training from the root node.

(3) If the current node is reached on the termination condition, then set the current node as the leaf node. The predicted output of the leaf node is $c(j)$, which has the largest number of samples in current leaf node, and it probability is $p(j)$. And then continue to train other nodes. If the current node does not reach the termination condition, the f-dimensional feature is randomly selected from the F-dimensional feature. Using this f-dimensional feature, we find the best one-dimensional feature k and a threshold th. if $f(k) < th$, the current node is divided into the left node and the rest is divided into the right node. Continue to train other nodes;

(4) Repeat (2) (3) until all nodes have been trained or labeled as leaf nodes;

(5) Repeat (2), (3), and (4) until all the trees have been trained.

The prediction process of the random forest is as follows:

For tree i = 1: t

(1) From the root node of the current tree, we can judge whether to enter the left node (<th) or into the right node (> = th) according to the threshold value th of the current node until it reaches a leaf node and output the predicted value.

(2) Repeat the execution (1) until all t trees output the predicted value. For a classification problem, the output is the largest sum of the predicted probabilities in all trees that is to accumulate all the p of $c(j)$.

IV. EXPERIMENTAL RESULTS

4.1 Experimental results of joints detection

In consideration of the flexibility of joints, this paper makes a reclassification of each joint. First of all, a joint model is shown in Fig. 3, and then the K-means method is used to cluster according to the relative position of each joint point. The results of joints clustering are shown in Fig. 4, in which blue represents the data samples and red represents the clustering centers.

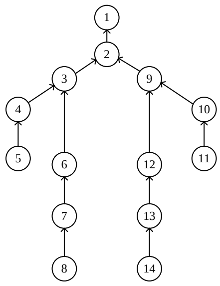
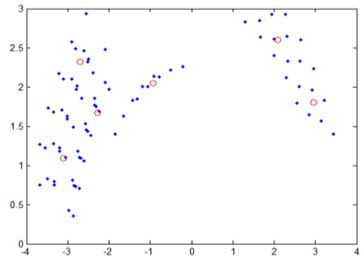
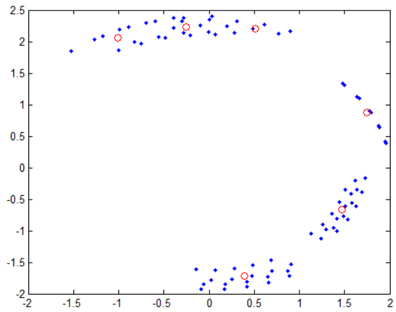


Figure 3 Joint model



(a)



(b)

Figure 4 The results of joints clustering. (a) right shoulder with respect to neck; (b) right hand with respect to right wrist.

The result of the recognition is shown in Fig. 5, and the color line segment is the connection of each joint.

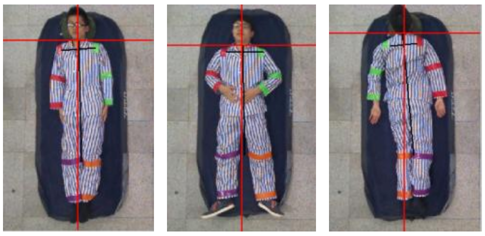
Figure 5 The results joints detection

Table 1 lists the results of the tests based on the random forest method for the detection of 150 images.

Table 1 The accuracy rate of the joints detection

Head	Shoulder	Elbow	Wrist	Buttocks	Knee	Ankle
95	92.6	91	89.5	89.4	90.3	90.9

The average detection rate of the joint is 91.2%; the average detection time is 1.9s, which satisfies the accuracy and real-time requirement of CT detection.4.2 Experiment results of postures judgmentAfter the calculation of the image to find the location of the joints in the human body, you can find the datum line in the different positions and then compared with the positioning line to determine whether the posture conforms to the requirements of CT detection. The distance and angle between the datum line and the positioning line can be used to determine whether the patient's posture and position are correctWe take the lung CT test as an example to determine the postures judgment process. In the lung CT test, the correct posture is shown in Fig. 6 (a), while Fig. 6 (b) and 6 (c) show two false pose. For the three pose shown in Fig. 6, the method is used to extract the joint points and then the datum line is found. The result of the datum line extraction is shown as the black line in the figure.



(a) (b) (c)

Figure 6 The results of postures judgment. (a) correct posture; (b)(c)wrong posture

The experimental results show that the system can accurately judge whether the postures are correct or not under the premise of accurate joint detection.

V. CONCLUSION

In this paper, we present a method for posture recognition of CT scan, which can replace the human to judge the position of the patient automatically. First, based on the random forest to achieve accurate detection of human joints, and then identify the human joints to find the datum line and calculate the relationship of relative position between the datum line and the standard positioning line to determine whether the patient posture is correct. The experimental results show that this method can detect the joint parts accurately and judge the body position of the patient and provide the basis of the correct judgment for the students who receive CT training.

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