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A NOVEL FUZZY BASED BACKGROUND SUBTRACTION FOR DYNAMIC SCENES

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ABSTRACT

Detection of moving objects in video streams is the initial relevant step of knowledge in several computer vision applications. Background Subtraction is widely used as the basis for moving object extraction and tracking in video sequences. For this, most of previous strategies rely on the idea that the background is static over short period of time. On the other hand, video sequences with dynamic background such as waving leaves, rippling water are not easy to process and it leads to poor extraction of foreground objects. In this paper, a completely unique thin Background Subtraction algorithmic program for scenes with dynamic background is planned to solve this drawback, which uses fuzzy color histogram in which Fuzzy C Means Clustering (FCM) module is based on correlation method and this can also be applied to medical image applications. Experimental results give substantiating proof that the proposed technique is effective for Background Subtraction to track the moving object in Dynamic texture scenes.

Keywords: *Background Subtraction (BS), Clustering-based feature, Fuzzy C Means Clustering (FCM), Fuzzy Color Histogram (FCH), Image Segmentation, Pixel Classification.*

1. INTRODUCTION

Background Subtraction (BS) is widely used approach for detecting moving objects of interest in video sequences in diverse applications including remote sensing, surveillance, diagnosis in medical field and underwater sensing. As a basic, the background must be a representation of the scene with no moving objects and must be kept regularly updated so as to adapt the varying luminance conditions and geometry settings.

Nowadays several approaches are on hand to detect, segment and track objects automatically in video sequences. Basic motion detection algorithms compare a static background with the current frame of a video scene pixel by pixel. The underlying principal in BS is to create a background model and compares this model with current frame to detect area where considerable variation occurs. In a nutshell, the intend of the Background Subtraction is to tell apart foreground moving object(s) from background. In practical situations background could contain stationary objects, moving objects like trees jolted by the wind, fumes and waves on the water, etc. In addition to that if a static object starts moving; background subtraction algorithmic program detects the item in motion. Static background model could be applicable for brief video sequences and indoor sequences, however is ineffective for most of the practical situations. Objective of this paper is to present a novel algorithm using clustering based feature with fuzzy color histogram to extract foreground moving object from a video with dynamic background ion nature.

The remainder of the paper is organized as follows: Section 2 discusses our proposed method. Experimental results achieved with our method are given in section 3 and their performance evaluations are in section 4. Discussions on our results are given in section5. Conclusive remarks square measure addressed at the tip of this paper

In general authors in most of the background techniques considered that the video sequence is made up of a fixed background B in front of which moving objects are observed. The main difference between existing BS methods lies in initialization procedure for background model, model behavior and the method used to update the model over time. Also background subtraction technique must be adaptable to incorporate changes in the background geometry, illumination variations, and motion changes [1]. A.Mclvor *et al.* [2] extract foreground objects by comparing the experimental image with an estimated image that does not contain any object of interest and this process results in two

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complementary sets in which the first set consists of foreground pixels and second set consists of background pixels. V.Kamatchi sundari *et al.* [3] proposed a technique to subtract the background objects and to extract the foreground details based on the assumption that that the background in the video sequence is static one and not dynamic in nature. V. Mahadevan *et al.* [4] discussed a spatio-temporal saliency algorithm especially for highly dynamic background. Pixel-based background subtraction techniques are proposed by El Maadi *et al.* [5] and R. Abbott *et al.* [6] with which lack of spatial consistency is compensated by constantly updating the model parameters. Seiki *et al.* [7] described a method based upon the assumption that neighboring blocks of background pixels should follow similar variations over time. This assumption suits for pixels belonging to the same background object, and not for pixels located at the border of multiple background objects. A solution to this problem is PCA and PCA reconstruction error is discussed by N. Oliver *et al.* [8].

A method for properly initializing a Gaussian background model from a video sequence in which moving objects are present is proposed by D. Gutchess *et al.* [9]. A. B. Chan *et al.* [10] had done his work by assuming that pixel's state change is due to noise and not from structured motion patterns. G. Dalley *et al.* [11] combined the relation between neighboring pixels in background likelihood estimation with the compactness of a semi-parametric MoG representation for classification of dynamic textures. Stauffer and Grimson *et al.* [12] discussed the most popular pixel level algorithm named as Gaussian Mixture Model (GMM) in which the distribution of each pixel value is considered as a Mixture of Gaussians (MoG), and then classified them into either background pixel or not. S.Zhang *et al* [13] proposed the spatiotemporal local binary pattern (STLBP) to model dynamic textures. S.Zhang *et al* [14] defined a covariance descriptor based on various spatial and texture features which is used to efficiently suppress dynamic textures in the background and eigenvalue-based distance metric is used to update the background model In a fixed threshold method moving object can be detected with (1)

$$D_k(x,y) = \begin{cases} 1 \; |Fk(x,y) - Bk - 1(x,y)| > T \\ 0 \; others \end{cases} \quad (1)$$

Where $F_k(x,y)$ is current frame , $B_{k-1}(x,y)$ is previous frame ,$D_k(x,y)$ is difference and T is value of fixed threshold. This method works well for ideal situations and not suitable for complex environments. This issue is solved by dynamic thresholding (Anastasios Dimou, Olivia Nemethova and Markus Rupp *et al* [15]) in which threshold value is T+ΔT and its mathematical expressions are

$$\Delta T = \lambda \frac{1}{MxN} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} |F(i,j) - B(i,j)| \quad (2)$$

$$D_k(x,y) = \begin{cases} 1 \; |Fk(x,y) - Bk - 1(x,y)| > T + \Delta T \\ 0 \; others \end{cases} \quad (3)$$

J. Han dynasty *et al* [16] introduced a completely unique descriptor on representing color pictures, known as fuzzy color bar chart (FCH), by considering the color resemblance of every pixel's color. Wonjun Kim *et al* [17] proposed a method based on Euclidean distance to track objects. Li L *et al* [18] proposed a statistical based model to detect foreground objects in complex background.

2. PROPOSED METHOD

Let $P(x_j)$ is the probability of color features selected from a given image. Let $P(w_i|x_j)$ be the degree of fitness for color options of the jth picture element to the ith color bin in FCH and N be the overall range of pixels. The conditional probability $P(w_i|x_j)$ value is 1 if the color feature of the selected jth pixel is quantized into the ith color bin and 0 otherwise The likelihood for pixels within the image belongs to the ith color bin is outlined as

$$1/N \sum_{j=1}^{N} P(wi\,|xj) \quad (4)$$

Next step is to calculate the membership value for that color quantization has been done within which initial RGB color area is uniformly and finely quantized into m histogram bins and then convert them into CIE Lab color space. Then these m colors are classified into c clusters. By conducting correlation based FCM clustering, membership values of a given picture element to FCH bins is obtained. Cluster center c_j and membership values u_{ij} are calculated [19] with (5) and (6) respectively

$$C_j^{(t)} = \left\{ \frac{\sum_{i=1}^{N} (u_{ij}^{[t-1]})^m x_i}{\sum_{i=1}^{N} (u_{ij}^{[t-1]})^m}; \quad j = 1,2 \ldots C \right. \quad (5)$$

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$$u_{ij}^{(t)} = 1 \Big/ \left(\sum_{k=1}^{C} \left[{d_{ij}^{(t)}} \Big/ {d_{ik}^{(t)}} \right]^{\frac{2}{(m-1)}} \right) \qquad (6)$$

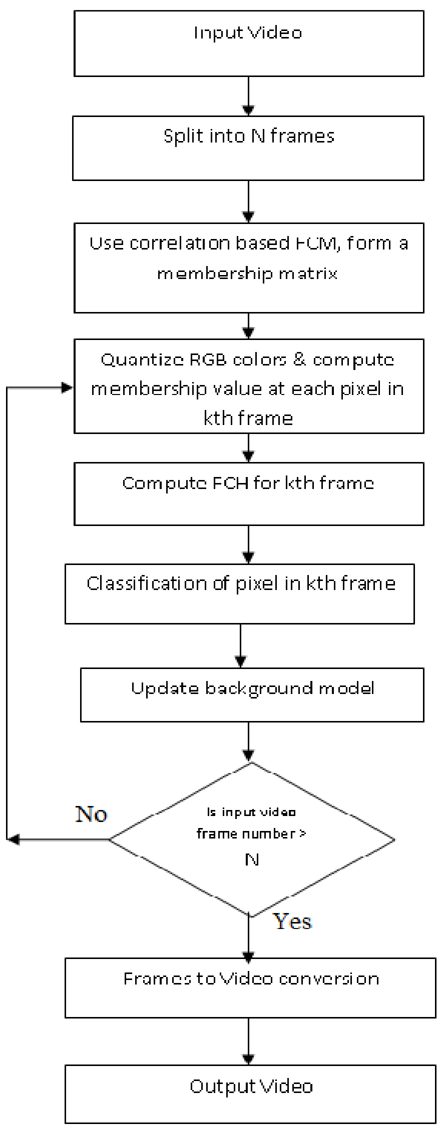

Figure 1: Flowchart of Our Proposed Method

Figure 1 shown above represents the flowchart of our proposed method.

Membership matrix is created with these membership values so that FCH can be easily built for all video frames. Local FCH vector value at the pixel position j for the frame k can easily be obtained by

$$E_j(k) = (f^k_{j,1}, f^k_{j,2} \ldots\ldots, f^k_{j,c}) \quad \&$$

$$f^k_{j,l} = \sum_{q \in w^k_j} u_{iq} \qquad (7)$$

where w^k_j denotes the set of neighboring pixels centered at ith position and u_{ij} denotes the membership value using (6) and background model can be built by using (7).

Compare the observed FCH vector with model FCH vector using (8) to categorize whether a given pixel belongs to background or not,

$$B_j(k) = \begin{cases} 1, & \text{if } S(E_j(k), \hat{E}_j(k)) > \tau \\ 0 & \text{Otherwise.} \end{cases} \qquad (8)$$

In videos with dynamic background, background model should be updated at each pixel position by

$$\hat{E}_j(k) = (1-\alpha).\ \hat{E}_j(k-1) + \alpha.\ E_j(k) \qquad (9)$$

Where α is learning rate whose value lies between 0 and 1. This process has been done for all frames and finally converts all the segmented frames into video in which the foreground moving object has been extracted and tracked successfully.

3. RESULTS

This algorithmic program is enforced in MATLAB R2010a. Several video sequences have been tested with our algorithm. Results obtained for water surface video sequence in which man is walking from left to right with water waves in the background that is dynamic in nature is given below.

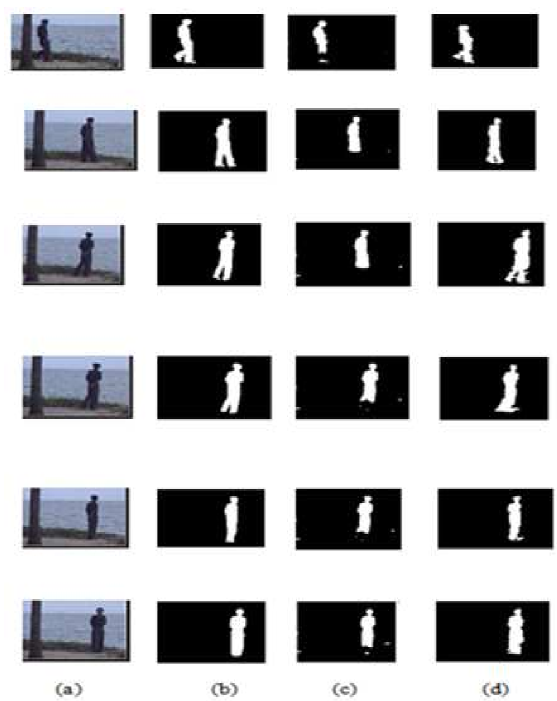

Figure 2: Experimental results with water surface sequences. Column (a) are original input video frames 20,76,96,97, 113 and 132 Column (b) are Ground truth

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frames and column (c) results using dynamic threshold optimization method and Column (d) are results obtained by proposed method.

Performance evaluation has been done by using the corresponding ground truth value obtained from the internet. Ground truth can be defined as reference point or baseline data to determine the actual path of a tracked object which is available for selected frames in the website https://sites.google.com/site/backgroundsubtraction/test-sequences.

4. PERFORMANCE EVALUATION

In performance evaluation each pixel in the output can be classified as True Positive (TP) for a correctly detected foreground pixel; False Positive (FP) for a background pixel incorrectly detected as foreground pixel; True Negative (TN) for a correctly detected background pixel and False Negative (FN) for a foreground pixel incorrectly detected as background pixel. Metrics such as sensitivity and specificity are statistical measure of the performance of binary classification test. These two metrics provide a objective measure for the correctness of the tracking methodology that is being evaluated with respect to ground truth and they are closely associated to type I , type II errors. The values of TP, TN, FP and FN are tabulated in table.1. and table.2. shows the several performance parameters calculated with our proposed method for water surface sequence.

Table 1: Values of TP, TN, FP and FN for water surface sequence.

Frame No	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)
19	14847	14049	1045	492
35	14629	13859	1229	526
43	14260	13681	1449	675
67	14797	14111	1121	466
68	14781	14147	1088	515
73	14701	13917	1212	471
79	14500	13731	1228	656
95	15055	13881	1026	303
114	14828	14207	1023	533
125	14454	13839	1332	598
135	14679	13885	1120	585

Sensitivity can be calculated using (10) and a test with high sensitivity value has low type II error rate.

Sensitivity =
Total number of TP/(Total number of TN + Total number of FN) (10)

Specificity can be calculated using (11) and a test with high specificity has low type I error rate.

Specificity =
Total number of TN / (Total number of TN + Total number of FP) (11)

Frame No	Specificity	Accuracy	Sensitivity	RMSE	PSNR	Precision
19	93.0767	94.9496	96.7925	0..306286	53.2695	93.4244
35	91.8545	94.197	96.5292	0.327287	52.9815	92.25
43	90.423	92.9353	95.4804	0.360054	52.5671	90.776
67	92.6405	94.7959	96.9469	0.311228	53.2	92.9577
68	92.8585	94.7496	96.6331	0.312793	53.1782	93.1439
73	91.9889	94.4457	96.8956	0.320503	53.0725	92.3836
79	91.7909	93.744	95.6717	0.339102	52.8275	92.1923
95	93.1173	95.6088	98.0271	0.284808	53.5853	93.6198
114	93.283	94.9135	96.5302	0.308173	53.2429	93.5461
125	91.2201	93.6141	96.0271	0.34327	52.7751	91.5621
135	92.5358	94.3672	96.1675	0.32259	53.0443	92.9109
144	90.8484	93.0296	95.182	0.35639	52.6115	91.3346

Table 2: Performance Parameters for Water Surface Sequence with Our Proposed Method.

Figure 3 and figure 4 shows TP, TN and FP, FN values respectively for selected frames which were based on the availability of ground truth value in the internet.

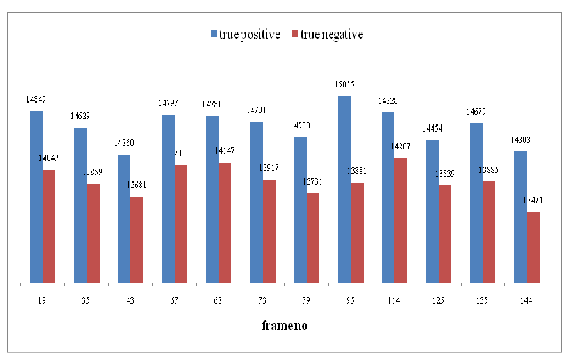

Figure 3: Results Of True Positive and True Negative On Water Surface Sequence.

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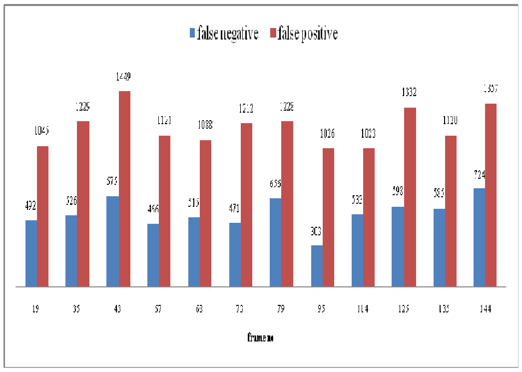

Figure 4: Results Of False Positive and False Negative On Water Surface Sequence.

Two well- best-known objective image quality metrics square measure Root Mean square Error (RMSE) and Peak Signal to Noise Ratio (PSNR). RMSE is often used to measure the difference between the values predicted by the model and the actual values. The table given below compares the RMSE values obtained for DTH technique with our proposed technique. Lower the RMSE worth shows the better result.

Table 3: Comparison of RMSE Values Obtained By Our Method with DTH Method.

Frame no	RMSE Values	
	DTH method	Proposed method
19	56.4365	0.306286
35	58..0027	0.327287
43	58.7704	0.360054
67	55.4342	0.311228
68	55.3796	0.312793
73	57.9143	0.320503
79	60.5427	0.339102
95	64.0567	0.284808
114	58.218	0.308173
125	62.395	0.34327
135	66.3208	0.32259
144	69.412	0.35639

The table given below compares the PSNR values obtained for DTH method with our proposed method and higher PSNR value shows better image quality in our result.

Table 4: Comparison of PSNR Values Obtained By Our Method with DTH Method.

Frame no	PSNRValues	
	DTH method	Proposed method
19	30.6152	53.2695
35	30.4963	52.9815
43	30.4392	52.5671
67	30.693	53.2
68	30.6973	53.1782
73	30.5029	53.0725
79	30.3102	52.8275
95	30.0652	53.5853
114	30.4802	53.2429
125	30.1793	52.7751
135	29.9143	53.0443
144	29.7334	52.6115

Specificity measures the proportion of negatives that are correctly identified. Specificity can be calculated using (11) and a test with high specificity has low type I error rate. The bar chart given below compares the specificity value of our method with DTH and it indicates low specificity value obtained with our method.

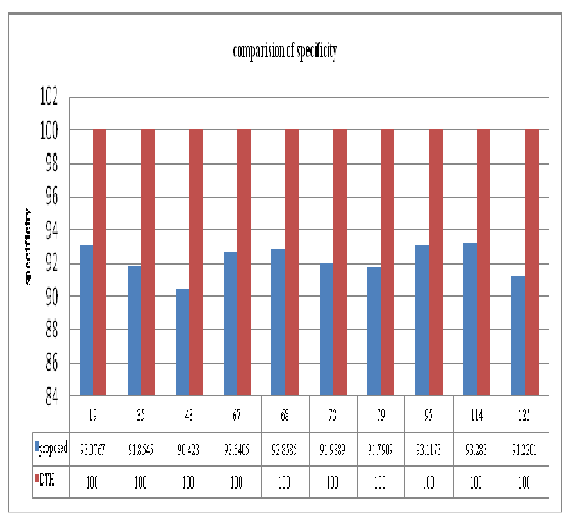

Figure 5: Comparison Results of Specificity Values Using Dynamic Thresholding (DTH) Method and Proposed Method.

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Sensitivity measures the proportion of actual positives that are correctly recognized. Sensitivity can be calculated using (10) and a test with high sensitivity value has low type II error rate. The bar chart given below compares the sensitivity value of our method with DTH and it shows that our method generates high sensitivity value.

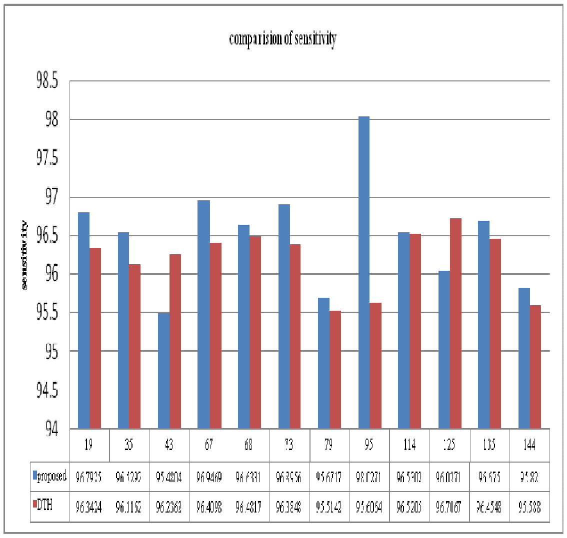

Figure 6: Comparison Results of Sensitivity Values Using Dynamic Thresholding (DTH) Method and Proposed Method.

4. DISCUSSION ON RESULTS

Many different metrics can be used to assess the output of a background subtraction algorithm given a series of ground truth values. These metrics typically engage True Positive, True Negative, False Positive, and False Negative. Our algorithm has produced high values of TP & TN which indicates the number of correctly classified foreground pixels and background pixels respectively. Besides, our algorithm has produced a smaller amount of incorrect classification given by FP &FN. High values of TP & TN shows correct classification by our algorithm. In addition to that high sensitivity values indicate lower value of type II error. We have calculated two well- best-known objective image quality metrics such as square measure Root Mean Square Error (RMSE) and Peak Signal to Noise Ratio (PSNR). Lower RMSE values and Higher PSNR values indicate better image quality in our final results. From these computations, we observed that our method provides promising results.

5. CONCLUSION

A simple and new Background Subtraction algorithm for tracking the object in video sequences with Dynamic background has been proposed in this paper. The main idea behind this is to minimize color variations due to background motions by using FCH in a local manner and then perform background subtraction by comparing the model FCH features with observed values. The presented results show that the proposed algorithm provides the reliable background subtraction in video with dynamic background and also the successful tracking of the extracted foreground object. In this proposed work single foreground object is considered and tracked in the video and in future this work can be extended to track multiple objects in the given video.

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