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Adaptive Foreground Object Extraction in Real Time Videos Using Fuzzy C Means with Weber Principle

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Abstract

Objectives: We propose a foreground extraction method for video surveillance system is to detect the objects in real time. **Methods:** The proposed foreground extraction technique models the background using cluster centroids and optimized using fuzzy-c-means technique. The foreground is extracted using background subtraction. The optical flow is used to eliminate the falsely extracted foreground pixels.**Findings:** Traditional techniques, cluster centroids are initialized using random values or histogram peaks, but in our proposed system the cluster centroids are initialized using weber principle. **Improvement:** This proposed real-time foreground extraction approach yields better results than the previous algorithms with respect to quality of extraction and memory consumption.

Keywords: Bit-Plane Slicing, Foreground Extraction, Fuzzy C-Means, GMM, K-Means, Optical Flow, Weber Principle

1. Introduction

Identifying or classifying moving objects in a video sequence is a fundamental and critical task in many computer-vision applications. The conventional approaches for the foreground object detection are background subtraction, temporal differencing, correlation, color based segmentation and optical flow. Background subtraction is a 'quick and dirty' way of localizing moving objects[1]. Typical background subtraction methods label "in motion" every pixel at a time t, whose color is significantly different from the pixels in the background. Temporal differencing[2] is used in a dynamic environment. It is obtained from the difference of current frame and the previous frame with a threshold value. Optical flow techniques[3] are also used in a dynamic environment and it is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer and the scene. The optical flow technique is used for motion detection, object segmentation, time-to-collision etc.

The cluster based techniques are also used for modeling the foreground. Clustering algorithms[4] are used to label the unlabeled data, based on the similarity measure between the data patterns. The clustering process includes characteristic representation, similarity, measurement, collecting the data points, data abstraction and output validation.Clustering techniques are mainly classsified into hierarchical and partitional. Hierarchical clustering is considered as non-parameterized clustering and it is further divided into agglomerative and divisive. Agglomerative clustering, at first takes N single point clusters and merge clusters to become larger and larger. Divisive clustering splits the entire dataset into a single point cluster. It is a reverse process of agglomerative clustering. The partition based clustering[4] is considered as parameterized clustering.The partition clustering methods need a number of centroids and initial value of centroids as priori information. It uses an iterative technique to optimize those values using appropriate objective function. The commonly used parameterized clustering is k-means clustering, which is the most popular and easily used clustering algorithm. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) and the number of clusters which is fixed as a priori. These centroids should be placed in a cunning way because placing of centroids in different locations leads to different results. So, the bet-

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ter choice is to place them as much as possible far away from each other[5]. The other most widely used clustering method *is a Gaussian mixture model* . In Gaussian Mixture Model[6] clusters are considered as Gaussian distributions. The Expectation-Maximization algorithm which is used in practice to find the mixture of Gaussians that can model the data[6]. The Fuzzy C-Means[7] is another clustering method which partition the image based on the membership values. The main difference between fuzzy clustering and other clustering techniques is that it generates fuzzy partitions to identify the pixel membership in each cluster to segment the overlapped objects accurately.

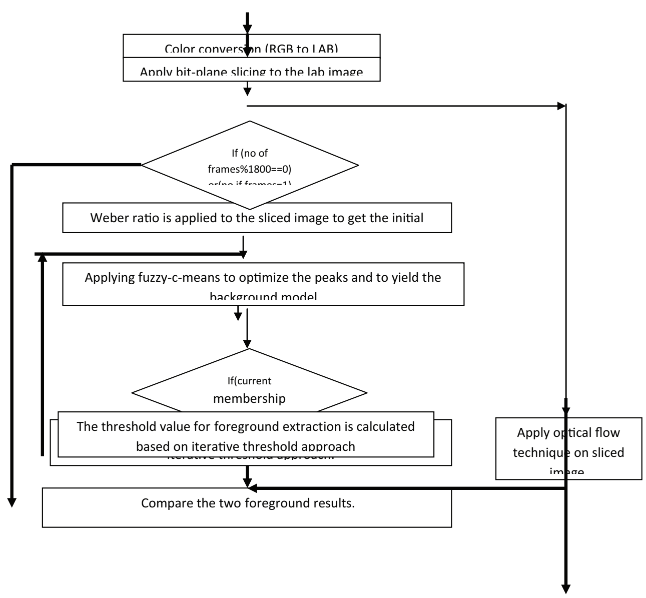
There are many techniques present in the literature for foreground object extraction. The most foreground detection method uses either the temporal or spatial information of the image sequence. Background subtraction [8,9] takes several seconds of frames to model each pixel of a background with a normal distribution. Then subtract the current image from the background image and apply threshold to get the foreground object. Temporal difference detects quickly the coarse region of multiple objects. Temporal difference[10,11] uses pixel-wise difference between two consecutive frames t, and t-1 in continuous image sequence to detect the moving regions in the videos. Optical flow[12,13] based foreground detection uses characteristics of flow vectors of moving objects over time to detect moving regions in an image sequence. Background subtraction[1,20,22,23] is a simple technique used before, now temporal difference is used for dynamic foreground extraction and to yield better results the optical flow method is used along with the temporal difference. A foreground is extracted based on the Gaussian mixture model[6]. The foreground region is extracted with graph-based region segmentation[8] by considering background difference and spatial homogeneity. A combination of classifiers to detect the foreground object[14]. They concentrated color and the depth.

The background is modeled using contrast histogram[16]. There were statistical and analytical[15] based foreground object detection in videos. Zhang S[5] presented the adaptive background subtraction by a local dependency histogram.Sivagami M[18] proposed the foreground detection method using fuzzy-c-means with optical flow. Wang SY[19] suggested the foreground extraction based on Scale Invariant Feature Transform (SIFT) trajectories. Kim[10] used the Gaussian family model and multi thresholds for foreground extraction.Singh[20] extracted the foreground based on background subtraction using tolerance value. Mohd B[21] segmented the foreground using LAB color space.

2. Proposed Methodology

We proposed an efficient foreground extraction technique. The proposed method is concerned with real-time video images. So the main purpose of the proposed FCMBPSWOF method is to present an algorithm with less memory consumption towards other algorithms. In this proposed method, the background is modeled using Fuzzy-C-Means clustering. Initial cluster centroids are found using weber principle and they are optimized using Fuzzy-C-Means clustering. The foreground is extracted by comparing the current input frames with the background model and the pixels are classified as background or foreground using iterative thresholding. Horn-Schunk optical flow technique is applied to mitigate the falsely detected foreground pixels. To adapt the changes in the environment, background is modeled at regular intervals. This proposed real-time foreground extraction approach results better than the state of the art techniques with respect to quality of extraction and memory consumption.

2.1 Flowchart



2.2 Space Compression

The real time video streaming requires more memory for processing. To reduce the memory utilization, bit-plane slicing technique is applied on each frame with respect to background model.

Separating a digital image into its bit planes is useful for analyzing the relative importance played by each bit of the image. Separating image as a different slices helps in determining ,how many bits to be considered to process the data without any data loss. Bit-plane slicing is a technique in which the image is sliced at different paths. The bit level arranges from 0 to 7. The 0 represents the least significant bit and 7 represent the most significant bit. The higher order bits usually contain most of the significant visual information. A lower order bits contain subtle details. In this proposed system , the most significant 4 bits are taken into

$$BPI_k(i,j) = R\left(\frac{1}{2}\,floor\left[\frac{1}{2^k}\right]I(i,j)\right) \tag{1}$$

consideration, it is obtained by processing the input image with a thresholding gray-level transformation function that (1) maps all levels in the image between 0 and 16 to one level (for example, 0); and (2) maps all levels between 17 to 255 to another (for example, 255).

where, I – original image. BPI_k - Bit-plane information for the bit k, R- Remainder.

2.3 Cluster Centroids Initialization

The number of clusters is to be given as a prior information in parameterized clustering. The Weber principle[23] is used to find the initial peaks for the FCMWOF.

$[c_1 : c_n]$ =WP (Bps) (2)

Where, c_1 and c_n are the centroids, WP is the weber principle method applied to the binary sliced image (Bps).

The ratio of incremental change in intensity to background illumination is called the Weber ratio. If the ratio ($\Delta i/I$) is small, then there is a good brightness adaptation, otherwise there will be a poor brightness adaptation. The current sensitivity level of the visual system is called the brightness adaptation level. So the function of visual system can be mapped with weber per principle. The Weber perception principle, is the difference of gray level W (I) that can be classified by the human eye as a nonlinear function of the gray level I. According to the Weber perception principle, the human eye can hardly classify the difference of gray levels between [I (n), I (n) + W (I (n))], then we can regard the gray levels between [I (n), I (n) + W (I (n))] at the same gray level I.

The Weber perception function is

$$\begin{cases} 20 - \dfrac{12l}{88} & 0 \le I \le 88 \\ 0.002\left(I-88\right)^2 & 88 \le I \le 138 \\ \dfrac{7\left(I-138\right)}{255-138} + 13 & 138 \le I \le 255 \end{cases} \tag{3}$$

Where, l is the luminance and I is the gray level.

2.4 Background Modeling

The background frame is modeled using fuzzy-c-means algorithm.

BI=FCM (Bps, N) (4)

where, BI is the background image, FCM is the fuzzy-c-means, I is the image and N is the number of centroids.

To model the background frame using FCMBPSWOF algorithm is given in the following steps:

Step 1: Initialize the number of clusters and initial values of cluster centroids using weber principle.

Step 2: Initialize the membership matrix

Step 3: While do step(4) to (10) until the difference of previous iteration and the current iteration of the objective function is less than £.

Step 4: Do step 5 for every pixel

$$u_{ij} = 1 \Big/ \sum_{k=1}^{c}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{2/p-1} \tag{5}$$

Step 5: Update the membership for every pixel.

Step 6: End

$$c_j = \frac{\sum_{i=1}^{n} u_j^p \cdot x_i}{\sum_{i=1}^{n} u_j^p} \tag{6}$$

Step 7: Do step 8 for every clusters

Step 8: Calculate the cluster centers using membership matrix and peaks.

Step 9: End

$$j_p = \sum_{i=1}^{n}\sum_{j=1}^{c} u_j^p \left\|x_i - c_j\right\|^2 \tag{7}$$

Step 10: Calculate the fuzzy objective function

Step 11: End

2.5 Foreground Extraction

The foreground extraction is done by comparing the input frames I with the background frame model M using the following equation.

F(x,y)=255, if[(I(x,y)-M(x,y))>T] (8)
F(x,y)=0, if[(I(x,y)-M(x,y))<T]

Where, T is the threshold value to detect the foreground object.The threshold of the outdoor video image should not be too low or high.If the threshold is high some of the foreground object is eliminated and if it is low few background pixels are wrongly considered as foreground pixels. In this system the threshold value is calculated based on the iterative threshold approach.The F (x, y) gives the foreground extracted by subtracting the current frame (I (x, y)) from the background frame .

2.6 Optical Flow

In the proposed method, gradient based Horn and Shunk optical flow technique is applied on every frame and background model.

$$I(x+u, y+v) = I(x, y) + \frac{\partial I}{\partial t}u + \frac{\partial I}{\partial t}v$$

$$where, \quad u = \frac{\partial x}{\partial t}, v = \frac{\partial y}{\partial t}$$

where, ∂I/∂x and ∂I/∂y are the derivatives of x and y. u and v are the velocities

$$where, \quad u = \frac{\partial x}{\partial t}, v = \frac{\partial y}{\partial t}$$

with respect of x and y direction

To solve *u* and *v* using the Horn-Schunck optical flow technique:

1. Compute I_x and I_y using the Sobel convolution kernel, [−1 −2 −1; 0 0 0 ;1 2 1], and it is transposed form, for each pixel in the background model.
2. Compute I_t between images background frame and current frame using the [-1 1] kernel.
   a. Assume the previous velocity to be 0, and compute the average velocity of each pixel using [0 1 0 ;1 0 1 ;0 1 0] as a convolution kernel.
3. For all the pixels the u and v vectors have to be updated using the following equation.

$$u_{x,y}^{k+1} = u_{x,y}^{k} - \frac{I_x\left[I_x u_{x,y}^{k} + I_y v_{x,y}^{k} + I_t\right]}{\alpha^2 + I_x{}^2 + I_y{}^2} \tag{10}$$

$$v_{x,y}^{k+1} = v_{x,y}^{k} - \frac{I_y\left[I_x u_{x,y}^{k} + I_y v_{x,y}^{k} + I_t\right]}{\alpha^2 + I_x{}^2 + I_y{}^2} \tag{11}$$

4. End

2.5 Eliminating the False Foreground Pixels

The falsely detected foreground pixels to be eliminated to get the efficient foreground extraction. In order to achieve that, the resultant images of fuzzy-c-means with weber (FCMBPSW) and Optical Flow (OF) are compared and eliminated the pixels which are present in both resultant images. The comparison and elimination are done using following steps to enhance the quality of extracted foreground:

For x =1:row
For y =1:col
If FI (x,y) pixel is identified as foreground object and OF(x,y) pixel has translated then
FI(x,y) pixel is rejected in the foreground pixel.
Else
FI(x,y) pixel is considered as the foreground pixel.
End
End
End

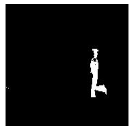
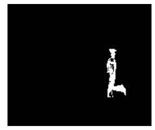
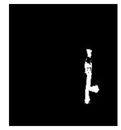
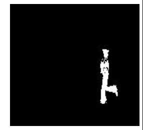
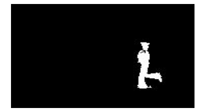
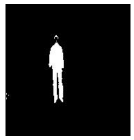
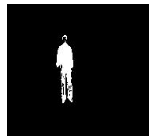
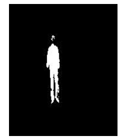
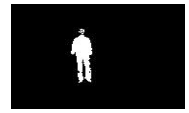
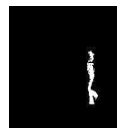
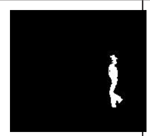
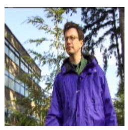
3. Experimental Result and Analysis

The proposed algorithm is implemented in mat lab version 7.13 on Windows XP platform. The videos are taken from Weizmann dataset. The proposed method is compared with the traditional and recent approaches.The traditional algorithms are i) Data clustering: A review (K-means)[7] ii) Histogram based foreground object extraction for indoor and outdoor scenes (GMM)[6] . The recent papers taken for comparison are Foreground object extraction using Fuzzy-C-Means with bit-plane slicing and Optical Flow (FCMOF)[20], foreground object detection via robust SIFT trajectories (MFOSIFT)[21] and Foreground Extraction technique using Gaussian family Models and Multiple Thresholds (FEGMT)[10] are taken for comparison with our proposed method.The foreground extraction results is shown in Table 3.

3.1 Evaluation Methods

The proposed system is evaluated based on the clustering indexes and Receiver Operating Characteristic (ROC)

Table 3. Foreground results

Image	Background Frame	Current Frame	GMM	K-Means	FCM	FCMOF	FCMBPSWOF
Run							
Jump							
Hopping							
Waving trees							

curve. The ROC evaluation is done to find the quality of foreground extraction.The whole system performance is evaluated by the execution time and the memory consumption.

3.1.1 Clustering Evaluation Methods

Clustering evaluation is done using special index functions called clustering validity indices and the J value. The clustering validity indices are

i) Fuzziness in partition matrix U
ii) Fukuyama-sugeno index
iii) Xie-Beni index

3.1.1.1 Fuzziness in Partition Matrix U

$$I_1(U) = \frac{1}{M}\left(\sum_{i=1}^{c}\sum_{k=1}^{M}\mu_{ik}^2\right) \quad (12)$$

$$I_2(U) = -\frac{1}{M}\left(\sum_{i=1}^{c}\sum_{k=1}^{M}\mu_{ik}\ln(\mu_{ik})\right) \quad (13)$$

There are two methods to measure the fuzziness degree

where, I_1 and I_2-validity, M –Number of data items c- Number of cluster and μ_{ik} – Membership degree.

The higher value of I_1, and lower value if I_2 gives the best result of clustering.

3.1.1.2 Fukuyama-Sugeno Index

This index enables the relationship of partition with geometric characteristics of clustered data. The minimum value gives the best result of clustering.

$$I_3(U,V,X) = \sum_{i=1}^{c}\sum_{k=1}^{M}\left(\mu_{ik}^m\right)\left(\|x_k - v_i\|_A^2\right) - \left(\|x_k - \bar{v}\|_A^2\right)$$
$$\bar{v} = \frac{1}{M}\sum_{k=1}^{M} x_k \quad (14)$$

where, M –Number of data items
C- Number of clusters and
μ_{ik} – Membership degree
v_i –cluster centers
x- data
v-mean of data.

3.1.1.3 Xie-Beni Index

$$I_4 = \frac{\sum_{i=1}^{c}\sum_{k=1}^{M}\left(\mu_{ik}^m\right)\|x_k - v_i\|^2}{M\left(\min_{i,j}\{\|v_i - v_j\|\}^2\right)}$$

This index is given by the formula:
where, M –Number of data items
c- Number of cluster and
V–cluster centers
x- Data

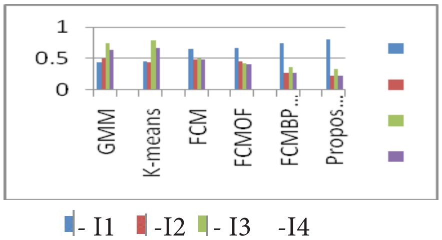


Figure1. Comparing the clustering results using indices

The minimum value of this gives the best result of clustering.Figure 1 shows the comparision results of different algorithm with our proposed method using clustering indices.

3.1.1.4 $\overline{J}$ Value

The Value[8] is used as the criterion to evaluate the performance on the segmented region.

$$J = \frac{(s_r - s_w)}{s_w} \quad (16)$$

$$s_r = \sum_{z \in Z} \|z - m\|^2 \quad (17)$$

$$s_w = \sum_{i=1}^{C} \sum_{z \in Z} \|z - m_i\|^2 \quad (18)$$

$$\overline{J} = \frac{1}{N} \Sigma_k M_k J_k \quad (19)$$

where, Z is the set of all pixels in the image, m is the average of all Z elements.Then the Z elements are classified into C classes.J_k is J computed over the region k, k is the no of segmented region, f is the number the pixels in each segmented regions, M_k is the number of pixels in the region k, and N is the total number of pixels in the image. The lower value of $\overline{J}$ gives the better segmentation.

3.1.2 Foreground Extraction Evaluation Methods

The Receiver operating characteristic curve uses ground truth and foreground extracted image to evaluate the quality of foreground extraction. Based on the two images, it computes true positives (TP),true negatives (TN), false positives(FP) and false negatives.The recall, precision and F-measure are the three methods which are used to evaluate the performance of the foreground extraction techniques. The metrics Recall, Pecision and F-measure of the proposed system compared with the state of the art technique and tabulated in Table 1.

Recall is defined as the ratio of the assigned foreground pixels (AFP) to the true foreground pixels (TFP).

Recall=AFP/TFP (20)

Precision is defined as a ratio of the true foreground pixels (TFP) to the assigned foreground pixels (AFP).

Precision=TFP/AFP (21)

F-measure compares the performance, considering both the recall and precision simultaneously.

$$F - measure = \frac{2pr}{p + r} \quad (22)$$

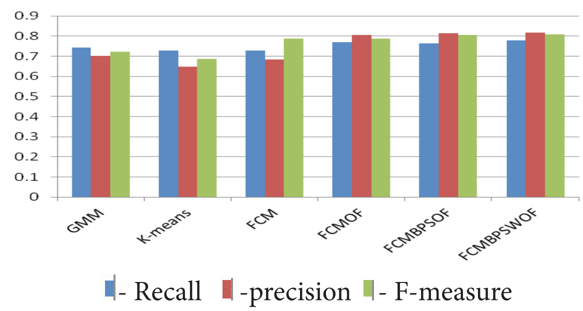


Figure 2. Comparing the foreground extraction results of the proposed technique with other clustering algorithms.

Where, p - precision and r - recall. High recall, high precision and high F-measure shows the high performance of the proposed system.Figure 2 shows the comparision ROC curve results of proposed method with different algorithms.

The quality of the extracted foreground objects of our proposed method is better than the GMM[6],K-means[7] and FCMOF[20]. The two contemporary papers Moving foreground object detection via robust SIFT trajectories (MFOSIFT)[21] and Foreground extraction technique using gaussian family model and multiple thresholds (FEGMT)[22] are taken into consideration for evaluating our proposed system using vehicle video sequence (Figure 4) from the web dataset.The MFOSIFT method works for the single object foreground extraction. The FEGMT[22] extracts the foreground based on gaussian mixture model and multiple thresholds. This algorithm fails to extract the foreground, when there is a sudden change in the background. Our proposed method FCMWP overcomes the constraints of the above methods (FEGMT[22] MFOSIFT[21]) and gives the high accuracy of foreground extraction.FCMWP extracts multiple objects in the foreground. The ROC analysis for this comparison are shown in the Table 4.

Table 4. ROC comparison results

Image	Methods	Recall	Precision	F-measure
Helico -pter	MFOSIFT	0.7254	0.6846	0.7045
	FEGMT	0.7645	0.7545	0.7615
	FCMWP	0.8147	0.7845	0.7996

Finally the system is evaluated based on execution time and memory consumption. The execution time and the memory usage of the proposed system are less when compared to GMM[6], K-means[7], FCM and FCMOF[20].

3.2 Complexity Analysis of FCMBPSWOF Method

The time complexity of our proposed system depends on Fuzzy-c-means, Bit-plane slicing, Weber principle and Optical flow. The Bit-plane slicing algorithm takes O (n^2). The Weber principle takes O (n^2), Fuzzy-c-means technique depends on the following parameters: I -dataset, n - Number of clusters, d - Number of dimensions.It takes O (n^2) polynomial time. At last, the optical flow algorithm takes O (n^2). So, the overall time complexity of the proposed method is O (n^2) polynomial time.

3.3 Space complexity

Apart from time complexity, space complexity is also important. A good algorithm keeps the memory space as small as possible for processing the data, too. This proposed method uses Bit-plane slicing technique. Using this technique only the most significant bits are stored and taken for the processing, so the memory space is reduced

Table 1. Results of the Evaluation Methods of clustering

S.N.	Image	Methods	Execution time (milli second)	Memory used (bytes)	$\overline{J}$	Fuzziness in partition matrix U I_1	I_2	Fukuyama-sugeno index I_3	Xie-Beni index I_4
1	Run	K-means	4.56786	3.924e+008	0.727	0.4366	0.4948	0.7387	0.6390
		GMM	6.03250	4.543e+008	0.659	0.4567	0.4408	0.7947	0.6628
		FCM	4.68675	4.445e+008	0.674	0.6457	0.4877	0.4980	0.4855
		FCMOF	4.81859	3.902e+008	0.652	0.6734	0.4487	0.4257	0.4105
		FCMBPSOF	3.83556	2.574e+008	0.667	0.7490	0.2676	0.3567	0.2668
		FCMWP	**4.11521**	**2.856e+008**	**0.645**	**0.7973**	**0.2264**	**0.3386**	**0.2257**
2	Jump	K-means	4.07613	3.967e+008	0.894	0.4822	0.4908	0.4767	0.7365
		GMM	4.55311	4.326e+008	0.655	0.4349	0.4635	0.5476	0.7655
		FCM	4.39564	4.747e+008	0.689	0.7654	0.1765	0.4687	0.3566
		FCMOF	4.45896	3.789e+008	0.597	0.7654	0.1765	0.4687	0.3566
		FCMBPSOF	3.76653	2.456e+008	0.592	0.8679	0.0478	0.3614	0.2077
		FCMWP	**3.84576**	**2.478e+008**	**0.590**	**0.8725**	**0.0482**	**0.3614**	**0.2077**
3	Hopping	K-means	4.04845	4.356e+008	0.735	0.4255	0.4894	0.49455	0.2556
		GMM	4.7245	4.156e+008	0.621	0.4647	0.5355	0.5356	0.29478
		FCM	4.3429	4.724e+008	0.584	0.6957	0.2576	0.3968	0.2478
		FCMOF	4.5730	4.936e+008	0.533	0.7524	0.2347	0.3168	0.2178
		FCMBPSOF	3.7514	3.249e+008	0.494	0.8422	0.0484	0.2757	0.1769
		FCMWP	**0.38196**	**3.347e+008**	**0.435**	**0.8746**	**0.0596**	**0.2486**	**0.1577**
4	Waving Trees	K-means	4.7353	5.343e+008	0.736	0.5296	0.6846	0.5421	0.3634
		GMM	5.3254	5.734e+008	0.673	0.4733	0.6438	0.4525	0.3263
		FCM	4.9376	5.445e+008	0.548	0.4326	0.5739	0.3735	0.2747
		FCMOF	5.1763	5.536e+008	0.520	0.4295	0.5973	0.3435	0.2536
		FCMBPSOF	4.5576	4.153e+008	0.495	0.4273	0.5486	0.3127	0.1946
		FCMWP	**4.6395**	4.264e+008	0.472	0.4185	0.5184	0.2937	0.1363

Table 2. Results of the Evaluation Methods of Foreground Extraction

S N.	Image	Methods	Recall	Precesion	F-measure
1	Run	GMM	0.7432	0.7022	0.7221
		K-means	0.7277	0.6482	0.6857
		FCM	0.7268	0.6835	0.7868
		FCMOF	0.7686	0.8059	0.7868
		FCMBPSOF	0.7634	0.8142	0.8045
		FCMBPSWOF	**0.7786**	**0.8159**	**0.8068**
2	Jump	GMM	0.8300	0.9321	0.8781
		K-means	0.8239	0.8929	0.8570
		FCM	0.8053	0.8990	0.8664
		FCMOF	0.8316	0.9427	0.8837
		FCMBPSOF	0.8515	0.9747	0.9131
		FCMBPSWOF	**0.8579**	**0.9773**	**0.9176**
3	Hopping	GMM	0.7991	0.6925	0.7420
		K-means	0.8111	0.7476	0.7781
		FCM	0.8424	0.7855	0.7805
		FCMOF	0.8765	0.7946	0.8291
		FCMBPSOF	0.8935	0.8664	0.7420
		FCMBPSWOF	**0.9154**	**0.8956**	**0.7781**
4	Waving trees	GMM	0.6297	0.6250	0.8781
		K-means	0.6836	0.7235	0.8570
		FCM	0.7266	0.8177	0.8664
		FCMOF	0.8464	0.8576	0.8837
		FCMBPSOF	0.8745	0.8946	0.9131
		FCMBPSWOF	**0.7475**	**0.7436**	**0.9176**

based on the bits used. The memory space is calculated for 50 frames and it is tabulated (Table 1 and 2) and compared with other methods shown in Figure 3.

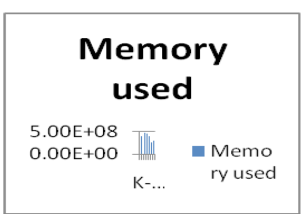


Figure 3. Space complexity .

4. Conclusion and Future Enhancements

The proposed system uses the bit-plane slicing to reduce the memory space, Weber principle to find the appropriate centroids, fuzzy-c-means for background modeling

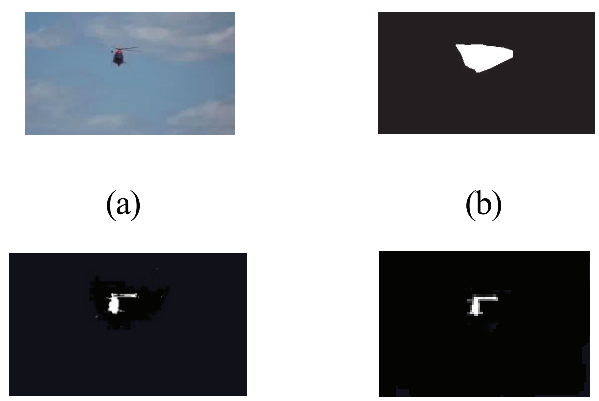

(a)
(b)
(c)
(d)

Figure 4. Comparison results of the proposed system with MFOSIFT [21] and FEGMT[22]. a) Current frame b) MFOSIFT c) FEGMT d) proposed method(FCMWP)

and optical flow for eliminating false foreground pixels. The quality of foreground extraction is evaluated using recall, precision, F-measure and four clustering index functions. The tabulated results show that our proposed method extracts the objects with less memory utilization and reduced processing time than GMM[6], K-means[7], FCM[20], MFOSIFT[21], FEGMT[22]. Finding proper centroids using the Weber principle in clustering helps to yield the better result in less number of iterations.So this technique will be appropriate for real time video processing with efficient space complexity. In future work, membership constraint in fuzzy clustering, will be eliminated by adaptive fuzzifier technique and Graphics Processing Unit (GPU) can be incorporated to accelerate the process.

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