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Dynamic Background Subtraction Using Histograms Based on Fuzzy C-Means Clustering and Fuzzy Nearness Degree

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ABSTRACT Background subtraction has been widely used in the detection of a moving object from a still scene. Due to the uncertainty in the classification of the pixels in the foreground and background, we propose a novel fuzzy approach for background subtraction using fuzzy histograms based on fuzzy c-means clustering and the fuzzy nearness degree, called FCFN. In this method, the temporal characteristics of the pixels are described by a fuzzy histogram using the fuzzy c-means algorithm. The segmentation threshold is adaptively calculated according to the distribution of the fuzzy nearness degree of the individual pixel. Fuzzy adaptive background maintenance is adopted in the background update framework. The performance of the FCFN is evaluated against several state-of-the-art methods in the complex dynamic scenes. The experimental results demonstrate that the proposed method doubles the improvements in performance than the classic fuzzy background modeling methods and outperforms most state-of-the-art methods.

INDEX TERMS Background subtraction, fuzzy c-means clustering, fuzzy nearness degree, fuzzy histogram.

I. INTRODUCTION

The background subtraction method is a common method for extracting foreground targets in video sequences. A practical background subtraction method should be able to eliminate the interference caused by pixel movements of non-foreground targets, such as a dynamic background, video noise and camera shake. When viewing video pixels as a random variable, a common method used to identify whether the pixel belongs to the foreground or background is to adopt a statistical method, establish a background model by using the video, set and update the threshold and identify whether the pixel belongs to the foreground or background.

Based on the statistical method, some classical background subtraction methods have been proposed, such as the Gaussian mixture model (GMM), kernel density estimation (KDE), ViBe and so on. The background modeling method of the GMM uses multiple normal distributions to fit the pixel variations [1]. The nonparametric modeling method based on the KDE uses the kernel density function to model the pixel distributions on the basis of the distribution of existing pixel samples [2]. Barnich and Droogenbroeck [3] proposed the ViBe method, which utilizes the consistency of the neighborhood pixel distribution. In this method, the background model can be initialized by the first frame, and this algorithm performs well. The pixel-based adaptive segmenter (PBAS) background modeling method was proposed based on ViBe by Hofmann *et al.* [4], who introduced a cybernetic method to update the threshold and background model adaptively. St-Charles *et al.* [5] proposed SuBSENSE which uses the principle of sample consistency and a feedback mechanism, which means that this background model can adapt to the diversity of complex backgrounds. More recently, low rank subspace learning models represent a new trend and acquire satisfactory results for background or foreground separation [6]–[8]. Video structure is decomposed into low rank plus sparse matrices by these models, which provide a suitable framework to separate moving objects from the background. In addition, inspired by the impressive achievement of deep learning, researchers have applied deep neural networks for background subtraction and achieved impressive results [9]–[11].

In the procedure of the background subtraction of processing pixels, problems such as uncertainty and inaccuracies are inevitable. To deal with these problems, in recent years, methods based on fuzzy concepts have been introduced into each stage of background modeling, which has obtained favorable results [12]. Different fuzzy methods have been developed and are classified in the recent survey by

Bouwmans [13]. The Type-2 Fuzzy Mixture of Gaussian Models (T2FMGM) [14] is used in the dynamic background modeling process that contains noise. Compared with the traditional GMM, the T2FMGM is more robust. The strategy of binary classification is used in most background model algorithms, and it defines a pixel as either a background pixel or a foreground pixel. Once a pixel has been incorrectly classified, the modeling effect will be deteriorated further during subsequent iterations of the algorithm. To address this issue, the concept of fuzzy background classification has been proposed in [15], which can reduce the effects of pixel classification errors. The method in [16] fuzzily combines the updating rules in different cases to eliminate the interferences of light and shadow in a dynamic background.

Using histograms to study the characteristics of data is a classical method. Since the probability density of histogram is not smooth, and it is greatly affected by the range of the segmentation interval, the traditional histogram method makes it hard to correctly describe the probability distribution of the pixel background model. However, it has been found that histograms using fuzzy theory have good data analysis abilities [17]. In [18], the fuzzy c-means algorithm (FCM) is used in fuzzy color histogram background modeling. This algorithm can greatly reduce the disturbance of foreground object detection caused by dynamic background changes. Yang *et al.* [19] proposed a Bayesian approach with Markov random fields statistical framework for foreground segmentation in video sequences, in which fuzzy clustering factor on multi-histogram is introduced into the prior energy. However, this complex method has high computational complexity. To address structured motion patterns of the background, fuzzy color histogram is adopted to attenuate the color variations caused by background motions [20], [21], in which FCM is used to obtain the fuzzy membership based on histogram features. Panda and Meher [22] use the color difference histogram (CDH) in the background subtraction algorithm. In this method, the color difference is fuzzified with a Gaussian membership function and FCM clustering algorithm is exploited to reduce the large dimensionality of the histogram bins. The above mentioned fuzzy histograms-based methods exhibit better performance for background subtraction. However, the background learning rate and the threshold of foreground of these methods are always arbitrarily set to a certain constant, which lead to a degradation of the model performance. This paper proposes a novel background subtraction method. The fuzzy histogram is adopted to construct the background model, and the fuzzy nearness of a pixel is calculated to identify whether the video pixel belongs to the foreground or background. Meanwhile, the background updates adaptively with fuzzy learning rules. The implementation steps of the proposed method are as follows. First, use the pixel values of the three RGB channels to calculate the fuzzy membership of the pixel to each cluster center of the FCM, and then iterate to accumulate the fuzzy histogram background. Second, fuzzify the pixel values with the FCM and calculate the fuzzy nearness degree between the pixel fuzzy membership vector and the background vector. Finally, use the historical data trends to adjust the threshold, and consider the combination of the foreground pixels of each color channel as the final foreground pixel.

II. PRELIMINARIES

A. HISTOGRAM BACKGROUND MODELING USING THE FCM

In the traditional histogram method, data is uniquely assigned to an interval, and the width of the interval and the noise of the data have a large influence on the histogram model. However, the fuzzy histogram can avoid these problems very well. In the fuzzy histogram method, sample data that belong to all intervals of the histogram have different membership degrees, that is, sample data are shared by all intervals. In a histogram, pixel values accumulate in each histogram interval with different probabilities in order to build the background histogram model.

We define a pixel as $X_{i,j,t}^{C}$, where i, j are the coordinates of the pixel, t is the ordinal number of video frames, $C \in \{R, G, B\}$ denotes the color channel, and the range of the brightness values for each color channel is from 0 to 255. The histogram is divided into N intervals, $P_n(x)$ is the probability that a pixel value x belongs to each histogram interval, and $\sum_{n=1}^{N} P_n(x) = 1$. In the sample training phase, the values of the fuzzy histogram are calculated as follows:

$$H_n = \frac{1}{M} \sum_{k=1}^{M} P_n(x_k) \tag{1}$$

where M is the total number of samples, and the histogram interval number $n = 1, 2, \ldots N$, H_n denotes the value of the nth interval of the histogram. The histogram of the sample training stage is accumulated iteratively. We assume that each sample is equally important and let the weight of each sample be 1/M. The probability $P_n(x)$, which is obtained by the FCM method, can express the fuzzy degree of the sample belonging to the corresponding histogram interval.

The FCM is a clustering algorithm based on the objective function. It is a fuzzy classification that determines the degree of uncertainty of elements belonging to each cluster center using the membership degree. The solution process that the FCM adopts uses iterative operations to minimize the objective function J. The optimal objective function [23] of the FCM is as follows:

$$\begin{aligned} min:\ J &= \sum_{i=1}^{N} \sum_{j=1}^{L} P_{ij}^{a} \|x_j - v_i\|^2 \\ s.t.\ \ &\sum_{i=1}^{N} P_{ij} = 1, \quad j = 1, 2, \ldots L \end{aligned} \tag{2}$$

where x denotes the pixel value, v is the clustering center, P_{ij} represents the fuzzy membership degree of the pixel value x_j of the clustering center v_i, N is the number of appointed clustering centers, and a is a fuzzification coefficient that is commonly set to 2. Lagrangian multiplication is used to

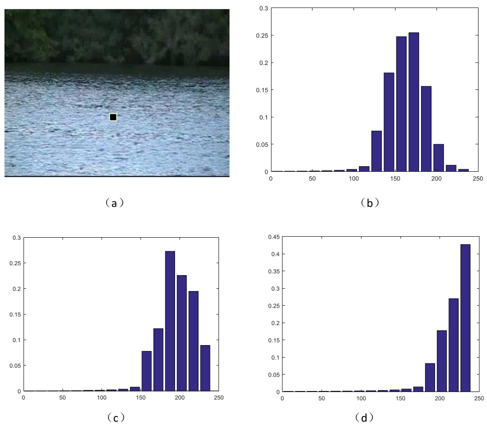

FIGURE 1. Fuzzy histograms of pixel values.

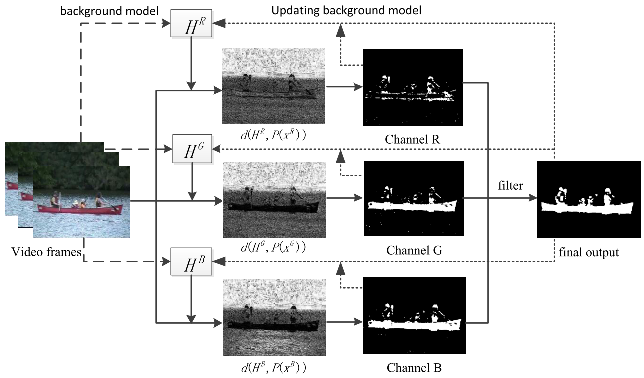

FIGURE 2. The outline of the FCFN.

solve the optimization objective in order to obtain the iterative formulas of the fuzzy membership degree and clustering center:

$$P_{ij} = \Big(\sum_{k=1}^{N}\Big(\frac{\|x_j - v_i\|}{\|x_j - v_k\|}\Big)^{\frac{2}{a-1}}\Big)^{-1} \tag{3}$$

$$v_i = \frac{\sum_{j=1}^{L} P_{ij}^{a} x_j}{\sum_{j=1}^{L} P_{ij}^{a}} \tag{4}$$

The value of the clustering center v and fuzzy membership degree P can be obtained by minimizing the objective function J through mutually iterating (3) and (4). In the process of pixel histogram clustering, the median value of the histogram interval is set to be the clustering center. In this model, the intervals of the pixel histogram are equal, and the clustering center v is determined once the number of intervals is specified. Therefore, the membership matrix P of a pixel to each histogram interval can be obtained by (3). It should be noted that the membership matrix only needs to be computed once. The membership values of the pixel values from 0~255 levels are stored in the matrix. When it is necessary to calculate the membership of the pixel value to the histogram interval, the membership matrix can be directly retrieved, which can greatly reduce the computing time.

The histogram background modeling result of the FCM is shown in Fig. 1. The dynamic background in Fig. 1 (a) is water wave motion. The fuzzy background histogram of the three RGB channels that belong to the pixel located in the black square point are shown in 1(b), 1(c) and 1(d), respectively. The pixel values are divided into 16 intervals, and the pixel values have different membership degrees to each interval of the fuzzy histogram. The values of each interval are involved in the judgment process of foreground pixels.

B. FUZZY NEARNESS DEGREE

The concept of the fuzzy nearness degree is introduced by Wang to represent the similarity of two fuzzy sets [24]. Later, other scholars improved and expanded it on this basis [25].

The axiomatic definition of the fuzzy nearness degree is as follows [25]:

if mapping $d : F(X) \times F(X) \rightarrow [0, 1], \forall A, B, C \in F(X)$, meets the following conditions:

(1) $d(A, A) = 1$;

(2) $d(A, B) = d(B, A)$;

(3) $A \subseteq B \subseteq C \Rightarrow d(A, C) \leqslant d(A, C) \wedge d(A, B)$.

Then d is called the fuzzy nearness degree function of $F(X)$ and $d(A, B)$ denotes the fuzzy nearness degree between A and B. The fuzzy nearness degree is defined in many ways, and the algorithm of the arithmetic mean minimum is used in this paper. The formula is as follows:

$$d(A, B) = \frac{2\sum_{k=1}^{n}(A(x_k) \wedge B(x_k))}{\sum_{k=1}^{n}(A(x_k) + B(x_k))} \tag{5}$$

In the proposed background subtraction modeling, the fuzzy nearness degree is used to assess the fuzzy nearness degree between the fuzzy membership degree vector P(x) and the fuzzy background histogram vector H of a pixel, and then determine whether the pixel belongs to foreground pixels. The determination formula of foreground pixels is as follows:

$$F(x) = \begin{cases} 1, & if\ d(H, P(x)) < T \\ 0, & if\ d(H, P(x)) \geqslant T \end{cases} \tag{6}$$

T is the threshold. The pixel is classified as foreground if $F(x)$ equals 1, and otherwise the pixel is classified as background.

III. THE PROPOSED METHOD

The outline of the proposed method is illustrated in Fig. 2. The input video frames establish the fuzzy background histogram model $H^C (C \in \{R, G, B\})$ in the R, G and B channels. Each channel x^C of the pixel and its corresponding fuzzy histogram background H^C are used to calculate the fuzzy nearness degree. The foreground pixels F^C of each channel pass through threshold judgment. The foreground pixels of each color channel are calculated by the OR operation and then processed using the median filter. Finally, the output foreground pixel F^f is synthesized. The calculation formula is as follows:

$$F^f = \bigcup \{F^R, F^G, F^B\} \quad (7)$$

In the proposed method, the fuzzy background updating method is used when the background updates. According to the difference between the final output F^f of a pixel and the foreground output F^C of the sub channel, different updating methods are adopted. The judgment thresholds of each channel are updated dynamically according to the distribution of the historical data. As is shown in Fig. 2, the procedure of the algorithm is performed in each pixel channel separately. Therefore, the proposed method can use parallel computing to improve the efficiency of the algorithm.

A. FUZZY ADAPTIVE BACKGROUND MAINTENANCE

In the traditional background update, a pixel either participates in the background update or does not participate in it at all. In the background maintenance of the proposed method, if the pixels are foreground, then they do not update the background, and otherwise the pixels participate in the background update to a certain extent.

The formula of traditional background update is as follows:

$$H_n^{k+1} = (1-\alpha)H_n^k + \alpha P_n(x_{k+1}), k = 1, 2, \ldots M \quad (8)$$

where $\alpha \in [0, 1]$ denotes learning rate. In this background maintenance method, all pixels update the background with the same weight. However, when a foreground pixel participates in the background update and has the same weight, the accuracy of the background model will be reduced, resulting in the increase of error pixels in the next judgment. To solve the problem, [16] proposed to use adaptive background maintenance. Inspired by this idea, the fuzzy adaptive background maintenance is adopted in the histogram model of the pixel for each channel and the fuzzy learning rules are set as follows:

(1) If the final merged result F^f is foreground, then each color channel does not update the background model;

(2) If the final merged result F^f and subchannel F^C are all background, then update the background model of the subchannel less; and

(3) If the final merged result F^f is background and subchannel F^C is foreground, then update the background model of the subchannel more.

Table 1 shows the selection of the learning rate for fuzzy rules. The value of 0 indicates that the update rate of the subchannel fuzzy background is 0, that is, the subchannel background is not updated. θ_H denotes a large update rate, and θ_L denotes a small rate.

TABLE 1. Learning rate.

	F^f is foreground	F^f is background
F^C is foreground	0	θ_H
F^C is background	0	θ_L

The background updating formula is as follows:

$$H_n^{k+1} = F^f H_n^{k+1} + (1-F^f)((1-\alpha)H_n^k + \alpha P_n(x_{k+1})), \quad k = 1, 2, \ldots M \quad (9)$$

When the final merged result $F^f = 1$ is foreground, the background histogram model does not update. When $F^f = 0$ is background, the background histogram model updates. $\alpha = \max(\theta_H F^C, \theta_L)$ indicates that when the subchannel is foreground, the background model chooses a large updating rate, and otherwise it chooses a small updating rate.

B. SELECTION OF DYNAMIC THRESHOLD

Statistics is used to select the threshold of the fuzzy nearness degree. It is assumed that the fuzzy nearness degree between a sample pixel value and the background histogram conforms to a normal distribution $d \sim N(\mu, \sigma^2)$. Let the significance level be β, and when the fuzzy nearness degree probability $P(d) < \beta$, it is classified as a foreground pixel, which is $P(d(x) > (\mu - b\sigma)) < \beta$. In the proposed method, let $\beta = 0.05$, and $b = 1.96$ can be obtained from the normal distribution characteristic [26]. The threshold T is set in two cases:

(1) If $\mu - b\sigma > \beta$, the threshold is $T = \mu - b\sigma$; and

(2) If $\mu - b\sigma \leqslant \beta$, it indicates that the pixel value is close to the background model, and the distribution of the fuzzy nearness degree is concentrated. Therefore, the percentile is used as the threshold, and the percentile is set as β. Then, the threshold is $T = \beta$. That is, when $P(d(x)) < \beta$, pixel x is a foreground pixel.

The formula for threshold selection is as follows:

$$T = (1 - s_t)\beta + s_t(\mu - b\sigma) \quad (10)$$

where $s_t = \begin{cases} 1, \mu - b\sigma > \beta \\ 0, \mu - b\sigma \leqslant \beta \end{cases}$. The change of the background fuzzy histogram caused by the change of the background is slow. Therefore, it is not necessary to update the threshold in real time, and it can be updated regularly.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

To verify the performance of the proposed method, the dynamic background videos from CDnet2014 [27] and SABS [41] are used to test the method. As a famous change detection benchmark dataset, CDnet2014 provides a realistic, diverse set of videos and covers a wide range of detection challenges. The main advantage of this dataset is that the ground truths for all video frames are provided, which can allow a precise quantitative comparison and a ranking of various algorithms. The SABS (Stuttgart Artificial Background Subtraction) is a synthetic video dataset for pixel-wise evaluation of the performance of background models for background subtraction. The video sequences of the dataset were artificially generated and further split into training and test frames. The high quality ground truth annotation of these sequences were provided for quantitative evaluation.

Ten fixed viewpoint with ground truth sequences were selected from these datasets for investigating the proposed

TABLE 2. The characteristics of dynamic background videos from CDnet2014.

Dataset	Video	Size	Frames	Dynamic scenes
CDnet2014	Boats	320×240	7999	water rippling
	Canoe	320×240	1189	water rippling
	Fountain01	432×288	1184	fountains
	Fountain02	432×288	1499	fountains
	Overpass	320×240	3000	waving trees
	Fall	720×480	4000	waving trees
SABS	Dynamic background	800×600	1401	traffic lights, waving trees

method. The characteristics of the dynamic background videos including a variety of dynamic scenes are shown in Table 2.

The performance of the background modeling method is evaluated at the pixel level, and the background modeling method classifies the pixels into foreground or background.

Six metrics were used for the evaluation:

$$Recall = \frac{TP}{TP+FN},$$
$$Precision = \frac{TP}{TP+FP},$$
$$FPR = \frac{FP}{FP+TN},$$
$$FNR = \frac{FN}{TP+FN},$$
$$PWC = 100 \times \frac{FN+FP}{TP+FN+FP+TN}, \text{ and}$$
$$F-measure = 2 \times \frac{Precision \times Recall}{Precision + Recall}.$$

Here, TP is the number of correctly detected foreground pixels, TN is the number of correctly detected background pixels, FP is the number of background pixels that were incorrectly marked as foreground pixels, and FN is the number of foreground pixels that were incorrectly marked as background pixels. $Recall$ reflects the number of pixels that are correctly classified in all foreground pixels, $Precision$ reflects the proportion of true foreground pixels that are classified as foreground pixels, and the $F-measure$ is the comprehensive evaluation index that is constituted by their weighted harmonic mean. The FPR is the number of background pixels that are misclassified as foreground pixels, FNR is the number of foreground pixels that are misclassified as background pixels, and PWC represents the percentage of misclassifications. Obviously, the higher the $Recall$, $Precision$ and $F-measure$ and the lower the FPR, FNR and PWC, the better the performance.

The framework of FCFN is summarized in Algorithm 1:

Functions and values of the parameters of Algorithm 1 are outlined in Table 3. The performance metrics of the background models are shown in Table 4. These models are obtained by adopting the proposed method to different scenarios of dynamic background dataset.

Algorithm 1 FCFN

Input:
$X^C_{i,j,t}$ is the video image;
$i = 1, 2, \ldots w_f,\ w_f$: width of the video frame;
$j = 1, 2, \ldots h_f,\ h_f$: height of the video frame;
$t = 1, 2, \ldots n_f,\ n_f$: frame number of the video frame.
Output:
output foreground F^f of the video image.
Training stage of the background model
Step 1: The L level pixel values are divided into N histogram intervals, and the central coordinates v_i, $i = 1, 2, \ldots N$ are determined. Calculate the membership matrix $P = \{P_{ij} | i = 1, 2, \ldots N, j = 1, 2, \ldots L\}$ using (3).
Step 2: Use M frame images and (1) to model the fuzzy background histograms $H = \{H_n | n = 1, 2, \ldots N\}$ of the respective RGB color channels. **Training stage of the foreground pixel**
Step 3: Retrieve the fuzzy membership matrix P, and the membership vector $P(x) = \{P_{ix} | i = 1, 2, \ldots N\}$ of the pixel value x, so the histogram interval can be obtained. Then, use (5) to calculate the fuzzy nearness degree $d(P(x), H)$ of the pixel to the background.
Step 4: According to the statistical characteristics of historical samples, the threshold value T wascalculated using (10), and the foreground pixel F^C was obtained by using (6).
Step 5: (7) was used to synthesize the final output foreground F^f, and then F^f was dealt with median filtering and morphology.
Step 6: (9) was used to update the histogram background H according to the difference between the color subchannel and the final output foreground.
Step 7: The threshold was updated regularly using formula (10) for a certain period of s_c.
Step 8: Return to Step 3.

A. COMPARISON WITH THE FUZZY BACKGROUND MODELING METHODS

To evaluate the proposed method, a subset of fuzzy background modeling was selected for comparison, which

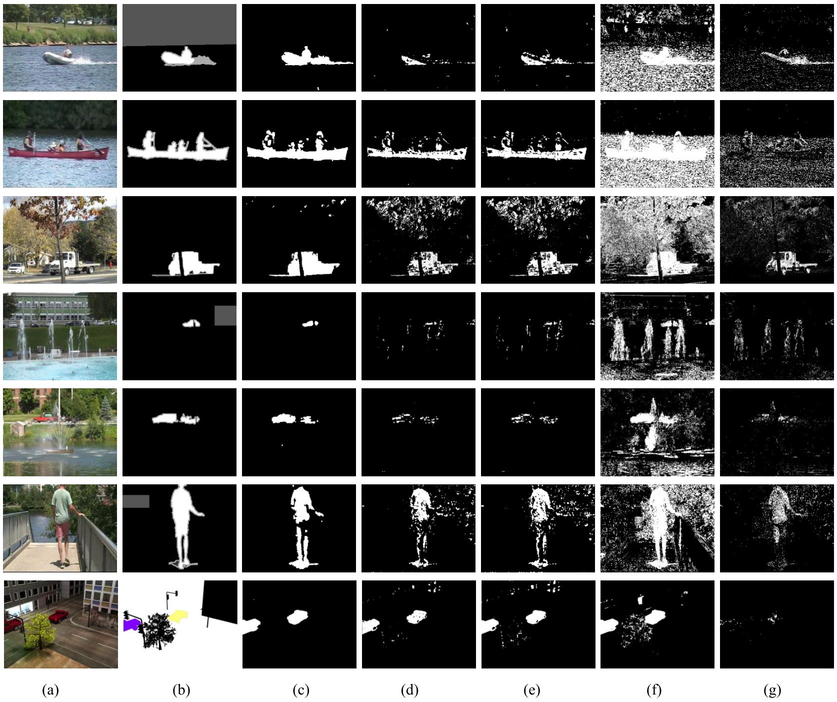

FIGURE 3. Comparisons of foreground segmentation results. (a) Original frame. (b) Ground truth. (c) FCFN. (d) Fuzzy Sugeno Integral. (e) Fuzzy Choquet Integral. (f) Fuzzy Gaussian. (g) T2FMGM with MRF.

TABLE 3. The parameters of the proposed method used in experiments.

Parameters	Description	Values
N	The histogram interval number	16
M	The number of training frames	100
F^C	The subchannel foreground	{0,1}
F^f	The final foreground	{0,1}
θ_H	Large update rate	0.15
θ_L	Small update rate	0.01
α	The learning rate of background model, $\alpha = max(\theta_H F^C, \theta_L)$	[0, 1]
T	Dynamic threshold	see (10)

included the Fuzzy Sugeno Integral [28], the Fuzzy Choquet Integral [29], the Fuzzy Gaussian [15], and the T2FMGM with the MRF [30]. The Fuzzy Sugeno Integral method uses fuzzy integral to fuse the texture and color features for background subtraction to deal with diverse small motions of background objects such as waving trees. The Choquet integral is used as aggregation operator in the Fuzzy Choquet Integral method to handle the uncertainty in the classification issue. In the Fuzzy Gaussian method, a linear saturation function take the place of the crisp limiter function is used to determine a pixel is foreground or no, and fuzzy running average is used to update the background model. T2FMGM-UV with MRF combines type-2 fuzzy mixture Gaussian model (T2-FGMM) with uncertain variance (UV) and Markova random field (MRF) for motion detection in dynamic scenes. The key idea of this method is that the prior knowledge of the spatial-temporal constraints is considered by MRF. For those methods, we used the implementation available in the BGSLibrary [31]. Fig. 3 shows several results of background subtraction with fuzzy background modeling. It is clear that the proposed algorithm outperformed the others.

The results of the quantitative comparisons are listed in Table 5. The best scores are highlighted in bold. The indicators of the proposed method are better than those of the other methods, except that the *FNR* of it is slightly higher

TABLE 4. Performance metrics of the FCFN.

Dataset	Video	Recall	FPR	FNR	PWC	Precision	F-measure
CDnet2014	boats	0.8321	0.0018	0.1679	0.3197	0.7906	0.8108
	canoe	0.9114	0.0017	0.0886	0.5464	0.9589	0.9346
	fountain01	0.8817	0.0004	0.1183	0.0528	0.6981	0.7792
	fountain02	0.9370	0.0002	0.0630	0.0345	0.9463	0.9416
	overpass	0.9007	0.0011	0.0993	0.2663	0.9326	0.9164
	fall	0.9160	0.0040	0.0840	0.5486	0.8185	0.8645
SABS	Dynamic background	0.9135	0.0066	0.0865	0.8209	0.7430	0.8195

TABLE 5. Comparisons with other fuzzy background modeling.

Dataset	Method	Recall	FPR	FNR	PWC	Precision	F-Measure
CDnet2014	FCFN	0.8965	**0.0015**	0.1035	**0.2947**	**0.8575**	**0.8745**
	Fuzzy Sugeno Integral	0.4914	0.0134	0.5086	1.8303	0.4899	0.4200
	Fuzzy Choquet Integral	0.5461	0.0175	0.4539	2.1718	0.4439	0.4210
	Fuzzy Gaussian	**0.9557**	0.3313	**0.0443**	32.6771	0.0334	0.0632
	T2FMGM-UV with MRF	0.2630	0.0514	0.7370	5.9857	0.0629	0.0958
SABS	FCFN	0.9135	0.0066	0.0865	**0.8209**	**0.7430**	**0.8195**
	Fuzzy Sugeno Integral	0.7106	0.0137	0.2894	1.9300	0.5197	0.6003
	Fuzzy Choquet Integral	0.7915	0.0294	0.2085	3.3098	0.3589	0.4938
	Fuzzy Gaussian	**0.9976**	0.3104	**0.0024**	30.4108	0.0627	0.1180
	T2FMGM-UV with MRF	0.2222	**0.0024**	0.7778	1.8223	0.6579	0.3322

FIGURE 4. Examples of background subtraction results (a) Original frame, (b) Ground truth, (c) FCFN, (d) SuBSENSE, (e) PBAS, (f) GMM, and (g) KDE.

than the *FNR* for the Fuzzy Gaussian. In particular, the most representative $F-Measure$ evaluation metric is much better than other fuzzy background modeling methods. Although the Fuzzy Gaussian method obtained a lower *FNR* index, as is shown in Fig. 3, it regarded the fluctuation of the water surface and the swaying of branches as foreground, which reduced the accuracy and influenced the $F-Measure$. Other fuzzy background modeling methods also have the same problem. Since the proposed method adopts multichannel processing, the background model has better robustness, and the interference of a dynamic background, such as moving water and swaying branches, can be effectively removed.

B. COMPARED WITH STATE-OF-THE-ART BACKGROUND SUBTRACTION ALGORITHMS

To test the proposed method more completely, we compare the FCFN with other state-of-the-art background subtraction methods. Because of the fast learning, noise tolerance and incremental update of learnt of the weightless neural networks (WNNs), WNNs is exploited to model pixel background in the CwisarDH[34] and CwisarDRP methods[32]. The main innovation of Wang and Dudek [33] method is that a small set of adaptive templates that model underlying distribution of background values are used to update background model. In this method the least useful background is replaced by new ones. Spectral-360[35] is a physics-based change detection approach, which is based on the dichromatic color reflectance model. In this approach, the foreground is segmented from a static background based on the similarity between the full-spectrum reflectance of the background and foreground pixels. For visual comparisons, the examples of the background subtraction results are presented in Fig. 4, where Fig. 4(a) is the input video frames, Fig. 4(b) is the ground truth, Fig. 4(c) presents the results of the proposed

TABLE 6. Comparisons with other methods.

Dataset	Method	Recall	FPR	FNR	PWC	Precision	F-Measure
CDnet2014	FCFN	0.8965	0.0015	0.1035	0.2947	0.8575	**0.8745**
	CwisarDRP[32]	0.8291	0.0008	0.1709	**0.2892**	0.8723	0.8487
	Bin Wang[33]	**0.9177**	0.0044	**0.0823**	0.4837	0.7990	0.8436
	CwisarDH[34]	0.8144	0.0015	0.1856	0.3270	0.8499	0.8274
	SuBSENSE [5]	0.7872	**0.0007**	0.2128	0.3837	**0.8768**	0.8138
	Spectral-360[35]	0.7819	0.0008	0.2181	0.3513	0.8456	0.7766
	ViBe+[36]	0.7616	0.0020	0.2384	0.3838	0.7291	0.7197
	KNN[37]	0.8047	0.0063	0.1953	0.8059	0.6931	0.6865
	PBAS[4]	0.6955	0.0011	0.3045	0.5394	0.8326	0.6829
	SC-SOBS[38]	0.8918	0.0164	0.1082	1.6899	0.6283	0.6686
	GMM [39]	0.8019	0.0097	0.1981	1.1725	0.6213	0.6328
	CP3-online[40]	0.7260	0.0037	0.2740	0.6613	0.6122	0.6111
	KDE [2]	0.8012	0.0144	0.1988	1.6393	0.5732	0.5961
SABS	FCFN	0.9135	0.0066	0.0865	**0.8209**	0.7430	**0.8195**
	LOBSTER[42]	0.9761	0.0165	0.0239	1.6642	0.5521	0.7053
	IMBS[43]	0.9539	0.0369	0.0461	3.7061	0.3501	0.5122
	SuBSENSE	0.9840	0.0151	0.0160	1.5121	0.5757	0.7264
	PBAS	0.8530	0.0059	0.1470	0.8787	0.7504	0.7984
	GMM	0.2447	**0.0015**	0.7553	1.6843	**0.7765**	0.3721
	KDE	**0.9991**	0.7256	**0.0009**	71.0853	0.0279	0.0542

method, and Fig. 4(d) - 4(g) present the results of other state-of-the-art foreground detection methods.

The results of the quantitative comparisons are listed in Table 6. The $F-Measure$ score is the most effective index of the quantified background subtraction algorithms. In comparison with other methods, the proposed method obtains the best average $F-Measure$. The experimental results demonstrate that, compared with the second best method, the relative improvement of the proposed method's average $F-Measure$ is 3%. The proposed method has the lowest FNR score, which means that it has the lowest number of foreground pixels that are misclassified as background. The other evaluation indicators are slightly worse than the other methods. The comparison results verify the superiority of the proposed method.

V. CONCLUSIONS

In this paper, an efficient and robust background subtraction approach was proposed. The basic idea is to establish a fuzzy histogram background model using the FCM, adopt the fuzzy nearness degree to measure the distance between the pixel and the background model, and then determine whether the pixel belongs to the foreground or background using the distance. Fuzzy adaptive background maintenance is adopted as the update mode of the background model.

The proposed method is a pixel-wise and statistical model-based background subtraction method, which is quite well suited for the gradual scene changes. The proposed model is established with the statistical characteristics of the history samples of individual pixel. When a pixel deviates appreciably from the background model, this pixel is considered to be a foreground, viz., the proposed methods care less about the size of the foreground object while care about the statistical property of individual pixel. Thus, both small and large foreground object, no matter what size of it, can be detected by FCFN in the dynamic backgrounds. And of course, the single foreground pixel will be removed through filtering in the proposed method. To verify the performance of the proposed method, the dynamic background database was used to conduct the experiments. Experiments on video surveillance datasets show that the proposed method has good performance for foreground detection, and we confirm that the proposed algorithm provides the most reliable background model for dynamic scenes.

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