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# Double Layer HMM Body Part Motion Recognition Based on Fuzzy Theory

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**ABSTRACT**

*Body part motion recognition is an important research direction in computer vision and artificial intelligence, widely used in motion analysis, rehabilitation medicine, and game interaction. Traditional methods for recognizing body part movements are usually based on image processing, machine learning, or deep learning techniques. This article proposes a body part motion recognition method based on fuzzy theory and a double-layer hidden Markov model (HMM). This method aims to improve the accuracy and robustness of motion recognition, providing an effective solution for real-time motion capture and pose recognition applications.*

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## 1. Introduction

Human actions include the body of the limbs, such as gestures or movements of the hands, limbs, head, face or body. Human action is a kind of information communication between people and environment, which expresses people's wishes [1]. However, capturing motion data requires very expensive equipment, which is relatively complex. Motion capture data is for specific human bodies, and it isn't easy to apply to other environments directly. And existing motion capture devices are hard to implement for some extra stunt moves. Therefore, the double-deck HMM motion recognition algorithm based on fuzzy theory has gradually entered the field of academic research [2].

Research on human movement can retrospect to the 1970s. Psychologist Johannsen conducted a series of experiments on motor perception: only the attachment points at the human joints allowed people to perceive the position and change of joint points [3]. The experimental results show that the human visual system can perceive only the attachment points at the human joints allowed people to perceive the position and change of joint points [3]. The experimental results show that the human visual system can perceive the types of movements, such as movement and walking.The human visual system can even perceive the motion category information of the moving time series in the course of movement. Therefore, the importance of human motion recognition can be seen. Since then, human body recognition research has been applied to many fields and has been developing for a long time [4]. Especially with the application and popularization of various types of video devices, the performance of computers has been continuously improved. The computer can automatically capture and analyze human motion information in the video, raising researchers' attention to computer vision.

## 2. The State of the Art

Pattern recognition is a process that uses a system to simulate human aggregation and a model to realize the law of automatic extraction. The basic principle is to obtain the characteristics of the object to be studied (including numbers, text, or logical relationships). Pattern recognition involves mathematical preprocessing, information analysis techniques, and the ability to identify and interpret information behind the law [5]. HMM is a statistical model developed based on Markov chains. The state of the model can't be observed directly. The observation time series is inconsistent with the model state but is associated with a set of probability distributions. In other words, the state of the model is hidden, and the sequence can be observed based on the generated states of model output in HMM [6]. HMM contains double-deck stochastic processes: Markov chains and general stochastic processes. The general stochastic process describes the relationship between states and their possible observations, and the transitions between states are described by Markov chains [7]. With the development of science and technology, the fuzzy pattern recognition method and artificial intelligence method are developed, and the research results of fuzzy mathematics and artificial intelligence are introduced.

## 3. Methodology

### 3.1. Motion Recognition Method Based on Fuzzy Theory

The method of motion recognition based on fuzzy theory is divided into the following steps. The first is image preprocessing. Motion picture input to the network must be unified file formats, graphics properties and specifications. The action picture should be fixed, and irrelevant scenes should be deleted. The action graph is obtained by view modification of graph transformation, edge tracking and two valued processing. Action line diagrams are obtained by action graph filling, thinning, and line processing. The second is to determine action elements. The root limb and other virtual limbs are defined to identify the fuzzy limb group. The position of the root of the limb is indicated in the action line. The action graph of other actions is searched according to the action element search chain instruction. The motion state parameters of the action elements are searched according to the limbs and their connections. The third is to extract action characteristics. The basic shape is selected. The action is clear and the limb settings are determined. Body movement status parameters and the basic shape of state control are determined. Action element status feature and status feature memberships are obtained. The fourth is to determine the basic movements. The basic action state is compared with a set of distinct limb states to exclude the basic movements that do not match. Matching membership degree with basic operating membership is calculated. The largest pattern of matching membership is found, and the basic action is determined in an action where the matching membership is greater than the threshold. The fifth is action pattern recognition. Compared with the action component in the standard action pattern, standard actions that are impossible to match are excluded. Matching membership degree with standard action is calculated to eliminate standard actions if the matching degree is less than the threshold value of membership. The standard action with the highest matching membership is the matching pattern. Standard actions and membership degrees are used to indicate action mode.

### 3.2. Double-deck HMM Statistical Model

The basic idea of hierarchical recognition is to recognize patterns separately and extract different features. The subspace is identified differently according to the different characteristics of the sample set. Since the retrieval space is reduced, the recognition speed is increased in each subspace search, and the division is improved. Multiple HMM models are joined together based on a double-deck HMM sports action recognition algorithm based on fuzzy theory. Modeling and statistical analysis of stochastic processes with multiple interconnected data chains are carried out. The first layer identification is based on rough classification features [8]. A few recognition subsets are formed after a rough classification, which divides the larger recognition space into several smaller recognition spaces. The second layer recognition is performed in each identified subset space. The model library in the subspace is used to identify according to the difference of the recognition subset to which the input pattern belongs [9]. As the first division of the sample after a rough classification, the subsequent identification is based on the results of the division. Therefore, the classification required for rough selection and classification methods is stable. That is to say, it can be divided into the original class at the probability of 100% with the same coarse classification method. This requires that the time and space complexity of the feature extraction algorithm are both on the order of $O(n)$, and can meet the needs of real-time processing. The double-deck HMM statistical model is shown in Figure 1.

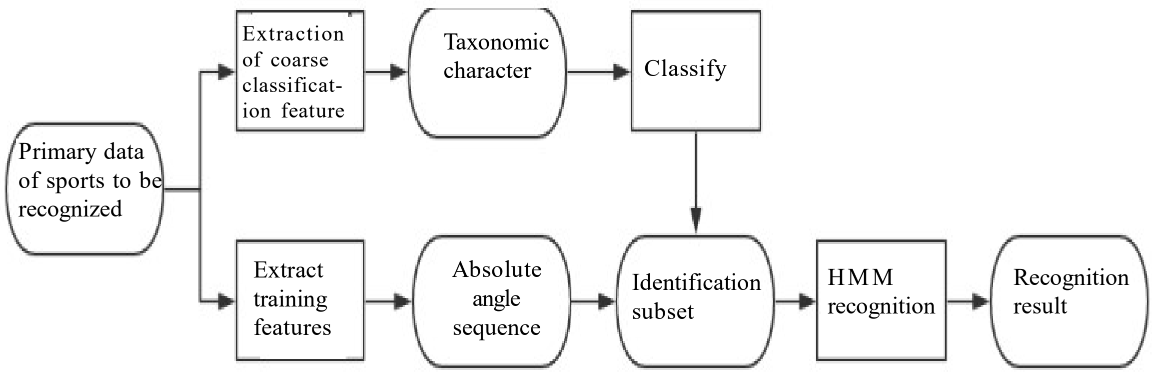


**Figure 1. Double-deck HMM statistical model**

### 3.3. Double-deck HMM Algorithm is used to Recognize the Sports Actions based on Fuzzy Theory

The double-deck HMM model based on fuzzy theory is the same as the HMM model, and the expectation-maximization algorithm is used to train the training parameters [10]. Generally, the initialization parameters with robustness are obtained using the Viterbi algorithm. Parameters are further trained through the Forward-Backward algorithm. The reliability of parameter training results is high. Therefore, this study used this method to train the established HMM model [11].

Then, the algorithm is applied to the data collected by the sports action recognition sensors. The original sensor data should be pre-processed to generate the observation sequence that can be identified by the double-layer HMM model based on fuzzy theory. The length of the double-deck HMM observation sequence based on fuzzy theory is T. Firstly, the output signals of each sensor node are divided into several windows. Then, the feature of each moving signal in each window is extracted to form the feature vectors. A feature vector of the window t ($t = (1, \cdots, T)$) of the n sensor node is considered as an observed value collected in the data matrix, which is also a training sample O.

$$O = \begin{pmatrix} O^1 \\ \vdots \\ O^N \end{pmatrix} \qquad (1)$$

If a human body action has several training samples, the training parameters of the HMM model based on fuzzy theory can be trained by using all training samples in the Viterbi algorithm. A double-deck HMM model is based on fuzzy theory to describe human action [12]. When training a two-layer HMM based on fuzzy theory, the number of state values of each data chain in the hidden state is the same[13]. Each data chain in the two-layer HMM model corresponds to the motion signals of a limb region based on the fuzzy theory in human action

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recognition. Therefore, the hidden state of the model can be understood as a "movement pattern" of limb movements, such as K movement patterns in the arm. The alternation of different motion patterns makes up the arms' movements.

For a double-deck HMM model based on fuzzy theory, the recognition of human actions can be reduced to a "valuation problem" similar to the HMM model. Supposing that the somatosensory network needs to recognize H sports movements, a double-deck HMM model based on fuzzy theory is established using each exercise's somatosensory network data. $\lambda_h (h = 1, \cdots, H)$ represents the set of parameters of the h double-deck HMM model based on fuzzy theory and describes the characteristics of the h human action. The following formula is used to determine the sequence's movements for unknown observation sequences O.

$$h = \arg\max_{h} \{P(O \mid \lambda_h)\} \qquad (2)$$

It can be seen that the double-deck HMM model based on fuzzy theory only needs to calculate the posterior probability of the observation sequence of the output position but does not need to solve the corresponding hidden state sequence in human action recognition. That is to say, what hidden states are output from the observation sequence (HMM type similar "decoding problem"). Although the explicit definition of the hidden state is not given when the double-deck HMM model based on fuzzy theory is established, it does not affect the recognition results of the double-layer HMM model based on fuzzy theory[14]. The sports action recognition scene is shown in Figure 2.

**Figure 2. Sports action recognition scene**

### 3.4. Double-deck HMM Algorithm based on Fuzzy Theory is used to Recognize Sports Actions

In this study, the double-layer HMM algorithm based on fuzzy theory was validated using the cross method and the leave-one method.

Firstly, a cross-validation method was used to train the algorithm network. The standard motion input and output samples were processed as training samples, and the standard input and output samples were used as validated samples. Generally speaking, the training error decreases monotonically with the increase of training steps during training. However, the verification error decreases and then increases, so there is a minimum point. The error accuracy is set as the minimum point of the verification error in the network training process, which can improve the system's ability to generalize effectively. However, the error changes slowly, and the training error decreases monotonically. Under the premise of guaranteeing the generalization ability of the system, the training steps can be extended the training error can be reduced, and the training accuracy of the system can be improved. The acquired motion data are compared with the training system after training. The motion data displayed in the action data is recognized and compared with the actual movements.

Secondly, all raw samples were cross-validated to obtain predictive values. On the one hand, exceptions can be eliminated by comparing prediction values to actual values. On the other hand, the prediction values are sorted, selected samples are used as calibration sets, and the model range is predicted. This method requires the number of samples to be specified in advance.

The formula for identifying the correct rate of physical exercises is:

$$\eta = \alpha_{correct} / n \qquad (3)$$

$\alpha_{correct}$ indicates that the correct number of times the action is recognized. n represents the number of sports data samples for identification and verification [15].

## 4. Result Analysis and Discussion

The sports action identification and monitoring system established in this study collected motion signals of the human body in actual activity. Twelve volunteers participated in the study, including 8 men and 4 women, who were aged between 21 and ~27. Five sensor nodes were used in the experiment, which were adorned on the volunteers' left wrist and right hand. The human movements performed in the experiment are shown in Table 1.

| Action number | Action description |
|---|---|
| A1 | "Stand" position remains static |
| A2 | "Sit" position remains still |
| A3 | "Recline " position remains still |
| A4 | "Walk" on the treadmill |
| A5 | "Jogging" on the treadmill |
| A6 | "Cycling" on a bicycle trainer |
| A7 | "Rowing" is on the rowing trainer. |

**Table 1. Human Movements Performed in Experiments**

A double-deck HMM motion recognition algorithm based on fuzzy theory was proposed in this study. This algorithm was used to identify nine different human actions performed in experiments. To further validate the effectiveness of the proposed approach, experiments were conducted with classification methods based on single and sequence. Human motion behaviour was identified through feature-level data fusion and decision-level data double-deck data fusion method, and the fusion classification method based on the sequence was the HMM model. The "majority principle" determined the final recognition results in decision data fusion. The length of the observation window selected was 160 sampling points (8 seconds) in the experimental preconditioning. For sequence classification methods, the length of the observation window selected in the preprocessing was 32 sampling points. The data of 16 sampling points overlapped between adjacent observation windows. 9 characteristic vectors formed observation sequences. The length of the observation sequence was the same as 8 seconds. For most human movements, 8 seconds were enough to include an action cycle.

Cross-validation method: the samples obtained by pretreatment were randomly divided into 7 equal parts, and each of the same number of samples belonged to the same effect. Cross-validation was carried out seven times, and a different subset was selected each time as the test data set. The remaining 7 subsets formed the training data set. The classification method's validity was tested using seven cross-validation mean results. Table 2 shows the average accuracy of the seven cross-validation results of the proposed and other comparison methods.

| | Action recognition method | A1 | A2 | A3 | A4 | A5 | A6 | A7 | Average accuracy |
|---|---|---|---|---|---|---|---|---|---|
| Feature fusion | NBC | 96.3 | 94.6 | 95.4 | 85.0 | 86.1 | 87.1 | 86.4 | 89.8 |
| | HMM | 94.8 | 95.6 | 95.2 | 91.3 | 92.4 | 90.1 | 92.2 | 92.5 |
| Feature fusion | NBC | 95.9 | 93.9 | 94.9 | 86.3 | 86.0 | 88.8 | 90.8 | 90.6 |
| | HMM | 95.2 | 95.0 | 95.0 | 91.3 | 92.5 | 93.2 | 93.3 | 92.7 |
| Double-deck HMM sport action recognition algorithm based on fuzzy theory | | 97.4 | 96.9 | 97.1 | 92.9 | 95.3 | 94.1 | 93.2 | 94.8 |

**Table 2. Average Accuracy Using Cross-Validation**

Next, the leave-one-out test was carried out. First of all, the sample set obtained by preprocessing was divided into 9 parts. All samples in each category belonged to the same volunteers. Cross-validation was conducted 9 times. A sample set of different volunteers was selected as the test data set at each time. A sample set of 8 volunteers was used to form a training dataset, and the average results of the 9 cross-validations were used to examine the validity of the classification method. Table 3 shows the average accuracy of the proposed method and other comparison methods in the cross-validation of the 7 recognition results.

It can be seen from Table 3 that the average recognition rate of the double-deck HMM sports recognition algorithm based on fuzzy theory was 94.8% and 85.9%, respectively, under the two verification methods, which was higher than the double-deck HMM motion recognition algorithm recognition algorithm based based on feature fusion and decision level fusion data fusion. It can be seen from Table 2 and Table 3 data that the proposed method was less accurate for the identified methods of the mobile A1 (Stand), A2 (Sit) and A3 (Lie), because the three movements did not involve coordinating the interaction of different parts of the body, the motion recognition algorithm model based on the dual HMM motion blur theory had no advantage. The proposed method achieved the highest recognition accuracy for actions A4 (Walk) and A5 (Jog) because these movements were accomplished by interacting with different body parts. The distinct sensor nodes between the data links were distinct. Therefore, the double-deck HMM motion recognition algorithm model based on fuzzy theory could well describe this association, thus improving the accuracy of motion recognition. Action A6 (Cycling) only had lower limb movement, and the upper body was static. Action A7 (Rowing) only had upper limb movement, and the lower limb was stationary. Therefore, although the algorithm proposed by the two actions has the ideal recognition accuracy, it is still slightly lower than some existing identification methods.



**Table 3. Accuracy Using the Leave One Test Method**

| | Action recognition method | A1 | A2 | A3 | A4 | A5 | A6 | A7 | Average accuracy |
|---|---|---|---|---|---|---|---|---|---|
| Feature fusion | NBC | 87.1 | 85.8 | 86.5 | 76.8 | 78.0 | 78.9 | 79.6 | 81.4 |
| | HMM | 86.2 | 86.4 | 86.3 | 82.8 | 81.6 | 83.6 | 83.5 | 83.9 |
| Feature fusion | NBC | 86.9 | 85.0 | 86.2 | 78.2 | 79.5 | 77.9 | 82.4 | 82.3 |
| | HMM | 86.2 | 85.7 | 86.2 | 83.0 | 84.5 | 84.0 | 84.2 | 84.7 |
| Double-deck HMM sport action recognition algorithm based on fuzzy theory | | 88.1 | 87.7 | 88.1 | 84.0 | 86.6 | 84.5 | 85.3 | 85.9 |

**Table 2. Average Accuracy Using Cross-Validation**

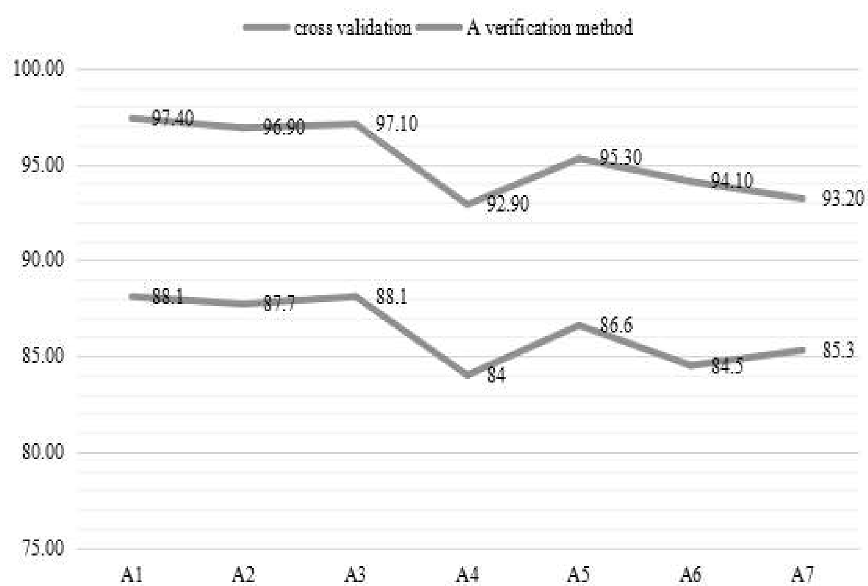


**Figure 3. Comparison of accuracy of sports action recognition under two kinds of verification methods**

## 5. Conclusion

Human actions carry a lot of information as the most important element in the human environment. Therefore, human sports action research has profound economic and social value. With the maturity of sports action identification technology, all kinds of human sports motion capture devices have been rapidly popularized and widely used. The double-deck HMM sports action recognition algorithm based on fuzzy theory is especially applied to daily sports action recognition, which includes a somatosensory network to identify the daily movement of the human body and auxiliary physical training. This paper studied the application of a double-deck HMM sports action recognition algorithm based on fuzzy theory. Firstly, the motion recognition method was based on fuzzy theory, and the double-layer HMM statistical models were introduced. Then, the application means of the double--deck HMM algorithm based on fuzzy theory was analyzed. Finally, the sports actions of the sample population were identified, and the correct rate of the double-deck HMM sports recognition algorithm based on fuzzy theory was verified by the "leave-one-out" and "cross-validation" methods.Experiments show that the correct rate of the double-deck HMM sports on fuzzy theory is higher than that of NBC, HMM, and other feature fusion and decision fusion methods. However, improving the recognition accuracy of actions is still necessary, as the movement status difference between the upper and lower limbs is greater.

## References


[1] Yepeng Liu., Jianbo., et al. (2016). An indoor pedestrian positioning method using HMM with a fuzzy pattern recognition algorithm in a WLAN fingerprint system. *Sensors, 16*(9), 1447.

[2] Ni Yong., Liu Jian., Liu Shaohua., et al. (2016). An indoor pedestrian positioning method using HMM with a fuzzy pattern recognition algorithm in a WLAN fingerprint system. *Sensors, 16*(9), 1447.

[3] Ujwalarekha Jadhav., Shahu Chatrapati., Vinaya Babu. (2015). A fast algorithm for HMM training using game theory for phoneme recognition. *International Journal of Computer Applications, 118*(11), 21–25.[4] Yuan, Ming., Chen, E., Gao, Lei. (2016). Posture selection based on two-layer AP with application to human action recognition using HMM. *IEEE International Symposium on Multimedia* (pp. 359–364). IEEE.

[5] Fredj Imen Ben., Ouni Kais. (2015). Fuzzy logic vs. HMM for phoneme recognition. *International Conference on Electrical Sciences and Technologies in Maghreb* (pp. 1–5). IEEE.

[6] Liang Shan-Fu., Chen Chih-Fang., Zeng Jia-Hong., et al. (2015). Application of genetic algorithm and fuzzy vector quantization on EEG-based automatic sleep staging using hidden Markov model. *International Conference on Machine Learning and Cybernetics* (pp. 567–572). IEEE.

[7] Pravinthraja, S., Umamaheswari, K., Soumiya, B, et al. (2016). IRIS recognition modality with fuzzy k-means clustering algorithm for improving security. In *Emerging Research in Computing, Information, Communication, and Applications* (pp. 1–10). Springer Singapore.

[8] Yusuf Shakiru, A., Brown David, J., Mackinnon Anthony. (2015). Application of acoustic directional data for audio event recognition via HMM/CRF in perimeter surveillance systems. *Robotics and Autonomous Systems, 72*(C), 15–28.

[9] Liang Shan-Fu., Chen Chih-Fang., Zeng Jia-Hong., et al. (2015). Application of genetic algorithm and fuzzy vector quantization on EEG-based automatic sleep staging using hidden Markov model. *International Conference on Machine Learning and Cybernetics* (pp. 567–572). IEEE.

[10] Elbahi Abdelkarim., Omri Mohamed Nejib., Mahjoub Mohamed Amine., et al. (2016). Mouse movement and probabilistic graphical models-based e-learning activity recognition improvement possibilistic model. *Arabian Journal for Science and Engineering, 41*(8), 2847–2862.

[11] Onka Daniel., Viszlay Peter., Juhýr Juraj. (2016). Fuzzy clustering in HMM-based triphone classes of 2DLDA in Slovak LVCSR. *International Conference on Systems, Signals, and Image Processing* (pp. 1–4). IEEE.

[12] Dhanalakshmi, N., Latha, Y. M., Damodaram A. (2016). Weighting multiple features and double fusion method for HMM-based video classification. In *Microelectronics, Electromagnetics, and Telecommunications* (pp. 1–10). Springer India.

[13] Teodorescu Horia-Nicolai. (2015). Fuzzy logic in speech technology: Introductory and overviewing glimpses. In *Fifty Years of Fuzzy Logic and Its Applications* (pp. 581–608). Springer International Publishing.

[14] Yao, Bin., Hagras, Hani., Alhaddad, Mohammed J., et al. (2015). A fuzzy logic-based system for the automation of human behavior recognition using machine vision in intelligent environments. *Soft Computing, 19*(2), 499–506.

[15] Cippitelli, Enea., Gasparrini, Silvia., Gambi, Ennio., et al. (2016). A human activity recognition system using skeleton data from RGBD sensors. *Computational Intelligence and Neuroscience, 2016*(3, Article 27), 1–14.