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FOREGROUND OBJECT EXTRACTION USING FUZZY C MEANS WITH BIT-PLANE SLICING AND OPTICAL FLOW

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ABSTRACT: This paper address the problem of extracting the foreground objects.We proposed a novel technique for foreground object extraction using Fuzzy-c-means with Bit-plane slicing and optical flow. Modeling the background is a challenging task in foreground extraction. Before modeling the adaptive background image, the image is processed by Lab color model and Bit-plane slicing. Then the frame is modeled as a background using Fuzzy C - means algorithm with threshold.The foreground is extracted based on this model. The background model is updated at regular intervals of time. At last, the optical flow is applied to the foreground extracted image to eliminate the errors caused due to the movement of background object such as tree leaves, etc. The videos are taken from the weizmann dataset and examined for this method. This method yields better results than the previous algorithms with respect to memory consumption and quality of the extracted image.

KEYWORDS: *Foreground extraction, Fuzzy C-Means, optical flow, GMM, K-means, Bit-Plane Slicing.*

1. INTRODUCTION

Identifying, moving objects from a video sequence is a fundamental and critical task in many computer-visions applications. Foreground object extraction is also known as background subtraction. 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]. It is the common approach for foreground extraction,which identifies moving object is made up of a color, which differs from those in the background. Typical background subtraction methods label "in motion" every pixel at a time t, whose color is significantly different from the ones in the background [1],[2],[3]. Temporal differencing [4],[5],[6] is used in dynamic environments. The resultant image is obtained from the difference of current frame and the previous frame by applying certain threshold value. Optical flow techniques are also used in dynamic environments to detect the moving objects using the flow vector. Optical flow 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.[7].The foreground extraction may falsely detect the moving background objects as foreground, to avoid that optical flow method is used.

The cluster based techniques are also used for foreground extraction. Clustering algorithms label the unlabeled data, based on the similarity measure between the data patterns. There are two types of clustering. They are hierarchical and partition clustering. The hierarchical clustering is considered as non-parameterized clustering and it is further divided into agglomerative and divisive. Agglomerative based clustering, at first takes N single point clusters and merge clusters to become larger and larger. There are three types of agglomerative clustering i) single-link algorithm [8] ii) complete-link algorithm [8] and iii) minimum-variance algorithm [8]. Divisive clustering splits the entire dataset into a single point cluster. It is a reverse process of agglomerative clustering. The partition based clustering is considered as parameterized clustering. It uses an iterative optimization technique to minimize the

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objective function. The commonly used parameterized clustering is k-means clustering, which is the most popular and easily used clustering algorithm. The clustering process includes characteristic representation, similarity measurement, collecting data points, data abstraction and output validation. K-means is the simplest unsupervised learning algorithm. It follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed as a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other [9].The other clustering method is the one based on learning a mixture of Gaussians[10],[11][12]: clusters consider as Gaussian distributions. The Expectation-Maximization algorithm which is used in practice to find the mixture of Gaussians that can model the data. The Fuzzy C-Means is soft clustering . It clusters the data based on the membership value . The main difference between fuzzy clustering and other clustering techniques is that it generates fuzzy partitions. The main advantage of this method is, identifying the pixel membership in each cluster to segment the overlapped objects accurately [9]. All the partition based clustering needs number of centroids as a parameter. The number of centroids can be detected using many ways one of them is histogram.The image is compressed to reduce the memory by using Bit-Plane slicing. Bit-Plane slicing is a technique in which image is sliced at different planes. It bit level ranges from 0(LSB) to 7(MSB).

2. RELATED WORKS

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. The conventional foreground extraction techniques are background subtraction [13], temporal differencing [5] and optical flow [7]. Background subtraction [3] 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 [3],[14] uses pixel-wise difference between two or more consecutive frames in an image to detect the moving regions. It is adaptive to dynamic environments. Optical flow based motion detection uses characteristics of flow vectors of moving objects over time to detect moving regions in an image sequence. Background subtraction 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. Olivier Barnich and Marc Van Droogenbroeck [2] proposed a universal background subtraction technique. Rita Cucchiara, Massimo Piccardi and Andrea Prati [4] proposed a method to identify the moving object with high accuracy and low false negatives.Mandar Kulkarni [9] proposed a technique for the foreground extraction that, the spatial histogram of a single background image is modeled as a Gaussian mixture model. To extract the foreground, input frames are compared with current background model and the foreground pixels are classified according to the intensity differences. To mitigate errors caused due to the movement of the background objects, the optical flow method is used. The paper [9, 14] uses optical flow for foreground extraction.

2.1 Lab Color Space

Color space defined by CIE, based on one channel for Luminance (L) and other two color channels for **a*** and **b***. The ‘a*’ axis is green at one extremity (represented by -a), and red at the other (+a). The b* axis have blue at one end (-b), and yellow (+b) at the other. Lab color space is much more intuitive than RGB. The LAB color space is also the "device independent" color space. In this model the color differences which correspond to the distance when measured calorimetrically. The ‘a’ axis extend from green (-a) to red (+a) and the b axis from blue to yellow (+b).The brightness increases from the bottom to the top of the three dimensional model. The luminance ranges from 0 to 100, the A component ranges from green to red and the B component ranges from blue to yellow. By means of this model we can handle color regardless of specific devices. This color space is better suited to many digital image manipulations than the RGB space, which is typically used in image editing programs. For example, the Lab space is useful for sharpening images and the removing artifacts in JPEG images or images from digital cameras and scanners.

2.2 Histogram

The histogram is the basis for numerous spatial domain processing techniques [11]. The histogram of the digital image is calculated using the following discrete function:

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$$H(r)_k = n_k \quad (1)$$

Where, r_k the k^{th} intensity value

n_k - is the number of pixels in the image with intensity r_k (k ranges from 0 to L-1).
The normalized histogram is given by

$$P(r_k) = n_k/MN \quad (2)$$

Where, M is the total number of rows in the image. N is the total number of columns in the image. K ranges from 0 to L -1.

2.3 Bit-Plane Slicing

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 bit usually contains most of the significant visual information. A lower order bits contain subtle details. It is the lossy compression technique which makes less storage space than the JPEG compression. The steps in implementing the bit-plane slicing:

i) Take the input image.
ii) Convert the color image to the gray level image.
iii) Generate the resultant k bit level image based on the level of bit plane.

2.4 Fuzzy C-Means

Fuzzy clustering, otherwise known as soft clustering. Fuzzy C-Means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This is frequently used in pattern recognition. It is based on minimization of the following objective function. This clustering method allows each pattern to be assigned to multiple clusters. This algorithm updates the cluster centroids iteratively.

2.5 Optical Flow

Optical flow [7],[15] is an approximation of the local image motion based upon local derivatives in a given sequence of images. That is, in 2D it specifies how much each image pixel moves between adjacent images. Thus the computation of deferential optical flow is, essentially, a two-step procedure:

1. Measure the spatial-temporal intensity derivatives (which is equivalent to measuring the velocities normal to the local intensity structures)

2. Integrate normal velocities into full velocity, for example, either locally via a least squares calculation or globally via regularization.

The optical flow is used to eliminate the errors caused due to the movement of background objects such as tree leaves, etc. The optical flow algorithms are classified into four approaches. They are gradient, phase, region and feature based methods.The gradient based method is also known as differential methods. There are three gradients based methods: Lucas–Kanade, Horn and Schunck and Proesmans. The phase based method finds the velocity of motion using a band - pass filter. Region based method calculates the flow vector by using the displacement of the pixel between two consecutive frames. There are two regions based methods. They are i) difference and ii) correlation. Feature matching based methods calculates the flow vectors by measuring the displacement of image features. The two features based methods are Harris and Scale Invariant Feature Transform (SIFT).

3. PROPOSED METHODOLOGY

The proposed method is concerned with static camera video images. The techniques used in this system are a CIELAB color model, histogram, Fuzzy C-Means with Bit-Plane Slicing and Optical Flow. The main purpose of the FCMBPSOF foreground extraction method is to present a fast algorithm with a less memory utilization towards other algorithms. The proposed algorithm is given below:

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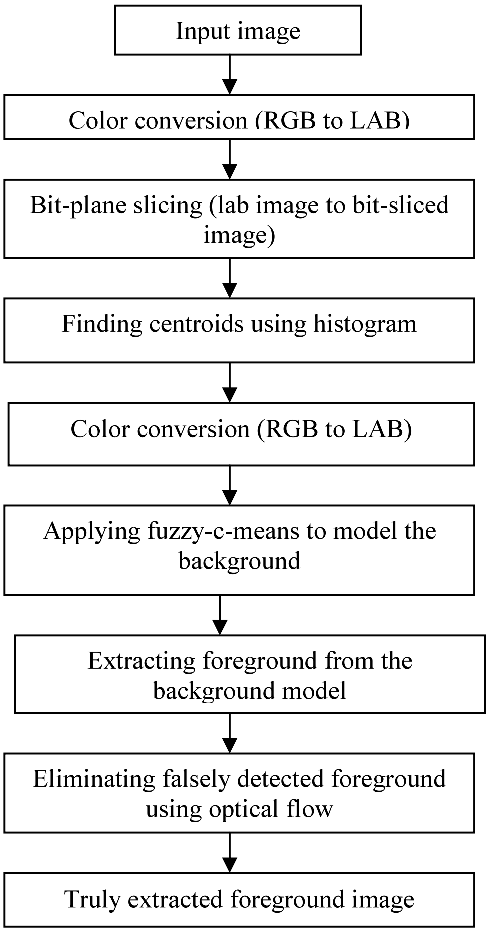

3.1 Color Conversion:

In this system the RGB color space is converted to the lab color space. The RGB color is device dependent. And so for efficiently processing the image, the RGB image is converted to the Lab color space. The Lab color model is derived from CIEXYZ color space and it is device independent. The RGB image is not directly converted to Lab color model, first the image RGB is converted to XYZ color space and then to Lab color model.

3.2 Bit-plane Slicing:

The Bit-plane slicing technique[16] is applied to the lab color image. This technique reduces the memory space. Here, only the most significant bits are taken for the further processing and by eliminating the processing and storage of other bits.

$$BPI_k(i,j) = R\left(\frac{1}{2}\, floor\left[\frac{1}{2^k}\right] I(i,j)\right) \quad (3)$$

where, I – original image.

BPI_k - Bit-plane information for the bit k.R-Remainder.

3.3 Foreground Extraction (Fuzzy-c-means):

The spatial histogram is applied to the binary sliced image to find the centroids. The background image is modeled using Fuzzy C means algorithms with the centroids as input.

$$j_p = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{p}\left\|x_i - c_j\right\|^2 \quad (4)$$

$$c_j = \frac{\sum_{i=1}^{n} u_{ij}^{p}\cdot x_i}{\sum_{i=1}^{n} u_{ij}^{p}} \quad (5)$$

where, p is a real number greater than 1. u_{ij} is the degree of membership of x_i in the cluster j, x_i is the i^{th} of d-dimensional measured data, c_j is the d-dimension center of the cluster.

$$u_{ij} = 1 \Big/ \sum_{k=1}^{c}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{2/p-1} \quad (6)$$

Then the foreground extraction is done by comparing each input frame I with the current background frame. The background frame is modeled at regular interval of time to incorporate the changes in the environment.Foreground is extracted using the equation below

$$F(x, y) = 255, \text{ if}[(I(x, y) - M(x, y)) > T)$$

$$F(x, y) = 0, \quad \text{otherwise} \quad (7)$$

where, M- background frame,I-current frame, T – threshold value to detect the foreground object. The threshold of the outdoor video image may 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 ranges from12 to 15.

3.4 Optical Flow

The gradient [15] based Horn and Schunck optical flow is applied to the foreground extracted image to eliminate the errors caused due to the movement of the background object like tree

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leaves, flags, electrical wires hanging on the road, etc. If optical flow has not applied, then the above movements are considered as foreground objects.

$$I(x+u, y+v) = I(x,y) + \frac{\partial I}{\partial t}u + \frac{\partial I}{\partial t}v \qquad (8)$$

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

Where, ∂I/∂x and ∂I/∂y are the derivatives of x and y coordinates of the pixel position in an image. u and v are the velocities with respect to x and y direction.

4. 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 foreground extraction results obtained using proposed algorithm is better than the previous algorithms with respect to memory consumption and better object extraction. The memory mentioned in the table (table-1) includes data memory and processing memory for each technique.

4.1 Figures

4.1.1 Run

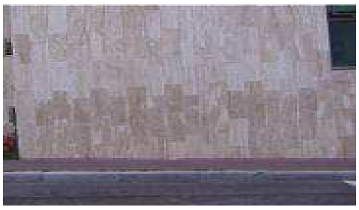

Figure 1. Background Frame

Figure 2. Current Frame

Figure 3. GMM

Figure 4. K-Means

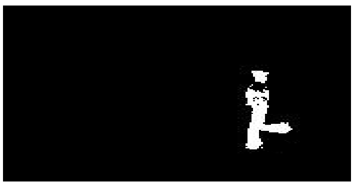

Figure 5. FCM

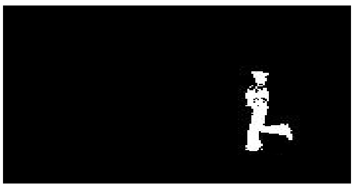

Figure 6. FCMBPSOF

Figure7. FCMBPSOF

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4.1.2 Jump

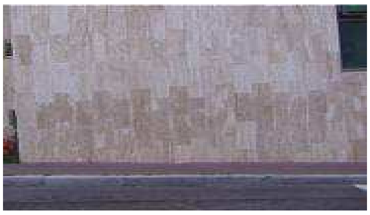

Figure 8.Background Frame

Figure 9. Current Frame

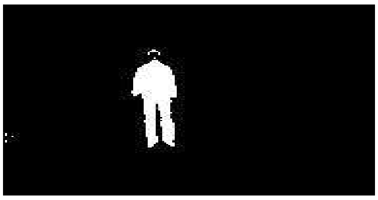

Figure 10. GMM

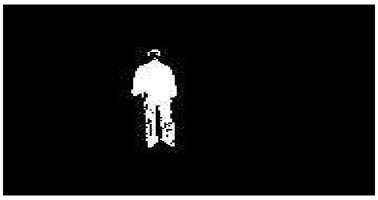

Figure 11. K-Means

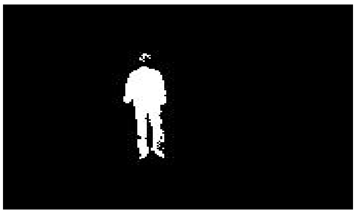

Figure 12. FCM

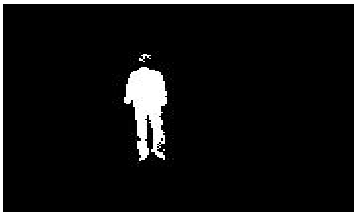

Figure 13. FCMOF

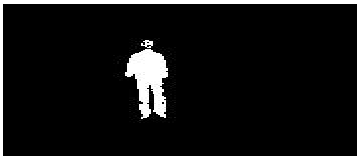

Figure.14. FCMBPSOF

4.2 Evaluation Methods

Segmentation is the initial process in the foreground extraction, so the quality of the segmentation is evaluated first. If the segmentation yields good results, then only the further processing steps in foreground extraction give the perfect result. If the segmentation evaluation fails to give the best results, then obviously the further processing tends to fail.

For appropriate performance evaluation of the proposed system should contain the following to be performed in the step by step manner

1) Segmentation based evaluation
2) Clustering based evaluation
3) Foreground Extraction based evaluation

The segmentation evaluation methods are PSNR, $\bar{J}$ and Goodness value .The clustering evaluation methods consist of Fuzziness in partition matrix U, Fukuyama-sugeno index and Xie-Beni index. The foreground extraction evaluation methods are Recall, Precision and F-measure. At last the whole system performance is evaluated by the execution time and the memory consumption.

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4.2.1 Segmentation Evaluation Methods

The PSNR [17] is calculated by the following function:

PSNR= 10 * log10 (256^2 /MSE) (9)

where, MSE is the Mean Squared Error. The higher value of PSNR indicates the good segmentation. The goodness function [15is given by the following equation:

$$F(I) = \sqrt{M} \times \sum_{i=1}^{n} e_i^2 \Big/ \sqrt{A} \qquad (10)$$

where, I is the image to be segmented, M is the number of regions in the segmented image, A_i is the area or i th region number of pixels and e_i he sum of the Euclidean distance of the color Vectors between the original image and the segmented image of each pixel in the region. The smaller the value of F gives the better segmentation.

The $\overline{J}$ Value [2] is used as the criterion to estimate the performance of the segmented region.

$$\overline{J} = \frac{1}{N} \sum_k M_k J_k \quad (11)$$

where, J_k is J computed over the region k, 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.

4.2.2 Clustering Evaluation Methods

Clustering evaluation is performed by means of special indexes called clustering validity indexes. The clustering validity indexes are

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

4.2.2.1 Fuzziness in partition matrix U

There are two methods to measure the fuzziness degree.

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

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

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

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

4.2.2.2 Fukuyama-sugeno index

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

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

$$\bar{v} = \frac{1}{M}\sum_{k=1}^{M} x_k \qquad (15)$$

where, M – Number of data items
c- Number of clusters and
μ_{ik} – Membership degree
v_i –cluster centers
x- data
V-mean value of the data

4.2.2.3 Xie-Beni index

This index is given by the formula

$$I_4 = \frac{\sum_{i=1}^{c}\sum_{k=1}^{M}\left(\mu_{ik}^m\right)\|x_k - v_i\|^2}{M\left(\min_{i,j}\{\|v_i - v_j\|^2\}\right)} \qquad (16)$$

where, M – Number of data items
c- Number of clusters and
μ_{ik} – Membership degree
V–cluster centers
x- Data

The minimum value of this gives good result of clustering.

4.2.3 Foreground Extraction Evaluation Methods

The recall, precision and F-measure [16] are the three methods which is used to evaluate the performance of the foreground extraction. Recall is defined as the ratio of the assigned foreground pixels (AFP) to the true foreground pixels (TFP).

Recall=AFP/TFP (17)

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

Precision=TFP/AFP (18)

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

$$\text{F-measure}=\frac{2pr}{p+r} \quad (19)$$

where, p - precision and r - recall. High recall, high precision and high F-measure shows the high performance of the proposed system.

Finally the system is evaluated based on execution time and memory consumption. The execution time and the memory required for the proposed system are less when compared to GMM and K-means.

4.3 Complexity Analysis of FCMBPSOF Method

The time complexity of our algorithm depends on following parameters
- m- value of fuzzifier
- n - Number of data points (mXn)
- d - Number of dimensions (2)
- c - Number of clusters

This proposed algorithm takes $O(n^4)$ polynomial time.

4.4 Tables

Table 1: Result for the Evaluation Methods of Segmentation

S. No	Image	Methods	Execution time (Milliseconds)	Memory used (Bytes)	Good -ness Function	$\bar{J}$	PSNR (db)
1	Run	GMM	0.603250	3.924e+008	2.0984	0.7276	38.5143
		K-means	0.456786	4.543e+008	2.6598	0.6596	38.5118
		FCM	0.468675	4.945e+008	2.2833	0.6743	38.5287
		FCMOF	0.481859	3.902e+008	1.2805	0.6521	38.5451
		Proposed method(FCMBPSOF)	0.481246	2.225e+008	1.2547	0.6673	38.5878
2	Jump	GMM	0.455311	3.967e+008	2.6812	0.8946	38.5567
		K-means	0.407613	4.326e+008	2.9055	0.6559	38.5245
		FCM	0.439564	4.747e+008	23486	0.6896	38.5158
		FCMOF	0.398986	3.789e+008	1.8430	0.5924	38.5742
		Proposed method(FCMBPSOF)	0.37665	2.456e+008	1.8430	0.5924	38.5742

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Table 2: Result for the Evaluation Methods of Clustering

S. No	Image	Methods	I_1	I_2	I_3	I_4
1	Run	GMM	0.4366	0.4948	0.7387	0.6390
		K-means	0.4567	0.4408	0.7947	0.6628
		FCM	0.6457	0.4877	0.4980	0.4855
		FCMOF	0.6457	0.4877	0.4980	0.4855
		Proposed method(FCMBPSOF)	0.7324	0.2397	0.3767	0.2634
2	Jump	GMM	0.4822	0.4908	0.4767	0.7365
		K-means	0.4349	0.4635	0.5476	0.7655
		FCM	0.7654	0.1765	0.4687	0.3566
		FCMOF	0.7654	0.1765	0.4687	0.3566
		Proposed method(FCMBPSOF)	0.8163	0.0946	0.3645	0.2025

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Table 3: Result for the Evaluation Methods of Foreground Extraction

S. no	Image	Methods	Recall	Precision	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
		Proposed method(FCMBPSOF)	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
		Proposed method(FCMBPSOF)	0.8579	0.9773	0.9078

5. CONCLUSION AND FUTURE ENHANCEMENTS

The proposed system uses Fuzzy C-Means for foreground extraction, the Bit-plane slicing to reduce the memory space and optical flow for eliminating false foreground pixels. It takes less memory and less execution time when compared with other methods. The performance is evaluated using recall, precision, F-measure and four clustering index functions. In future GPU is used to speed up the process to handle real time video images and the membership constraint in the fuzzy clustering will be eliminated.

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