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DYNAMIC HAND GESTURE SEGMENTATION METHOD BASED ON UNEQUAL-PROBABILITIES BACKGROUND DIFFERENCE AND IMPROVED FCM ALGORITHM

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Abstract. *To extract complete hand gesture region under complex dynamic background and to effectively solve problems of skin-color interference and varying illumination, we present a novel dynamic hand gesture segmentation method which combines unequal-probabilities and improved Fuzzy C-Means (FCM) algorithm. Firstly, this method utilizes unequal-probabilities to build background model of complex dynamic background and detects motion region of hand gesture with background difference. Secondly, FCM algorithm is improved to accelerate the rate of convergence, cluster hand gesture image and distinguish skin-color region and non-skin-color region. Finally, we process motion region and skin-color region with logic operation and morphological operation, and complete dynamic gesture segmentation under complex background. The experimental results illustrate that the proposed method has high accuracy and is robust to skin-color interference and varying illumination.*
Keywords: Human-computer interaction, Dynamic hand gesture segmentation, Unequal-probabilities background difference, Fuzzy C-means algorithm, Morphological processing

1. **Introduction.** With the development of computer technology, interactive modes between human and computer draw more and more people's attention. As one of the Human-Computer Interactions, hand gesture recognition has been applied to many fields, such as clinical medicine, telecommunication, mechanical control and language interpretation. The technology of hand gesture segmentation is the essential procedure of hand gesture recognition and its segmentation effects will influence feature extraction and recognition directly. Therefore, the research on dynamic hand gesture segmentation with complex background has theoretical and practical values [1-3].

For existing hand gesture segmentation approaches, main problems include illumination effects, skin-color or similar color interference, poor time complexity. When other hands and faces exist in video sequence, hand gesture will be greatly affected and the recognition rate of hand gesture system is influenced, too. Therefore, it will be the key for hand gesture segmentation to solve the problem that backgrounds contain non-target hand gesture and faces. Improving the accuracy will increase the recognition rate of hand gesture recognition, and improving the time complexity of algorithm will shorten running time of the whole hand gesture recognition system.

To solve the problem of real-time dynamic hand gesture segmentation with complex background and segment hand gesture objection integrally, this paper proposes a kind of dynamic hand gesture approach which combines unequal-probabilities background difference and improved FCM algorithm. There are many motion detection approaches, such as optical flow, frame difference and background difference. For optical flow, the calculation of optical flow is too large to meet the demand of real time. Poor motion detection ability is one of the disadvantages of original frame difference and background difference. However, for dynamic hand gesture, motion information is an important feature of dynamic hand gesture. To solve this problem, this paper proposes unequal-probabilities background difference to improve motion detection ability of motion objection. On the basis of original background difference, this paper deals first N frame images of video sequence with unequal-probabilities weighting and builds background model of background difference. The unequal-probabilities background difference is used to detect motion hand gesture region of video sequence. As an important feature of hands, skin color is widely used for hand gesture segmentation. Threshold approach is the most common skin color detection approach, which sets different thresholds in different color spaces to detect skin-color region. Threshold approach needs setting threshold manually and its skin-color detection ability differs a lot. FCM algorithm can be used to cluster image and segment skin-color region. However, FCM algorithm implements by iteration and it has long running time. Aiming at the problem of poor real-time of FCM algorithm, this paper improves the FCM algorithm to cluster skin-color region and non-skin-color region of images efficiently. Regions of motion hand gesture and skin-color are combined so that motion hand gesture can be segmented from video sequences.

The rest of this paper is organized as follows. Section 2 describes related work. Section 3 describes theories of background difference, FCM algorithm and morphological process. A detailed dynamic hand gesture segmentation approach is described in Section 4, and this section includes unequal-probabilities background difference, improved FCM algorithm and morphological process. Subsequently, Section 5 gives the experimental results and analyses as compared with skin-color interference and varying illumination. Finally, we conclude our paper in Section 6.

2. **Related Work.** For now, the technology of dynamic hand gesture segmentation includes optical flow, frame difference and background difference. Optical flow defines motion objection by analyzing illumination variation of video sequences. The approach of frame difference judges and segments motion hand gesture by utilizing the difference between current frame image and adjacent frame image. The principle of background difference is similar to frame difference and it segments motion objection by difference between current frame image and background model [2,3].

Alvarez et al. [4] proposed an approach that utilizes background difference to detect motion hand gesture and segments hand gesture by combining shadow detection and skin-color. Toni and Darko [5] proposed an approach based on background difference and this approach made the processed image use for skin-color detection and follow-up work. Main problems of optical flow are high time complexity, large calculation and poor real-time [6,7]. Frame difference and background difference have good real-time, but segmentation effects of motion hand gesture cannot be satisfied. Frame difference and background difference are easily influenced by factors of various illumination conditions and shadows, which can make segmentation of motion hand gesture difficult. With the application of tracking algorithm in the field of dynamic hand gesture segmentation, more and more researchers utilize Kalman filter, Particle Filter and Camshift algorithm to track and segment motion hand gesture of video sequence [8-10]. Ghotkar and Kharate [11] proposed an approach that utilizes Camshift algorithm to track moving hand gesture of video sequence and segments hand gesture with threshold method in HSV color space.

Clustering algorithm has a superior clustering feature, which is widely used in the field of image segmentation. The main idea of clustering algorithm is to judge the Euclidean distance between data of samples and clustering centers. The image regions with similar characteristics are clustered together. Clustering algorithm is intuitive and it segments image without threshold and manual intervention [12,13]. Zhu et al. [14] proposed an approach that defines three sets (color set, motion set and fuzzy set) for video sequences. Color set and motion set are processed with fuzzy operation so that hand gesture can be segmented from video sequence. Disadvantage of clustering algorithm is high time complexity caused by iteration, which cannot meet the demand of real-time. Ghosh and Ari [15] proposed to use threshold approach in YCbCr color space to segment hand gesture image at stage of skin-color segmentation. Their proposed approach was easily implemented, but it was easily interfered by other factors. Chen et al. [16] proposed to combine background difference and threshold method to segment motion hand gesture of video sequence. Bhuyan et al. [17] proposed to use the result of logical operation of HSV and YCbCr color spaces to segment hand gesture. Hasan and Abdul-Kareem [18] introduced edge detection method and threshold segmentation method. Bouchrika et al. [19] proposed to train classifier to segment hand gesture region. With the application of depth sensor, some researchers started to use Kinect camera to obtain hand gesture image. The depth information of image can be used to solve the problem of skin-color interference. Most cameras are not equipped with depth sensor. Therefore, the application of depth sensor is limited [20-25].

For now, the difficulties of hand gesture segmentation focus on background, skin-color interference and illumination variation. When dynamic hand gestures are segmented, the time complexity of algorithm of hand gesture segmentation is high and has poor real-time. Lots of researchers have been working on these problems and enhancing the ability of adapting environment. Aiming at difficulties of technology, this paper proposes a novel hand gesture segmentation approach which combines unequal-probabilities background difference and improved FCM algorithm.

3. Problem Statement and Preliminaries.

3.1. Background difference.

Background difference is a motion detection method which compares current frame of video sequence with background model. Its main idea is judging motion objection by the difference between current frame image and background model. The performance depends on the used background model technology.

The most commonly used background models include mean background model, Kalman filter model, Gaussian model and Gaussian mixture model. These methods are sensitive to illumination and computational complexity. It is hard for traditional background difference to detect motion hand gesture of video sequence integrally and accurately. There also exist a lot of mistakes in the detected region of motion hand gesture. Results of most background difference approaches only have partial contour of motion objection, which will influence the segmentation results directly. The detection of motion hand gesture depends on background difference approach greatly. The construction of some background models is too complicated to increase running time. Therefore, this paper determines to improve original background difference approach to shorten running time and obtain better segmentation results.

3.2. Morphology theory.

Binary image morphology is a most basic morphology theory. Binary image means that gray image can only have two possible values [26]. Math morphology includes dilation, erosion, opening and closing operations. Dilation and erosion operations, as the base of math morphology, can highlight useful information of images [27].

Set $A \in E^n$. Structural elements $B \in E^n$ or points set of subspace. Two vectors a and b are elements of A and B. The definitions of dilation and erosion based on Minkowski sum and difference are as follows:

$$A \oplus B = \{z \in E^n : a + b \in A, a \in A, b \in B\} = \bigcup_{b \in B} (A)_b \tag{1}$$

$$A \ominus B = \{z \in E^n : z + b \in A, \forall b \in B\} = \bigcap_{b \in B} (A)_{-b} \tag{2}$$

where $(A)_b$ is the translational transformation of vector b to set A.

$$(A)_b = \{z \in E^n, z = a + b, a \in A\} \tag{3}$$

Apply dilation and erosion definition of Minkowski to binary images. The new definitions of dilation and erosion are as follows:

$$A \oplus B = \{z \in E^n : a + b \in A, a \in A, b \in B\} = \bigcup_{b \in B} (A)_b = \left\{ x \middle| \left[\left(\widehat{B} \right)_x \cap A \right] \neq \emptyset \right\} \tag{4}$$

$$A \ominus B = \{z \in E^n : z + b \in A, \forall b \in B\} = \bigcap_{b \in B} (A)_{-b} = \{x | [(B)_x \cap A] = \emptyset\} \tag{5}$$

where suppose A is an image, b is a structural element, and $\widehat{B}$ is the mapping of B.

$$\widehat{B} = \{x | x = -b, b \in B\} \tag{6}$$

Binary erosion operation has effects on eliminating the boundary points of the object in math morphological operation. Erosion operation can eliminate the result that is smaller than the structural element. In this way, selecting structural elements with different sizes can eliminate objects with different sizes in the original images. If there is tiny connectivity between two objects, separate two objects with erosion operation when the structural element is big enough. It illustrates that erosion operation has the effect on eliminating noise. Erosion operation can also fill holes inside images when structural elements do not include origin.

Binary dilation operation is different from filtering operation for external images. If structural element is a round, dilation operation can be used to fill images whose holes are bigger than structural element and the small portion of image edge can be processed, too. Dilation operation can also connect two objects with relatively close distance.

Under natural conditions, the illumination environment of hand gesture experiment is uneven and intensity of illumination is uncertain. These conditions will bring optical noise to hand gesture images, which has great effect on binary images of hand gesture segmentation. In addition, surface of hand skin and experiment background will be reflective. The phenomenon of uneven illumination will influence the experimental results of hand gesture segmentation. To reduce effects of these factors on experiments, median filtering methods or illumination compensation method can be used to process original RGB hand gesture images. Nevertheless, using median filtering method or illumination compensation method to process RGB color images will bring other problems. The processing images procedure of these two kinds of methods will cause additional time consuming on segmentation experiment, which makes the real-time unavailable. Therefore, this paper uses morphology method to process binary images so that the problem of handling images interference and reducing time consuming can be solved.

4. Proposed Scheme.

4.1. Hand gesture segmentation procedure.
FCM algorithm is used to process original hand gesture image in this paper, and original hand gesture image is divided into skin-color class and none skin-color class, which achieves the purpose that segments hand gesture from complex background.

According to the description mentioned in Section 3, this paper improves original background difference approach and proposes unequal-probabilities background difference approach. The purpose is to segment motion hand gesture of video sequence. Therefore, the proposed background difference approach is used to determine motion region of video sequence, and the improved FCM algorithm is used to distinguish skin-color region and non-skin-color region. The main idea of dynamic hand gesture segmentation focuses on motion information and skin-color information. Therefore, this paper combines motion region obtained from unequal-probabilities background difference approach and skin-color-region obtained from the improved FCM algorithm so that motion hand gesture can be segmented from video sequence.

The hand gesture segmentation approach designed by this paper includes following steps. The flow chart of the proposed scheme is shown in Figure 1.

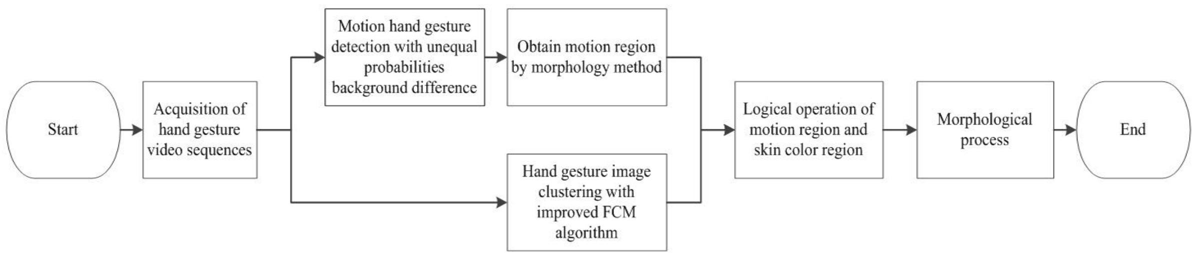


FIGURE 1. The flow chart of the proposed scheme

Step 1: Acquire hand gesture image from video sequence.

Step 2: Detect motion region of hand gesture with unequal-probabilities background difference.

Step 3: Cluster image of video sequence with improved FCM algorithm and distinguish skin-color region and non-skin-color region.

Step 4: Process motion region and skin-color region with logical operation.

Step 5: Process segmentation results with morphological operation.

Definition of logical operation: Suppose that $I_{motion}(i,j)$ and $I_{FCM}(i,j)$ are pixels of motion image and clustering image, and $I(i,j)$ is logic image. Formula of logic operation is as follows:

$$I(i,j) = \begin{cases} 1 & \text{if } I_{motion}(i,j) = I_{FCM}(i,j) = 1 \\ 0 & \text{else} \end{cases} \tag{7}$$

4.2. Complex dynamic background modeling based on unequal-probabilities background difference.
This paper improves original background difference and proposes an unequal-probabilities background difference. The novel background difference is used to detect motion hand gesture of video sequence, which determines the region of motion hand gesture. Because of factors of various illumination conditions and vibration, experimental background will change slowly. This paper processes background model with unequal-probabilities to reduce inference on background model and avoid influences caused by changing background on motion objection.

Formula of unequal-probabilities background difference is as follows:

$$I_{background} = \frac{\sum\limits_{i=1}^{N} \frac{i}{N} I(i)}{\sum\limits_{i=1}^{N} \frac{i}{N}} \tag{8}$$

where $I_{background}$ is background model built by unequal-probabilities method, N is the number of first N frames of video sequence, and $I(i)$ is the i-th frame image, $i < N$.

This paper utilizes the improved unequal background difference to detect motion hand gesture of video sequence, look for hand gesture target, and obtain initial motion hand gesture image and motion region, which can reduce background interference and improve real-time.

4.3. **Improved FCM algorithm.** FCM algorithm has superior clustering feature and is widely applied in the field of image segmentation. FCM is simple and easy to be implemented. It also has good segmentation results. The reason why FCM algorithm can obtain satisfying segmentation results is that membership function is used in the FCM algorithm. Compared with K-means algorithm, a kind of hard clustering algorithm, FCM algorithm will obtain more accurate segmentation results. FCM algorithm segments image by iteration procedure and the time complexity of FCM algorithm is high, which means that it is hard to meet the demand of real-time. Therefore, this paper improves original FCM algorithm to meet the demand of real-time and obtain better segmentation results.

Under the premise that the segmentation accuracy is guaranteed, the four parts of traditional FCM algorithm are improved in this paper.

(1) Whether FCM algorithm will run continually is determined by iteration condition and Euclidean distance between samples and clustering centers. FCM algorithm will not run when iteration condition is met. Iteration stop coefficient ε is important for running FCM algorithm. In the premise of ensuring the accuracy of segmentation, enlarge iteration stop coefficient ε so that the number of operation can be reduced.

(2) Iteration parameter of FCM algorithm is used to measure running times. Shorten running time of FCM algorithm by reducing running times of iteration parameter.

(3) Membership function is an important part of FCM algorithm. This paper modifies original membership function to accelerate convergence procedure.

(4) FCM algorithm updates membership function and clustering centers and optimizes objective function by iteration procedure. Original objective function is improved in this paper so that it can be optimized as soon as possible.

Defining $J_m(U, V)$ as improved objective function, formula of improved objective function is as follows:

$$J_m(U, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} (\xi U_{ij})^m \left[(1-\xi) d_{ij}^2(x_j, v_i)\right]^2 \tag{9}$$

where $V = \{v_1, v_2, \ldots, v_c\}$ is set of clustering center. m is weighted index, $m \in [1, \infty)$, ξ is weighted coefficient, $\xi < 1$, and d_{ij}^2 is the distance between j-th sample point x_j and i-th clustering center point v_i. Formula of Euclidean distance is as follows.

$$d_{ij}^2(x_j, v_i) = ||x_j, v_i||_A^2 = (x_j - v_i)^T A (x_j - v_i) \tag{10}$$

where $A = p \times p$ is positive definite matrix, and when $A = I$, d_{ij}^2 is Euclidean distance.

Cluster dataset $X = \{x_1, x_2, \ldots, x_n\}$ into c classes. u_{ij} is the i-th membership for x_j of dataset X.

The improved FCM algorithm updates membership function and clustering center points to optimize objection function by iteration. Optimization steps are as follows.

Step 1: Clustering center: initialize $V = \{v_1, v_2, \ldots, v_c\}$.

Step 2: Calculate improved membership function.

$$M_{ij} = \left[\sum_{k=1}^{c}\left[\frac{d_{ik}(x_k, v_i)}{d_{jk}(x_k, v_j)}\right]^{\frac{2}{m-1}}\right]^{-1} \tag{11}$$

$$U_{ij} = \lambda M_{ij} + (1-\lambda)M_{ij}^2 + \lambda(1-\lambda)M_{ij}^3 \tag{12}$$

where λ is weighted coefficient, $0 < \lambda < 1$.

Step 3: Update clustering centers:

$$v_i = \frac{\sum_{j=1}^{n}(U_{ij})^m x_j}{\sum_{j=1}^{n}(U_{ij})^m} \qquad i = 1, 2, \ldots, c \tag{13}$$

Step 4: Repeat **Step 2** and **Step 3**, until objective function $J_m(U, V)$ converges.

Steps of segmenting hand gesture image with improved FCM algorithm are as follows.

Define $X = \{x_1, x_2, \ldots, x_n\}$ as hand gesture sample set of n classes, where x_i ($i = 1, 2, \ldots, n$) is sample point.

Step 1: Determine the clustering number c ($2 \leq c \leq n$), fuzzy index m ($1 < m < \infty$), iteration stop coefficient $\varepsilon > 0$, weighted coefficients ξ and λ, clustering center $v(0)$, $t = 1$.

Step 2: Calculate $U^{(t)}$.

Step 3: Update clustering center $v^{(t+1)}$.

Step 4: If $||v^{(t+1)} - v^{(t)}|| < \varepsilon$, iteration ends; else $t = t + 1$, repeat **Step 2** and **Step 3**, until iteration stop condition is met.

Step 5: According to the final clustering center and membership matrix, this algorithm clusters all image pixels with the principle of the largest membership.

Improved FCM algorithm avoids the problem of setting threshold. It solves the problem of uncertain clustering of pixels because of the introduced membership function, which segments hand gesture image automatically. According to the purpose of hand gesture segmentation and the meaning of practical application, this paper determines two classes for clustering. For parameters of improved FCM, this paper decides that the number of clustering is 2, which means that clustering parameter c of FCM algorithm is 2. It can divide image into skin-color region and non-skin-color region in this way. Meanwhile, we set ε as iteration end coefficient, ξ and λ as weighted coefficients and m as membership index. Experiments illustrate that best performance can be obtained when $m = 2$. Regard the image in RGB color space as the original data sample set of improved FCM algorithm, and handle the image with the improved FCM algorithm. And segment hand gesture image into skin-color region and non-skin-color region with improved FCM algorithm whose clustering number is 2.

4.4. **Morphological process.** The image that needs to be processed is obtained by logical operation of other images. Therefore, there will be a lot of interference points, such as image holes, connection of image points, saw tooth and cracks of image edge. To get rid of all these interference factors, morphological open and close operations are used to process binary images in this paper. Handle holes and saw tooth in binary image with structural elements of morphology algorithm. Reduce effects of these factors and get better binary image so that binary image can be used for hand gesture recognition perfectly.

Steps of morphological process are as follows.

Step 1: Process binary image of motion hand gesture that is detected by unequal-probabilities background difference with morphological operation and determine the region of motion hand gesture.

Step 2: Utilize morphological operation to process binary logic results of motion and skin-color region to improve results of hand gesture segmentation.

5. **Experimental Results and Analysis.** To examine the performance of the proposed approach, this paper designs different motion hand gestures with different illumination conditions in experiment parts. Other hand and face are as interference factors. The size of each image of video sequence is 640×480.

In Experiment One, three kinds of motion hand gestures of video sequences are segmented. Experimental light source is normal laboratory lights. Setting threshold method in YCbCr and HSV color spaces is used for comparing with the proposed approach in this paper. Segmentation effects are shown in Figure 2; on the basis of Experiment One, Experiment Two changes illumination conditions and segments three kinds of motion hand gesture under dark condition. Setting threshold method in YCbCr and HSV color spaces is used for comparing with the proposed approach in this paper. Segmentation effects are shown in Figure 3. Non-target hand of video sequence is regarded as interference in Experiments One and Two; in Experiment Three, experimental light source is normal laboratory lights and face of video sequence is seen as interference factor. Setting threshold method in HSV color space is used for comparing with the proposed approach in this paper. Segmentation effects are shown in Figure 4. In Experiment Four, this paper utilizes frame difference approach and the proposed approach in [17] to compare with the proposed approach in this paper to prove that our proposed approach has better segmentation results.

The experimental hardware platform is Inter Core i3, 2450M, 2G, 2.27GHz, and software environment is the MATLAB2012b under win 7.

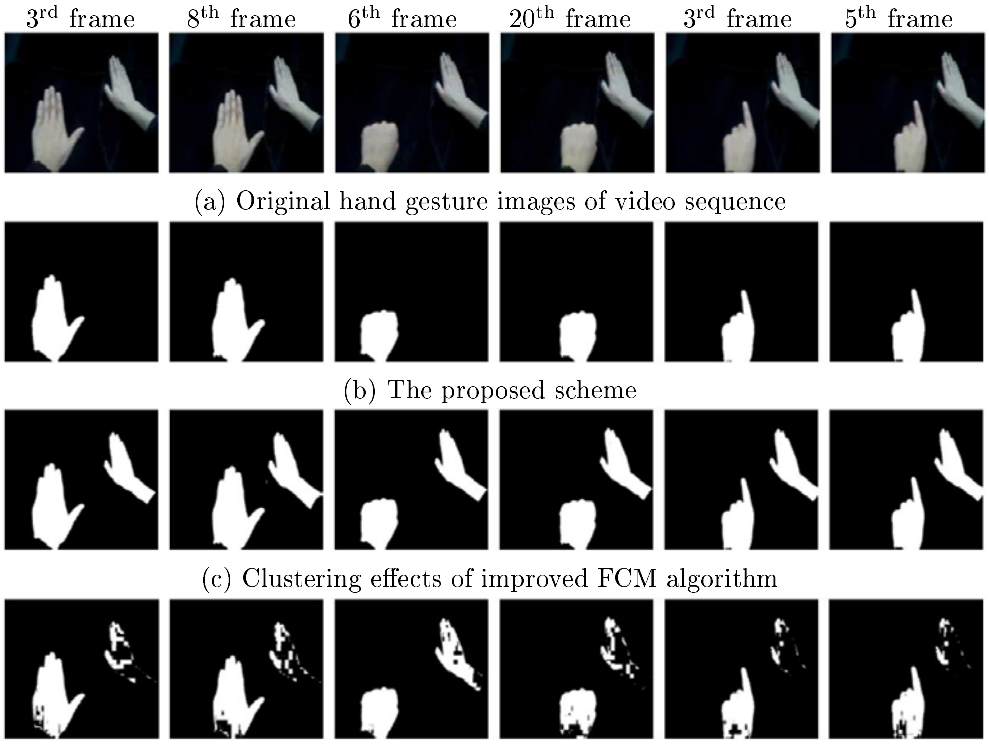
Experiment One: Different hand gestures of video sequences with the interference of non-target hand. Left hand is the target hand gesture which will be processed. The segmentation effects are shown in Figure 2.

Experiment Two: Different hand gestures of video sequences with dark illumination condition. Left hand is the target hand gesture which will be processed. The segmentation effects are shown in Figure 3.

Experiment Three: Motion hand gestures of video sequences with the interference of face. The segmentation effects are shown in Figure 4.

Experiment Four: Hand gesture segmentation of some extant techniques. The segmentation effects are shown in Figure 5.

According to the experimental results of Experiment One (see Figure 2), Experiment Two (see Figure 3) and Experiment Three (see Figure 4), it can be concluded that the proposed approach can segment target hand gesture from video sequence with interference of non-target hand and face, and get high accuracy segmentation image, which proves that the proposed approach has practical value. In the premise of ensuring the accuracy of segmentation, this paper improves original FCM algorithm to reduce the number iteration. To illustrate that the proposed approach has better segmentation results, this paper determines to utilize threshold method to compare with the improved FCM algorithm. Setting threshold method in YCbCr and HSV color spaces cannot detect skin-color region of hand gesture image accurately. Compared with the proposed approach, setting threshold in YCbCr and HSV color space is sensitive to illumination variation. It needs higher chrominance and luminance of image. To prove that the proposed approach is robust to



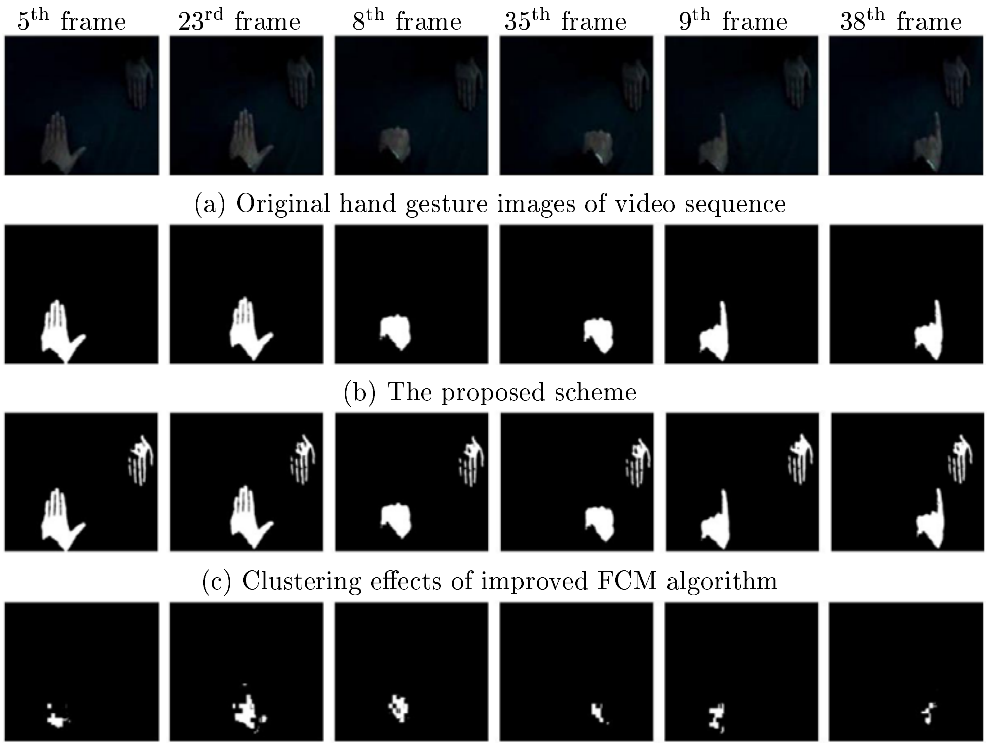
(a) Original hand gesture images of video sequence

(b) The proposed scheme

(c) Clustering effects of improved FCM algorithm

(d) Skin-color detection effects of threshold method in YCbCr color space

FIGURE 2. Segmentation effects with the interference of non-target hand and normal lights



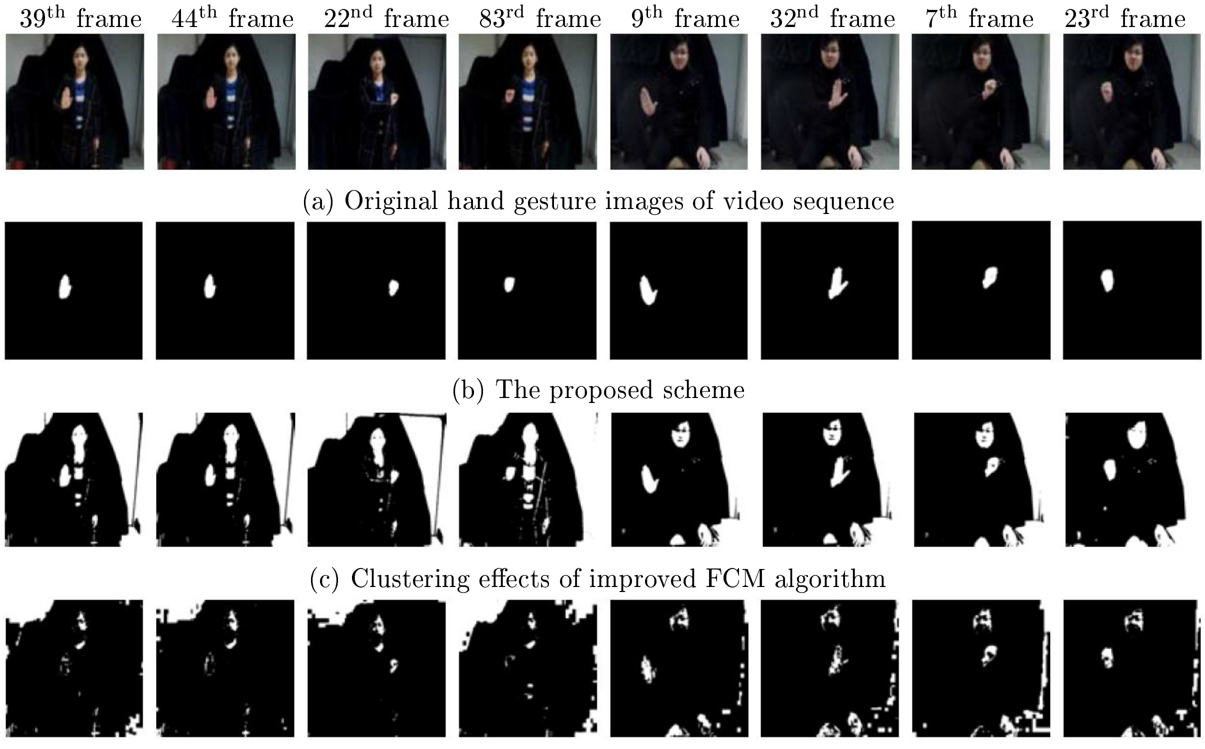
(a) Original hand gesture images of video sequence

(b) The proposed scheme

(c) Clustering effects of improved FCM algorithm

(d) Skin-color detection effects of threshold method in HSV color space

FIGURE 3. Segmentation effects with the interference of non-target hand and dark light



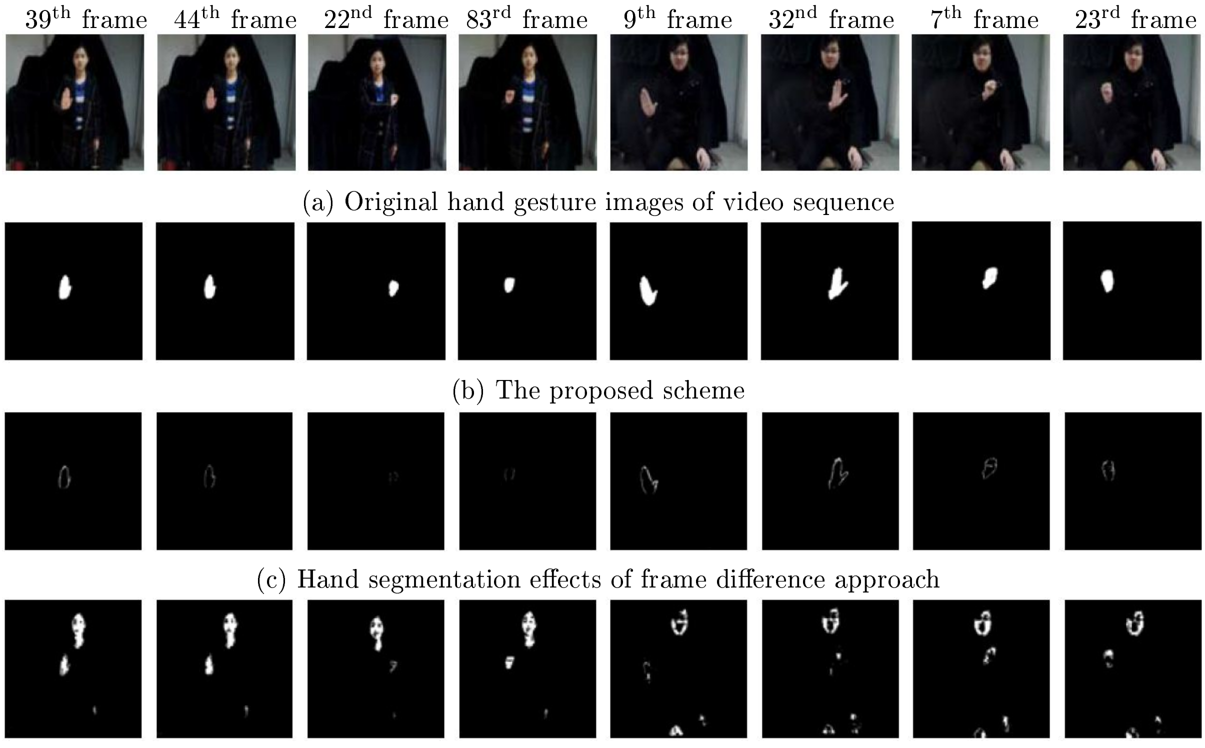
(a) Original hand gesture images of video sequence

(b) The proposed scheme

(c) Clustering effects of improved FCM algorithm

(d) Skin-color detection effects of threshold method in HSV color space

FIGURE 4. Segmentation effects with the interference of face and normal light



(a) Original hand gesture images of video sequence

(b) The proposed scheme

(c) Hand segmentation effects of frame difference approach

(d) Hand segmentation effects of the proposed approach in [17]

FIGURE 5. Segmentation effects of some extant techniques

illumination, this paper designs Experiment Two. By comparing original hand gesture image and segmentation results of Experiments One and Two, it can be concluded that the proposed approach can segment hand gesture accurately from video sequence when illumination conditions change. It also has proved that the proposed approach is robust to illumination. By observing and comparing the experimental results of Experiment Three (see Figure 4) and Experiment Four (see Figure 5), we can conclude that using the proposed approach in this paper can obtain better hand segmentation effects than frame difference approach and the propose approach in [17]. And it can meet the demand of dynamic hand gesture segmentation.

6. **Conclusions.** This paper proposes a novel dynamic hand gesture segmentation approach that combines unequal-probabilities background difference and improved FCM algorithm. In this paper, original background difference is improved to enhance the detection ability of motion hand gesture of video sequence. Original FCM algorithm is improved to enhance clustering effects and accelerate the running time of algorithm. Experiment results illustrate that the proposed approach can accurately segment target hand gesture from video sequence with interference of non-target hand gesture and face. It is also robust to illumination and has practical value.

How to segment real-time hand gesture and multi hand gestures will be the focus of our research in the future.

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REFERENCES

[1] H. Li and M. Greenspan, Model-based segmentation and recognition of dynamic gestures in continuous video streams, *Pattern Recognition*, vol.44, no.8, pp.1614-1628, 2011.

[2] H. Xu, X. Hou and R. Su, Real-time hand gesture recognition system based on associative, *Proc. of the 2nd IEEE International Conference on Computer Science and Information Technology (ICCSIT 2009)*, Beijing, China, pp.14-18, 2009.

[3] H. Duan and Y. Luo, A method of gesture segmentation based on skin-color and background difference method, *Proc. of the 2nd International Conference on Computer Science and Electronics Engineering*, Hangzhou, China, pp.355-357, 2013.

[4] S. Alvarez, D. F. Llorca, G. Lacey and S. Ameling, Spatial hand segmentation using skin-color and background subtraction, *Trinity College Dublin's Computer Science Technical Report*, Dublin, 2010.

[5] B. Toni and J. Darko, A robust hand detection and tracking algorithm with application to natural user interface, *Proc. of the 35th IEEE International Convention on MIPRO*, Opatija, Croatia, pp.1768-1774, 2012.

[6] X. Shen, G. Hua and L. Williams, Dynamic hand gesture recognition: An exemplar-based approach from motion divergence fields, *Image and Vision Computing*, vol.30, no.3, pp.227-235, 2012.

[7] S. Zhang and H. Wang, Human-computer interaction by a robust hand tracking method, *Proc. of the 3rd International Conference on Teaching and Computational Science (WTCS 2009)*, pp.425-431, 2012.

[8] M. S. M. Asaari and S. A. Suandi, Real time hand tracking system using predictive Eigen hand tracker, *Australian Journal of Basic and Applied Sciences*, vol.6, no.2, pp.190-198, 2012.

[9] S. Mo, S. Cheng and X. Xing, Hand gesture segmentation based on improved kalman filter and TSL skin-color model, *Proc. of IEEE International Conference on Multimedia Technology (ICMT)*, Hangzhou, China, pp.3543-3546, 2011.

[10] R. Araki, S. Gohshi and T. Ikenaga, Real-time both hands tracking using camshift with motion mask and probability reduction by motion prediction, *Proc. of Signal & Information Processing Association Annual Summit and Conference (APSIPA ASC)*, 2012.

[11] A. S. Ghotkar and G. K. Kharate, Hand segmentation techniques to hand gesture recognition for natural human computer interaction, *International Journal of Human Computer Interaction (IJHCI)*, vol.3, no.1, pp.15, 2012.
[12] H. Cao, H. W. Deng and Y. P. Wang, Segmentation of M-FISH images for improved classification of chromosomes with an adaptive fuzzy c-means clustering algorithm, *IEEE Transactions on Fuzzy Systems*, vol.20, no.1, pp.1-8, 2012.
[13] S. N. Sulaiman and N. A. M. Isa, Adaptive fuzzy-K-means clustering algorithm for image segmentation, *IEEE Transactions on Consumer Electronics*, vol.56, no.4, pp.2661-2668, 2010.
[14] J. Y. Zhu, X. Y. Wang and W. X. Wang, A method of gesture segmentation based on fuzzy set theory, *Computer Engineering and Application*, vol.42, no.23, pp.12-23, 2006.
[15] D. K. Ghosh and S. Ari, Static hand gesture recognition using mixture of features and SVM classifier, *Proc. of the 5th IEEE International Conference on Communication Systems and Network Technologies (CSNT-2015)*, Gwalior, India, 2015.
[16] Z. H. Chen, J. T. Kim, J. N. Liang, J. Zhang and Y. B. Yuan, Real-time hand gesture recognition using finger segmentation, *The Scientific World Journal*, vol.2014, Article ID 267872, 2014.
[17] K. Bhuyan, M. Ajay Kumar, D. MacDorman and K. F. Iwahori, A novel set of features for continuous hand gesture recognition, *Journal on Multimodal User Interfaces*, vol.8, no.4, pp.333-343, 2014.
[18] H. Hasan and S. Abdul-Kareem, Static hand gesture recognition using neural networks, *Artificial Intelligence Review*, vol.41, no.2, pp.147-181, 2014.
[19] T. Bouchrika, M. Zaied, O. Jemai and C. B. Amar, Neural solutions to interact with computers by hand gesture recognition, *Multimedia Tools and Applications*, vol.72, no.3, pp.2949-2975, 2014.
[20] P. F. Xu and H. Y. Zhang, Hand gesture segmentation and fingertip detection based on depth image of the Kinect, *Journal of Southwest University of Science and Technology*, vol.29, no.1, pp.49-54, 2014.
[21] Y. Yao and Y. Fu, Contour model based hand-gesture recognition using Kinect sensor, *IEEE Transactions on Circuits and Systems for Video Technology*, vol.24, no.11, pp.1935-1944, 2014.
[22] Z. J. Ju, D. X. Gao, J. T. Cao and H. H. Liu, A novel approach to extract hand gesture feature in depth images, *Multimedia Tools and Applications*, pp.1-15, 2015.
[23] K. Liu, C. Chen and R. Jafari, Fusion of inertial and depth sensor data for robust hand gesture recognition, *IEEE Sensors Journal*, vol.14, no.6, pp.1896-1903, 2014.
[24] P. Molchanov, S. Gupta, K. Kim and K. Pulli, Multi-sensor system for driver's hand-gesture recognition, *Proc. of IEEE Conference on Automatic Face and Gesture Recognition*, Ljubljana, Slovenia, pp.1-8, 2015.
[25] Y. She, Y. Z. Jia, T. Gu, Q. He and Q. Q. Wu, An integrated approach of real-time hand gesture recognition based on feature points, *International Journal of Multimedia and Ubiquitous Engineering*, vol.10, no.4, pp.413-428, 2015.
[26] N. T. L. Anh, Y. C. Kim and G. S. Lee, Morphological gradient applied to new active contour model for color image segmentation, *Proc. of the 6th International Conference on Ubiquitous Information Management and Communication*, 2012.
[27] J. Angulo, Geometric algebra color image representations and derived total orderings for morphological operators – Part I: Color quaternions, *Journal of Visual Communication and Image Representation*, vol.21, no.1, pp.33-48, 2010.