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Object localization and Tracking Using Background Subtraction and Dual-Tree Complex Wavelet Transform

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Abstract*: As seen, the object localization is coupled to many vision applications such as tracking, activity recognition region, security concern, etc. Therefore, segmenting the region of interest to assert the best detection of the target in the sequence of frames is the primary aim of this research. This paper presents an algorithm that detects and tracks the moving object in complex video sequence using the background subtraction and wavelet transform. The work proposes an adaptive background model based on clustering method for regularizing the objection extraction phase. Afterward, it computes the energy of the moving mask using the wavelet coefficient and updates the position of the object by matching this energy to that of moving mask corresponding to next frame. The work also com-pares qualitative and quantitative performance of the proposed method with other existing state-of-the-arts motion detection methods.

***Index Terms*: Background subtraction, Wavelet transform, Object tracking, Fuzzy clustering.**

I. INTRODUCTION

In recent years, surveillance of object in the video sequences has been an active area of research due to security concern, supervision of traffic flow including security concern, collision prediction of pedestrians and many more. Since, many complex conditions arise in the scene, therefore still it is difficult to de-sign an automated system for object detection and tracking [1-2]. These difficulties arise due to local motion in the back-ground of scene, changing illumination condition, dim size of the target and many more. Some techniques have been pro-posed to locate the target in the scene but background subtraction is more reliable and efficiently applicable technique under the static camera condition. The optical flow used widely for the vehicles navigation, and object tracking. Since, the optical flow estimation provides more motion parameters of moving objects and most suited method to handle the occlusion and overlapping of objects [3]. Once the target localizes in the scene its feature can be easily extracted and utilized as an input for many post processing ap-plications. Background subtraction techniques requires the up-dating scheme of the reference background model so that a large surface of relevant pixels of the moving object can be achieved under varying condition in the scene [4]. The back-ground subtraction technique requires a proper selection process of threshold point so that the moving pixels could be separated efficiently from the background [5]. To do so, the clustering method is chosen that efficiently provides the threshold points in multimodal scenario of picture. The proposed method utilizes the Fuzzy C-mean clustering algorithm for threshold selection that helps to form the clusters for the available distinguished pixels in the background frame [6-7]. For the robust tracking, the feature of the target is extracted through the wavelet trans-form that represents the object suitably in space and frequency domain and reflects the singularity of the points [8]. Wavelet is a small wave whose average value is zero over a finite interval of time. The Wavelet transform represent any signal or function as a superposition of a set of such wavelets or basis functions.

The basis function is computed by dilations or contractions (scaling) and translations (shifts) from a prototype, which is often called mother wavelet. Among many wavelet function, the complex value extension of the discrete wavelet transform is the complex wavelet transform (CWT) [8-9]. Since the complex wavelet transform has the shift invariant feature which means that the spatial location of the pixels in transform domain and in spatial domain is identical. Moreover, it provides the better phase information about the candidates in the region of interest. The feature extracted through complex wavelet can be easily utilized in the recognition of dim and smaller object. The useful characteristics of this wavelet are that it provides multiresolution, sparse representation and information regarding the structure of the image. The approach is to find the motion mask in video frames using the background techniques. The work is divided in to two phase: first one is the object extraction and second is the object tracking phase. The background subtraction scheme requires a background model and an updating procedure for the initial background frame. Initially, the frame work registers the three reference background frame. The first reference frame is the normal background image in which the no object is moving, the other two reference background frame are registered by applying the 3-class Fuzzy C-mean clustering method. Later on, these background frames are updated with the help of threshold points detected using the Fuzzy C-mean clustering method. Afterward, the trajectory of the moving object is traced with help of blob detected through the background subtraction method and feature obtained from complex wavelet.

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Applying the wavelet, the magnitude of energy of moving blob is calculated using the approximate coefficient. In a while, the center of the trajectory is updated by considering the difference of energy between the two consecutive frames [4]. As this system is implemented on some complex video in a modular fashion with a step by step and the better detection rate is achieved over other existing object tracking methods. The rest of the pa-per is organized as follows; section II reviews some existing state-of-the-art object detection and tracking methods. Section III illustrates the proposed method of the object tracking and background modeling. Section IV represent the results through this work and section V concludes this paper.

II. LITERATURE REVIEW

Background subtraction plays a vital role in order to detect the interesting moving objects and tracking of such objects in the consecutives frame of video sequence. Some effective background subtraction method which assisted the object tracking are re-viewed in this section.

In Gaussian mixture model [10], the background and fore-ground pixel are separated by fitting the current frame in to one of the modelled Gaussian distribution model. Though, the method handles well the object detection in several complex condition, but fails to handle the detection task whenever the size of object is very small and the probability distribution be-tween foreground and background region is equivalent.

In [9], author utilizes the temporal difference of the wavelet coefficient of two consecutive frames to locate the object in the scene. Later on, it uses the median filtering to remove the noise from the foreground. The method gets difficulties to handle the object under sleeping mode condition.

The method [11] uses frame difference method to locate object in the scene by using adaptive background updating model. Later on, it uses the weighted centroid method in associate with kalman filter to predict the actual location of the target. However, frame difference method is fast and computationally efficient, but it affects the segmentation when moving object be-came stationary and creates hole inside the moving entity.

The spatial sample difference consensus is applied in [12] to get the precise moving area of the moving blob. The method acquired good result in intermittent object detection and handle effectively the aperture distortion while tracking the moving entities. Though, the method serves better to handle a very small object in scene, but has sluggish response to handle in abandon or sleeping mode condition.

In [13], authors address a multi-frames integration object detection technique which relies on time-domain and space-domain. The multi-frames integration techniques proposed an improved median selection process to reduce the background clutter. Though, the method provides better result against high frequency noise and illumination, but the extracted object has hollow space inside it.

In [7], authors used feature extraction technique to determine the motion based information and position. It utilized the simple background subtraction method to remove the common pixels from the scene using fixed threshold. Later on, an adaptive K-mean clustering method is applied to detect the relevant features on the foreground. Due to fixed thresholding and absence of background updating scheme, the method lacks on some challenging condition in scene.

The method [14] combines the background subtraction and K-mean clustering to detect and track the moving object in complex environment. It used Gaussian mixture model to remove the background pixels and produced good results against some complex condition such as objects occlusion, shadows and camera jitter. However, the use of Gaussian mixture model can be hurdle under condition when the foreground and background pixels have equal probability distribution.

In [15], authors constructed the background model by calculating the maximum value of probability distribution of each block. In order to, classify the background and foreground pixels it used the weighted variance and mean to get the threshold point. The method applied the traditional adaptive filter to update the background model and faced complexity in detection where the variance between foreground and background were equal.

The existing literatures reveal that background subtraction produces more suitable size of moving blob than corner or edges. One can also observe that whether the target is moving or in sleeping condition, it should be continuously detected. Some existing background subtraction schemes discussed in this paper lack of object handling when target become non-stationary as well as affected by aperture distortion. This happen due to lack of background up-dating and improper threshold value. Moreover, to handle the object tracking feature based method is effective under reduced size of blob and occlusion condition.

III. PROPOSED METHOD

This paper proposes a background subtraction based object localizing phase, afterward it deals the blob tracking by incorporating the feature extracted using wavelet transform. The background can have some quasi-stationary behaviour due to some sustained oscillation such as moving curtain, tree, wavering of water or fountain. In background subtraction phase, a background model is generated by using some initial frame of the video sequence. The initial frames should not contain any moving object. The object is localized by subtracting the current frame from the background model by using a suitable threshold value. The background subtraction method requires an updating stage of the reference background model that adapts the changes of environmental condition. Consider a video having the N frames such that $I_t(x,y)=\{I_1,I_2,I_3,\ldots\ldots\ldots I_{N-1}\}$. Using initial 'k' frame, the reference background $B_t(x,y)$ is computed by averaging all the frame.

A 3-class fuzzy C-mean clustering

The 3-class Fuzzy K-mean clustering is applied on the reference background model $B_t(x,y)$. The Fuzzy C-Means (FCM) arrange one piece of data in to two or more and produces a membership matrix.

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The Fuzzy C-mean clustering is justified by minimizing the sum of the square error, which is computed as:

$$SSE=\sum_{i=1}^{N}\sum_{j=1}^{C} Q_{ij}^{m}\left\|P_i\text{-}c_j\right\|^2 \qquad (1)$$

Where, 1<m<∞, the 'Q' the membership function, P_i is the 'i^{th}' pixel in 'j^{th}' cluster. The 'c_j' represents the center of 'j^{th}' cluster. The 'N' represents the number of pixel, while C is the number of cluster, which '3' in this paper.

Fuzzy clustering is carried out by optimizing iteratively the objective function given in equation (1) and for each iteration the membership 'Q_{ij}' and the cluster centers 'c_j' are updated using the equation (2 and 3).

$$Q_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\|x_i-c_j\|}{\|x_i-c_k\|}\right)^{\frac{2}{m-1}}} \qquad (2)$$

$$c_j = \frac{\sum_i^N Q_{ij}^m . x_i}{\sum_i^N Q_{ij}^m} \qquad (3)$$

To stop the process, the termination criteria is given by following equation where the value of 'ε' is kept between 0 to 1.

$$\mathbf{Max}\ ij\{\|Q_{ij}^{k+1} - Q_{ij}^{k}\|\} < \varepsilon \qquad (4)$$

The Fuzzy C-mean clustering method give three centres for three clusters. The first threshold value "L_1' is calculated by averaging the data which corresponds to large centre and the middle centre, however, the second level 'L_2' 'is calculated by averaging the data which corresponds to middle centre and the small centre.

L_1 = 0.5*(max ((y=large centre) + min ((y=middle centre))) (5)

L_2 = 0.5*(max ((y=middle centre) + min ((y=small centre))) (6)

Using the above equation, the two background image are registered $B_t^1(x,y)$ and $B_t^2(x,y)$. The block diagram of the proposed method is shown in Figure 1.

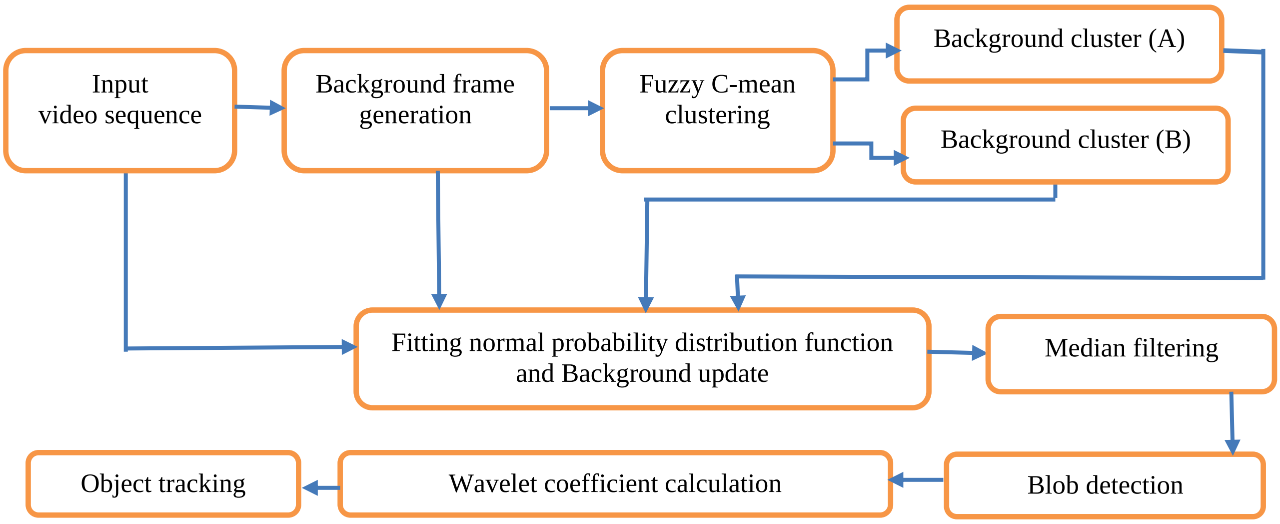

Fig.1: Block diagram of proposed method

B. Blob detection and background update stage

The incoming current frame of video sequence is fitted in normal probability distribution curve. The normal probability distribution function is a two-parameter family of curves. The normal probability distribution is given as follows:

$$f\left(\frac{x}{\mu},\sigma\right) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)} \qquad (7)$$

The first parameter 'μ' belongs to mean, while the second parameter 'σ' represents the standard deviation of the probability distribution function. Since, the framework contains three background frame $B_t(x,y)$, $B_t^1(x,y)$ and $B_t^2(x,y)$ respectively, therefore the function in equation (7) are fitted individually for all background frame.

The probability function decides whether the new intensity pixels fit into the background mode or not. Typically, in a fixed camera arrangement system, a majority of observed pixels in a video sequence belongs to background. Therefore, registered or clustered background models would account for much more remark than foreground pixels. In this paper, each background cluster is composed by individual normal distribution. The first blob is found by using the following equation:

$$M_t^A(x,y) = \left(f(I_t(x,y), B_t^1(x,y), \sigma) \cup f(I_t(x,y), B_t^2(x,y), \sigma)\right) \quad (8)$$

The second blob is detected as follows:

$$M_t^B(x,y) = f(I_t(x,y), B_t(x,y), \sigma) \qquad (9)$$

The final decision for the moving blob is taken by multiplying the above two blobs $M_t^A(x, y)$ and $M_t^B(x,y)$. The foreground may still contain some noisy pixels. Therefore, the median filter with 5×5 mask is applied to remove those noise from the detected blob. The median filter provides more actual information at particular location than mean filter. In this paper, the threshold level to separate out the moving pixels through normal distribution function is kept in between 0.001 to 0.004. The value of sigma(σ) is experimentally taken in between 4.8 to 5.5.

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Background update is necessary to adopt the environmental changes in the background model to remove the distortion in moving pixels due to ghost, trail, illumination and aperture effect. The background $B_t^1(x,y)$ and $B_t^2(x,y)$ are updated in this method using the following rule:

$$\begin{aligned} &if \min(B_t^1(x,y) < I_t(x,y) < L_1 \\ B_t^1 = \ &\{I_t(x,y), stationary\, pixels\} \\ &else \\ B_t^2 = &\{I_t(x,y), stationary\ pixels\} \end{aligned} \quad (10)$$

In order to fill the small gap in moving blobs and remove the spurious pixels from the foreground, one iteration of morphological operation is applied on the foreground mask.

C. Object tracking stage

The proposed technique uses dual-tree complex wavelet transforms to validate the actual centroid of the moving blob. When, the motion mask is detected on the foreground, a complex wavelet transform is applied to calculate the approximate coefficient of the moving entity. Since, the complex wavelet transform is shift invariant in nature and provide the phase information as well, therefore that helps to provide the rigid information and phase congruency of the moving mask object. The steps for tracking the object is given as follows:

(i) The approximate coefficient of the moving mask under a bounding box is extracted through the dual-tree complex wavelet.

(ii)The magnitude of energy under a bounding region which includes centroid is calculated as follows:

$$Energy = \sum_{k \in bounna\ direaion} f(i,j)^2 \quad (11)$$

Where f(i,j) represents the wavelet coefficient.

(iii) The centroid of the moving mask is updated by sensing the difference of energy between the consecutive frames.

(iv) The tolerance of energy difference between the consecutive frame ranging between 0 to 1.

(iv)If the object becomes stationary, then the searching window is reinitialized.

(v)The centroid will be updated if a match is found between current and previous magnitude of the extracted feature of the moving object.

The object tracking module is incorporated by calculating and updating the centroid of the object. Initially, the centroid is calculated that belongs to moving target. That target is reflected here by plotting a bounding box over an object. The region of the bounding box also includes the centroid as well. At each subsequent stage, the difference between the current position of centroid and previous centroid position is calculated using Euclidian distance formula. If the distance is above the threshold, the previous centroid is updated with the current centroid but the condition is that the energy through wavelet's approximate coefficient should have a certain level of magnitude. The current magnitude of approximate coefficient and the reference approximate coefficient through the complex wavelet transform is compared. If the difference magnitude is found within the threshold, then the current coordinate position of this match will be recent centroid position.

IV. RESULTS AND DISCUSSION

This paper proposes a background subtraction based object localizing phase, afterward it deals the blob tracking by incorporating the feature extracted using wavelet transform. The background can have some quasi-stationary behaviour due to some sustained oscillation such as moving curtain, tree, wavering of water or fountain. In background subtraction phase, a background model is generated by using some initial frame of the video sequence. The initial frames should not contain any moving object. The object is localized by subtracting the current frame from the background model by using a suitable threshold value. The background subtraction method requires an updating stage of the reference background model that adapts the changes of environmental condition. The visual inspection and quantitative analysis are demonstrated in this section on some complex video sequence. The videos are taken from change detection and PETS datasets. Some standard videos are namely IR, PEDSTRAIN, CURTAIN, HIGHWAY, and WATERSURFACE, which address some complex situation, while detecting the moving entity. The WATERSURFACE and CURTAIN sequence have some quasi-stationary characteristics in background. In these video, the object moves and became stationary for a long time. The moving target in IR and HIGHWAY videos is changing its aperture in the consecutive frames. The PEDSTRAIN video address the problem of changing illumination and varying speed of the moving object. Some factors such as aperture problem, ghost image, hollow space and sleeping object condition directly affect the shape and contour of the object. Moreover, if background is not modelled properly, it can lead to erroneous pixels on the foreground. The aperture effect arises when actual correspondence of the location of object mismatch in consecutives frames. The ghost image lead to a duplicate image of the object on the foreground. The Hollow space is creation of hole inside the moving entity, while the sleeping object is the condition when moving object becomes stationary in the scene. The section compares the results of the proposed method with some of existing background subtraction methods such as GMM [10], FD (frame difference) [11], and method [15]. One can observe that the proposed technique effectively suppresses the ghost image and eliminated the aperture distortion. Moreover, this method has better visual quality and shape retention capability than method [11], method [15] and GMM [10]. The 3-class C-means fuzzy clustering effectively made a foundation of reference background model. The reference model is adapted accordingly as discussed in previous section and removed the clutter from the background. The proposed background model removes the clutter that arises due to quasi-stationary condition in the background of WATERSURFACE AND CURTAIN video sequences.

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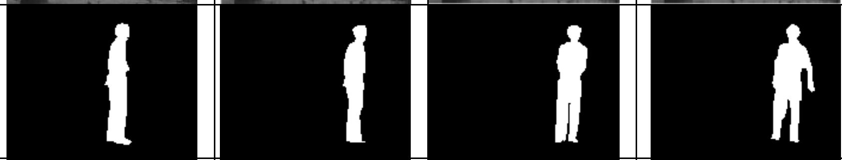
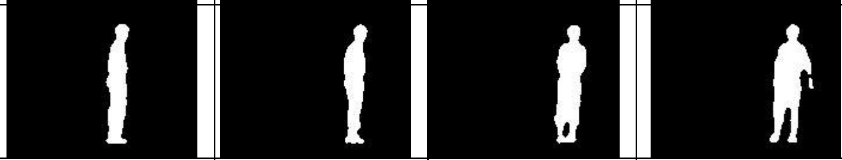
Frames with tracking result				
Ground truth				
Proposed method output				
	S-0.8869 F-0.9401	S-0.9234 F-0.9602	S-0.9004 F-0.9476	S-0.8922 F-0.9430

Fig.2: Output Binary motion mask of WATERSURFACE video with tracking performance and accuracy metrics S(similarity) and F(F-measure)

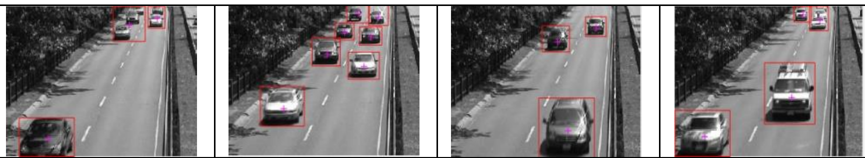
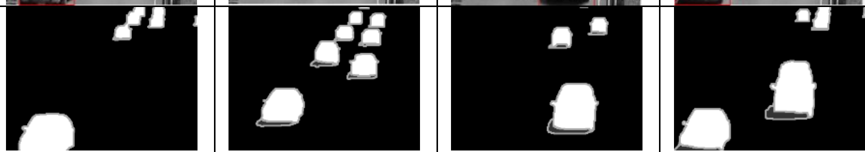
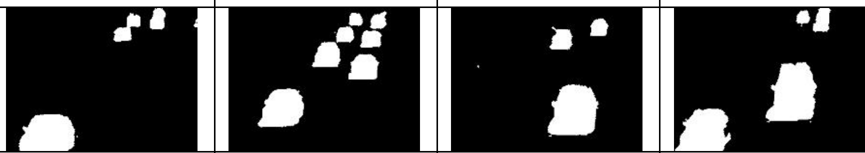
Frames with tracking result				
Ground truth				
Proposed method output				
	S-0.8780 F-0.9351	S-0.8724 F-0.9318	S-0.9059 F-0.9506	S-0.9080 F-0.9518

Fig.3: Output Binary motion mask of HIGHWAY video with tracking performance and accuracy metrics S(similarity) and F(F-measure)

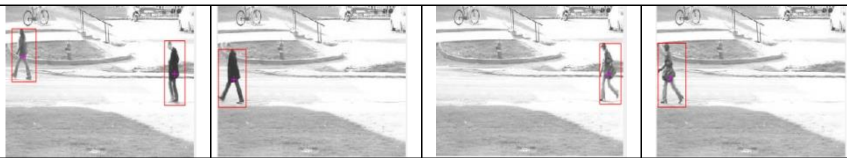
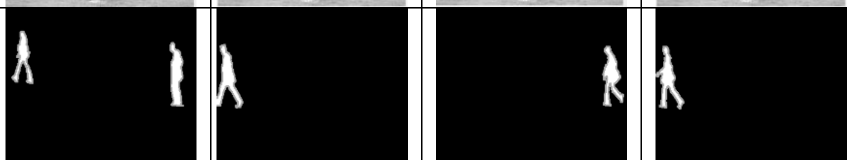
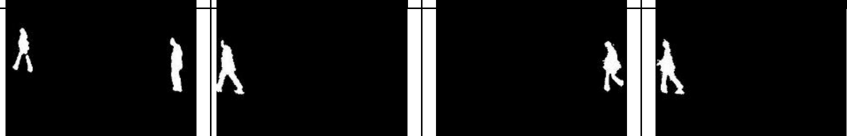
Frames with tracking result				
Ground truth				
Proposed method output				
	S-0.8374 F-0.9115	S-0.8395 F-0.9127	S-0.8112 F-0.8958	S-0.8215 F-0.9020

Fig.4: Output Binary motion mask of PEDSTRAIN video with tracking performance and accuracy metrics S(similarity) and F(F-measure)

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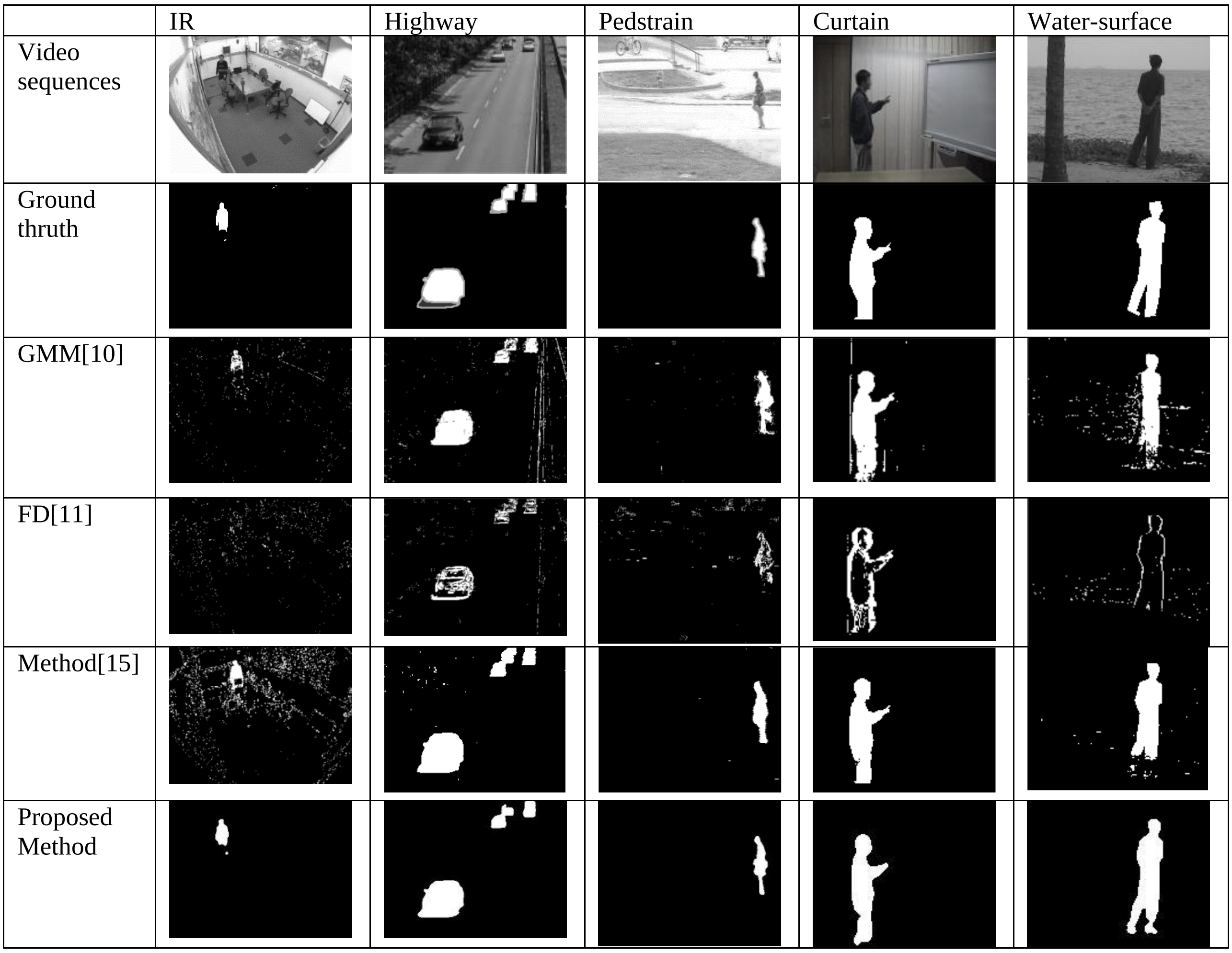

Fig.5: Comparative analysis of Output Binary motion mask between Proposed method and other existing background subtraction methods

Table 1. Comparative analysis between proposed method and existing methods using Similarity(S) and F-measure accuracy metrics

	Proposed method	FD[11]	GMM[10]	Method [15]
Highway	S-0.8884 F-0.9437	S-0.4368 F-0.5959	S-0.5352 F-0.6907	S-0.6712 F-0.8031
Pedestrian	S-0.8200 F-0.9004	S-0.2385 F-0.3879	S-0.6614 F-0.7661	S-0.7211 F-0.8375
Water surface	S-0.8952 F-0.9439	S-0.1528 F-0.2574	S-0.5344 F-0.6918	S-0.5173 F-0.6818
IR	S-0.8216 F-0.9015	S-0.2273 F-0.3707	S-0.4844 F-0.6526	S-0.6944 F-0.8200
Curtain	S-0.8001 F-0.8874	S-0.2176 F-0.3686	S-0.6500 F-0.7685	S-0.7000 F-0.8239

Fig 4 compares the quality of detected moving blob in stationary as well as in moving condition, where one can observe that the proposed method has detected sufficient blob's area for tracking.

The quantitative performance is evaluated by calculating the detection rate Precision, Recall, F-measure(F) and Similarity(S) [16-17]. In this paper, the results are compared by considering F-measures and Similarity. It requires, 'tp', 'tn', 'fp' and 'fn' to calculate the above parameters. The 'tp' and 'tn' abbreviate for true positive and true negative respectively, where the 'tp' represents the correctly marked foreground and 'tn' represents truly background pixels. The 'fp' and 'fn' abbreviate for false positive and false negative respectively, where the 'fp' represents the foreground pixel wrongly detected as background and 'fn' represents those background pixels wrongly detected as foreground. The relevant and irrelevant on the binary blobs are represented by 'Recall' and Precision metrics respectively.

The accuracy metric F-measure is computed as follows:

F-measure(F)=2*Recall*Precision/(Recall+Precision) (12)

The similarity metric is given as:

Similarity (S)=tp/(tp+fp+fn) (13)

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Table 1 shows the comparative analysis of similarity metric and accuracy metric F-measure between proposed method and other state-of-art background methods. One can observe that the moving blob detected through proposed method is more accurate and precise than those achieved through GMM [10], FD [11], and method [15]. The proposed method secures more the 80% similarity metric and 88% F-measure metric for each sequence taken under observation.

V. CONCLUSION

In this work, an efficient background model is contributed and tested to handle some complex situations in the video sequences and object tracking task. Initially, the fuzzy c-mean clustering method is applied to make a more robust reference background. Afterward, the moving mask is detected by using the probabilistic approach. The obtained binary motion masks have found with sufficient area to perform the task of tracking. As seen, the dual-tree complex wavelet transform can detect and track the small and dim object and preserve the spatial location in consecutive frame due to its shift invariant nature. The background model is updated to remove the background clutter during each incoming frame. The proposed method localizes the object without over-segmentation error and aperture distortion and attains more promising accuracy metric than other existing background subtraction methods reported in this paper.

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