Human Posture Recognition Method Based On Skeleton Vector With Depth Sensor

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Abstract. This paper proposes a human body gesture recognition method. The method collects bone information of the human body through the Kinect depth sensor, and then uses the direction cosine method for feature extraction. Finally, the feature vector is sent to the BP neural network for training and recognition. In the case of less sample training, the system can still accurately identify the five postures of standing, sitting, leaning forward, leaning backward and underarm. The input is composed of low-dimensional bone information, so the speed and recognition response speed during network training is better than the conventional RGB image recognition method. Experiments show that the recognition rate and real-time performance of the system can meet the needs of practical applications.

1. Introduction
Human posture recognition has broad application prospects in many fields such as human-computer interaction, medical health, augmented reality, sports analysis and robot control[1]. The identification of human action began in the 1990s[2], the related research and papers increased year by year. There are generally two methods: one is to collect human body posture data through a wearable sensor, and then use a machine learning method such as a support vector machine to classify[3][4]. The advantages are high accuracy and high real-time performance. The disadvantage is that the user must wear the sensor at a specified position on the body, which will reduce the user's comfort, so the attention is not high and the development is slow[5]; the other is based on A non-invasive detection method for computer vision. This method processes and analyzes raw RGB image data collected by a color camera, and uses a deep learning method to recognize a person's posture[6]. The feature is that the recognition rate is high, but the network level is deeper and deeper[7]. The real-time performance in recognition is not good.

2. The realization of ideas
We solve this problem by reducing the dimension of the input features. The depth image sensor can provide the third-dimensional depth data[8][9][10], as shown in Figure 1. First, the image segmentation technique is used to peel off the human body in the image from the background environment, and then according to The “skeletal tracking” human joint points generate a skeleton system, obtain the feature information needed for machine learning, and finally use the machine learning method to construct the classifier, and optimize the classifier to improve the accuracy. The kinect depth sensor used in this study has provided three kinds of data stream output of color image, depth image data and human bone data.
Bone vector feature extraction

In order to reduce the feature data dimension and real-time response rate, compared with the commonly used convolution feature extraction, this paper adopts a feature extraction method based on the skeletal vector direction cosine. The specific ideas are as follows: stratify the 20 joint points of the human body, such as Figure 2 shows: first layer: body torso joint points. This layer mainly includes 8 joint points (number 1) such as head, left and right shoulders and spine. The second layer: joint points of the limbs. Includes 8 joint points for the left and right elbows, wrists, left and right knees, and ankle (number 2). The third layer: hands and feet. The remaining 4 joint points of the left and right hands and feet are classified into the third layer (number 3). The role of the palms and feet in the human posture studied in this paper is very small, so it can be ignored.

For Connect each of the 16 joint points to form a skeleton, define it as a vector, mark the 7 vectors of the first layer as \{a_{1}, a_{2},..., a_{8}\}; the second layer is marked as \{a_{9}, a_{9},...,a_{16}\}. When people make different postures, they have different position and angle information for each segment of the human body. Define the direction of the cosine of the 16 skeletal vectors to represent a certain type of posture. Now take the shoulder joint of the right hand to the elbow joint (the vector labeled a_{8}) for detailed algorithm analysis: Set Kinect to obtain the three-dimensional coordinates of the shoulder joint. For \((x_{1}, y_{1}, z_{1})\), the three-dimensional coordinates of the elbow joint are \((x_{2}, y_{2}, z_{2})\), as shown in Figure 3. Thus, the skeletal vector can be expressed as (here, rotated image representation, so \(a_{10}\), not \(a_{8}\)): \(a_{10}=[x_{2}-x_{1}, y_{2}-y_{1}, z_{2}-z_{1}]\), set vector \(a_{8}\) and Kinect coordinate system. The three directions are: \(\alpha, \beta, \gamma\). Then the feature vector of the bone can be defined as \(\cos \alpha, \cos \beta, \cos \gamma\). The formula is as in equation (1), (2), (3).

\[
\cos \alpha = \frac{x_{1}-x_{2}}{\sqrt{(x_{2}-x_{1})^{2}+(y_{2}-y_{1})^{2}+(z_{2}-z_{1})^{2}}}
\]

\[
\cos \beta = \frac{y_{2}-y_{1}}{\sqrt{(x_{2}-x_{1})^{2}+(y_{2}-y_{1})^{2}+(z_{2}-z_{1})^{2}}}
\]

\[
\cos \gamma = \frac{z_{2}-z_{1}}{\sqrt{(x_{2}-x_{1})^{2}+(y_{2}-y_{1})^{2}+(z_{2}-z_{1})^{2}}}
\]
Through the above algorithm, the direction cosine of 16 bone vectors can be obtained, which can be sent as a feature value to the neural network for training and recognition.

4. BP neural network design

The structure of the BP neural network is shown in Figure 4. It consists of a 16-node input layer, two 1024-node hidden layers, and 5-node output layer, where \( \{x_1, x_2, \ldots, x_{16}\} \) is the skeletal feature vector input, \( \{o_1, o_2, o_3, o_4, o_5\} \) is the output.

![Figure 4. Figure with short caption (caption centred).](image)

The output of the hidden layer is as in equation (4).

\[ b_j = f\left(\sum_{i=1}^{N} \omega_{ij}x_i - \theta_j\right) \]  \hspace{1cm} (4)

The output of the output layer neuron is as in equation (5).

\[ c_t = f\left(\sum_{j=1}^{p} v_{jt}b_j - r_t\right) \]  \hspace{1cm} (5)

Where \( \omega_{ij} \) represents the connection weight between the \( i \)-th neuron of the input layer and the \( j \)-th neuron of the hidden layer; \( v_{jt} \) represents the connection weight between the \( j \)-th neuron of the hidden layer and the \( t \)-th neuron of the output layer; \( \theta_j, r_t \) represents the activation threshold of the corresponding neuron; \( f(x) \) represents the activation function of the neuron. The network uses the softmax activation function, which maps the output of multiple neurons to the (0,1) interval and can be interpreted as a probability to make multiple classifications. The loss function is as in equation (6).

\[ \varepsilon = \frac{1}{K} \sum_{k=1}^{K} \sum_{t=1}^{T} (y_{kt} - c_t)^2 \]  \hspace{1cm} (6)

\( y_t \) represents the expected output value of the \( t \)-th neural network; \( c_t \) represents the actual output value of the \( t \)-th neural network; when the total number of training samples is \( K \) the global output error of the network is calculated by the minimum variance. The weight \( w_{ij} \) adjustment here uses the gradient descent algorithm. The gradient value \( d \) of the connection weight between the hidden layer and the output layer is as in equation (7).

\[ d_t^k = (y_t^k - c_t) \cdot (1 - c_t), (t = 1, 2, \ldots, q) \]  \hspace{1cm} (7)

Use \( d_t^k, b_j, v_{jt}, \) and \( r_t \) to calculate the new connection weight and threshold between the next hidden layer and the output layer is as in equation (8), (9).

\[ v_{jt}(N) = v_{jt}(N - 1) + a \cdot d_t^k \cdot b_j \]  \hspace{1cm} (8)

\[ r_t(N) = r_t(N - 1) + a \cdot d_t^k \]  \hspace{1cm} (9)

The correction amount \( e \) of the connection right between the input layer and the hidden layer as in equation (10).

\[ e_j^k = \sum_{l=1}^{p} (d_l v_{jl}) \cdot b_j \left(1 - b_j\right), (j = 1, 2, \ldots, p) \]  \hspace{1cm} (10)

Calculate the new threshold and connection weight between the next input layer and the middle layer with \( e_j^k, a_l^k, \omega_{ij}, \) and \( \theta_j \) as in equation (11), (12).

\[ \theta_j(N) = \beta \cdot e_j^k + \theta_j(N - 1) \]  \hspace{1cm} (11)
\[ \omega_{ij}(N) = \beta \cdot e_{ij}^k \cdot a_{ij}^k + \omega_{ij}(N - 1), (i = 1, 2, ..., n) \quad (12) \]

After each sample is learned, adjust the corresponding connection weight until the K samples are all finished learning, then determine whether the global output error function reaches the set convergence limit value until the error function reaches the limit value, and the network training ends; otherwise, if the error is still greater than the set value when the maximum number of learning is reached, the training is also over, then the network training fails.

5. Experiment and result

We experiment our way in Microsoft’s kinect second-generation sensor with Microsoft’s kinect second-generation sensor, the camera resolution is color 1080p, and the depth camera is 512*424. The software running environment is windows10, VisualStudio2016, python 2.7, Kinect SDK 1.5, and the development language adopts C#.Net. to analyze the results in more detail, we show the confusion matrix (Tab. 1) and rate of activity recognition (Tab. 2). The results show that the method achieves the expected goal.

![Confusion Matrix for result of experiment.](image)

**Table 1. Confusion Matrix for result of experiment.**

| Activity       | accuracy rates |
|----------------|----------------|
| standing       | 91.57%         |
| sitting        | 90.30%         |
| leaning forward| 91.68%         |
| leaning down   | 92.71%         |
| squat          | 96.03%         |

![Recognition rate for result of experiment.](image)

**Table 2. Recognition rate for result of experiment.**

| Predict Class | Standing | sitting | leaning forward | leaning down | squat |
|---------------|----------|---------|-----------------|--------------|-------|
| standing      | 91       | 0       | 4               | 5            | 0     |
| sitting       | 1        | 90      | 0               | 7            | 2     |
| leaning forward| 6       | 0       | 91              | 1            | 2     |
| leaning down  | 7        | 0       | 1               | 92           | 1     |
| squat         | 0        | 3       | 0               | 1            | 96    |

6. Conclusion

In this paper, we propose a human posture recognition method based on bone vector. Compared with existing studies, it has the advantages of high recognition rate and simple network structure. To evaluate the method, we design and implement a set of experiments. The results show that the recognition rate of various actions can reach more than 90%, which is effective in various application scenarios. We intend to expand our work by refining the data set and improving recognition performance.

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