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Multitextured Segmentation for Improving Moving Objects Detection and Tracking

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Abstract

Image segmentation based on multiple texture features has significant issues in the areas of content based image extraction, image outline recognition, medical image processing, remote sensing, image segmentation through pattern identification and monitoring in crowded public places. Active contour color recognition methods were developed for detecting and tracking object in sequential images. However, the presence of dynamic shadows was a critical issue in foreground segmentation. Therefore, multitextured-based object segmentation (MTOS) technique is proposed in this study for improving the detection and tracking of moving objects. The proposed technique first locates the objects and boundaries of images with the same label distributed with certain visual characteristics. Next, preprocessing technique is performed using median filtering to reduce the distortion and noise in video frames. Then, texture-based segmentation is carried out using an adaptive threshold-based approach to avoid distortions while detecting moving objects. Detecting moving regions is accomplished by comparing the current video frame from a reference background in a pixel-by-pixel manner with multiple texture features. The effectiveness of moving object image segmentation through texture features is evaluated. The experimental results show that our proposed technique performs better in terms of segmentation accuracy, segmentation time, peak signal to noise ratio and object detection rate.

Keywords: Moving object detection, object tracking, multiple textures, object segmentation.

INTRODUCTION

Moving objects segmentation in image sequences is essential for several multimedia applications. The extraction of foreground (moving object) from the background is vital for image segmentation. Active contour models (ACMs) was developed in [1] for detecting and tracking an object system. However, the presence of dynamic shadows was not addressed. An advanced fuzzy aggregation-based background subtraction (AFABS) was designed in [2] for moving object detection in dynamic background conditions. However, the quality of the video was compromised.

In [3], the moving object detection and tracking using reference background subtraction was developed. However, this method is not effective for images captured using moving cameras. In [4], a multiple object tracking framework based on continuous energy minimization was developed. However, detecting multiple objects in crowded scenes remains unaddressed.

In [5], an efficient tracking of segments using a least square tracking approach was introduced. However, a more sophisticated system is required to track specific objects in one video and generalize it across other videos. A probabilistic consensus foreground object template was designed in [6] for detecting moving objects. However, this method is designed only to detect foreground object in a close-up scene of a video captured by a freely moving camera. In [7], a novel method was developed to handle the problem of objects representation for surveillance video retrieval system. This only addresses the issues related to the problems of indexing and retrieval from video databases.

A video object segmentation and video object tracking approach was developed in [8] for smart cameras in visual surveillance networks. Here the issue in object tracking, such as occlusion and foreground clutter, requires the development of additional methods. A combination of two approaches namely, a novel bottom-up approach removes chromatic moving shadows, and a top-down approach based on motion-filters keeps track of both objects and shadows to handle chromatic shadow misdetections was developed in [9] for video surveillance. However, the problem of multiple occlusions remains unaddressed.

An automatic estimation of multiple motion algorithms was designed in [10] to increase the identification of trajectories. However, this framework requires improvement for motion estimation in denser environments such as crowds of moving people.

In order to solve the existing issues, Multitextured Object Segmentation (MTOS) technique is proposed. The major contribution of MTOS technique is described as follows: -,

- First, MTOS technique performs video image segmentation to locate the moving objects and boundaries in video frames. Multimedia data (i.e. frames) is segmented by shots. Each shot is an unbroken sequence of video frames, captured using single camera.

This is used to extract the appropriate information about the structure of moving objects.

- Next, the distortion and noise present in video frames needs to be minimized. The proposed MTOS technique performs preprocessing using median filtering for all the sliding windows. Here, median processing is applied for the entire pixels to identify the noisy-level and it changes the median values accordingly to remove noise present in the frames. This resulted in improved video quality and also increased the PSNR rate.
- Next, for detecting the foreground objects more accurately, adaptive threshold-based on multiple texture features segmentation is performed. This signifies the detection process by identifying the regions of interest (ROI) from frames with the help of visual and motion properties. MTOS technique thereby improved the rate of segmentation accuracy.
- Next, detection of moving regions is performed using threshold value based on multiple textures features. Here, high gradient pixel values are selected to segment the video frames with minimum time. Finally, the proposed MTOS technique improved the moving object detection rate and accuracy.

The paper is organized as follows: Section 2 presents related work in the areas of moving object detection and segmentation technique. Section 3 describes the MTOS approach for improving the accuracy of moving object detection. Section 4 presents the experimental setup. Section 5 presents the performance evaluation and Section 6 concludes the paper along with future research directions.

RELATED WORKS

In [11], various texture-based methods were developed for object recognition and feature extraction. However, these techniques can be applied only when an image has textural properties. In [12], a real time online moving object detection and segmentation algorithm for the video captured by freely moving cameras was proposed. However, the algorithm is suitable only for two-layer iteration to accurately estimate the affine transformation parameters between two successive frames.

A novel moving object segmentation algorithm was designed for two consecutive frames. A new method called a DEtecting Contiguous Outliers in the LOw-rank Representation (DECOLOR) was developed in [13] for detecting the object and learning the background. However, the online version of DECOLOR that can work incrementally was not supported.

In [14], an open active contour model to track the trajectories of moving objects at high density was developed. However, this algorithm does not consider the case of new objects entering the image. A canonical correlation analysis (CCA) was presented in [15] to enhance the accuracy of moving object detection. However, the object segmentation was not effective. A novel spatio-temporal-based approach was introduced in [16] to segment the video object to produce a weighted method. However, foreground motion detection was not addressed. In [17], video object segmentation algorithm was developed to resolve the issues of uncovered background, Temporary poses and Global motion of background. The issues related to dynamic background, chromatic shadows are yet to be solved.

A novel MVS tracking method with multiple views of SVMs was proposed in [18]. However, MVS framework needs to be embedded with more expressive power in order to cover other views of features. A technology for detecting and tracking multiple moving objects for home and business surveillance system was proposed in [19]. However, this method can track only vehicle and human beings. A novel three-view constraint called the parallax-based multiplanar constraint was proposed in [20]. However, this method can detect the motion objects followed by a moving camera only in the same direction.

Based on the above mentioned methods and techniques, an efficient MTOS technique is developed to improve moving object detection and tracking.

MTOS TECHNIQUE

Segmentation of moving objects in image sequences is an essential task in multimedia applications. Segmentation is used to extract the appropriate information about the structure of moving objects from video frames. Multitextured Segmentation is used to facilitate the representation of moving objects into a more relevant number of components. The main objective of segmentation is that it signifies and detects the region of interest from frames with the help of the visual and motion properties. Texture denotes the different physical composition of a surface. Periodicity, scalability, stiffness, inherent direction and pattern difficulty are the distinct properties of texture. Texture of an image is referred as a feature that includes important characteristic of that image. Texture is based on the distribution of intensity across the image rather than being described for an individual pixel. Texture is denoted by the spatial distribution of gray scales in an image. Texture extraction is performed by means of converting RGB image into gray image. Therefore, a basic Red, Green, and Blue (RGB) plane of the input image is isolated so as to create texture object mask for segmentation. The two sources of information used for detection and tracking of moving objects in a video sequence are the visual features (e.g. texture and intensity) and the motion information. Therefore, segmentation based on the multiple texture features is performed to improve the moving objects detection and tracking. Therefore, the MTOS technique is introduced to improve segmentation accuracy with minimum time. The overall architecture diagram is illustrated in figure 1.

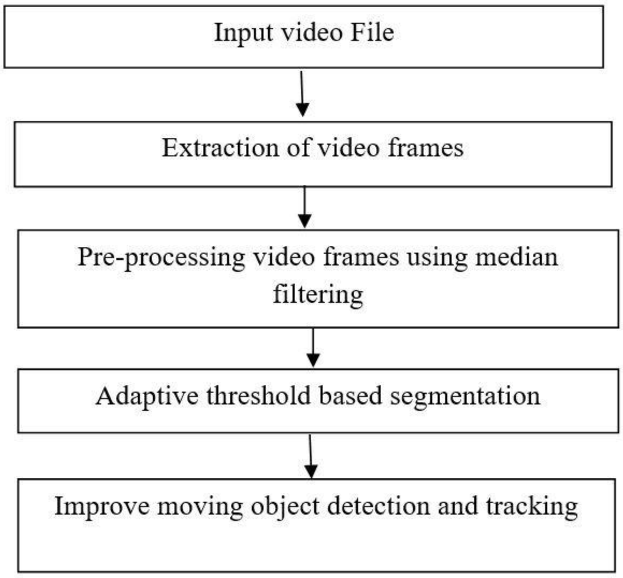

Figure 1. Architecture of MTOS technique

Figure 1 shows the architecture of moving object detection and tracking through multi textured segmentation.

The MTOS technique considers the video file as input as shown in figure 2.

Figure 2. Input video file

This video file is partitioned into number of frames as shown in figure 3. These frames have different qualities like texture, colour, shape and intensity. Therefore, the proposed MTOS technique considers the multiple texture features to segment the image and improve the object tracking.

Figure 3. Extracted input frames

Next, pre-processing is done to remove the noise present in the video frames. Next, an adaptive threshold-based technique is applied to select the most relevant pixel of the texture to form segmentation. The present video frame is compared with the reference background in a pixel-by-pixel manner with multiple texture features. Finally, the MTOS technique performs foreground segmentation based on multiple textures for improving segmentation accuracy and segmentation time. The effectiveness of the proposed method is evaluated with higher pre-processing capability and moving object detection accuracy.

Video file pre-processing for improving moving object detection

The first process in the segmentation of the moving object is pre-processing for removing the noise such as Impulse noise, Amplifier noise (Gaussian noise), Shot noise, Quantization noise (uniform noise), Film grain, on-isotropic noise, Multiplicative noise (Speckle noise) and Periodic noise during the moving object detection. The video file is partitioned into number of video frames. Texture feature is a pattern of intensity variation and it depends on the distribution of intensity over the image rather than being defined for a separate pixel.

Figure 2 and 3 shows that the video file is divided into number of frames. Let us consider a video file "VF_i" that is split into number of sequence of images illustrated as follows:-,

$$VF_i = VF_1, VF_2, VF_3 .., VF_n \tag{1}$$

From (1) the "n" number of video frames $(VF_1, VF_2, VF_3 .., VF_n)$ is obtained for preprocessing. An efficient median filtering technique is employed for preprocessing the video frames and removing different types of noises from the frame.

The video frames are preprocessed using median filtering technique to improve the results of later processing like image classification, pattern matching etc., on an image. The median filter changes each entry with the median value of its neighbour pixel. These Neighbour patterns are also known as windows. The median filtering of a single 3x3 window is shown in figure 4.

4	5	0
38	15	56
13	17	12

*	*	*
*	13	*
*	*	*

Figure 4. (a) Unfiltered values (**b**) Filtered values using median filter

Figure 4 clearly illustrates the filtered and unfiltered values of pixel. The median filtering of a single 3X3 window is measured by first sorting the entire pixel values from the surrounding neighborhood into numerical order. Thus, this median value is used to restore the noisy pixels and is calculated as follows: -,

$$Median\ [m,n] = med\left\{\frac{m*n}{VF_n}\right\} \tag{2}$$

From (2), the median value for a 3X3 window size can be obtained. Here "med" is the median of column "m" and row "n" in the window. Here, "VF_n" is the total video frame. Therefore, the effectiveness of moving object image segmentation through texture features is evaluated with higher pre-processing capability and improves the moving object detection and tracking.

The median filtering-based preprocessing algorithm is described as follows: -,

Input: Video file 'VF_i',
Frame color
Frame Size
Frame intensity
Output: Video files preprocessing (for removing noise)
Step 1: Begin
Step 2: *for* each video file VF_i
Step 3: partition the video file into number of video frame using (1)
Step 4: *for* each video frame
Step 5: measure the median value from adjacent neighborhood
Step 6: if number of pixels is even in the neighborhood
Step:7 Restore the noisy pixels by median value using (2)
Step 8: else
Step 9: noisy pixels are not stored
Step 10: *end for*
Step 11: *end for*
Step 12: End
Step 13: End

Algorithm 1. Video file pre-processing using median filtering

The above algorithm shows video file pre-processing using median filtering and the result of median filtering is as shown in figure 5.

Figure 5. After median filtering

Next, the segmentation of the texture object in video frames is carried out using adaptive threshold-based segmentation in order to improve moving object detection and tracking.

Adaptive threshold-based Multitextured segmentation

Once the video frames are preprocessed, segmentation is carried out based on the multiple texture features of the moving objects. Another significant issue in foreground segmentation is dynamic shadows. When objects are moving, objects can be hidden by other objects, in which case both their size and shape are distorted. The proposed MTOS technique extracts moving objects and shadows of the moving objects. As a result, the performance of foreground detection is minimized in scene monitoring, object recognition, target tracking and people counting. Threshold based techniques like local, global and adaptive threshold techniques can be used. With local threshold technique, a single threshold value cannot handle the problem of varying illumination. Also, global threshold method is not appropriate whenever the background illumination and ambient lights are uneven. Therefore, the image is partitioned in to smaller segments, and the appropriate threshold values are chosen using adaptive threshold-based method. The MTOS technique uses an adaptive threshold-based technique for multiple texture feature segmentation to accurately detect the moving object. The main advantage of this approach is that it provides more accurate information about the foreground objects and suppresses the dynamic shadows. Therefore, this technique is more reliable.

The proposed adaptive threshold-based multi-textured segmentation takes a grayscale or color image as input, processes the simplest implementation and provides binary output image, which represents the result of segmentation. Hence the foreground is effectively extracted thereby eliminating dynamic shadows. By taking illumination into account, the proposed MTOS method is able to segment objects with non-uniform intensities caused by spatial variations in illumination and ambient light.

The threshold based textured segmentation approach searches for pixels with high gradient values using prewitt operator. These pixels are framed to form a segment which represents the boundary of the object. All of the pixels in a region are identical with respect to the characteristic such as color, intensity, or texture and adjacent areas are considerably distinct with respect to the characteristics. The proposed approach sets the objects position and boundaries and assigns similar labels to all the pixels with specific similarities. In this textured segmentation, an input video file is partitioned into two or more frames and is compared with the predefined threshold value. The threshold based segmentation focuses on the foreground objects' pixel variations. An effective adaptive threshold-based technique is used for segmentation based on the texture feature related to gray level, neighborhood and pixel value of the image. For reducing the memory, storage space and object detection time, RGB2IND function is used for converting RGB images into indexed image. Indexed image has an advantage in terms of resource usage over RGB color. An indexed image includes data matrix, color-map

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matrix and a map. Each row of a map corresponds to red, green and blue elements of a single color. Indexed image performs direct mapping of pixel values into color map values. The pixel value of each color image is detected by using the respective value of an index. The gradient prewitt operator identifies the edges by examining higher and lower first derivative of the image. Sharp edges are segmented by appropriate threshold. Then the detection of moving regions (i.e., the foreground) is obtained by comparing the current image in a pixel-by-pixel basis based on multiple texture features. If the pixel value is higher than the threshold value, then the region is said to be a foreground. This helps to detect the moving region by segmenting the objects based on the texture feature. The adaptive threshold-based approach is more appropriate for efficient segmentation and is used for categorizing the pixels according to their spatial values, the gradient of their gray levels and the homogeneity of their textures. This effectively reduces the dynamic shadows of moving objects.

Figure 6. Adaptive threshold object

Figure 6 clearly shows the output of adaptive threshold-based multitextured segmentation approach. The adaptive threshold-based method is used to segment a video frame based on texture feature by locating all the pixel's values. The threshold value is measured for all pixels in the video frames. If the pixel value of the texture is lesser than the threshold then it is set as the background value, or else it is considered as the foreground value. The adaptive threshold-based method uses an accurate predefined value to partition the image pixels into several classes and separate the objects from the background based on texture features as shown in figure 7.

Figure 7. Texture extraction

Adaptive threshold method is formulated as follows: -,

$$AT = AT[a, b, p(a, b), f(a, b)] \tag{3}$$

From (3), the adaptive threshold AT is measured based on the pixel coordinates (a, b) of the threshold value point. Here, $p(a, b)$ and $f(a, b)$ represents the gray-level frame pixels. Based on the threshold property, the moving object region (foreground) is obtained using texture features on pixel-by-pixel basis.

The threshold value of all pixels is specified as either 0 or 1. The threshold frame g (a, b) is expressed as: -,

$$g(a, b) = \begin{cases} 1 & if \quad f(a, b) > T_{H.} \\ 0 & \quad otherwise \end{cases} \tag{4}$$

From (4), if the pixel value of the frame is greater than the threshold value, then it is considered as the foreground value and it is represented as 1, otherwise it is considered as a background. From the threshold measurement, the moving object region is obtained from the background for object segmentation. Next, it evaluates the optimum threshold factor in such a way that the added spread variance is minimal. Finally, the quality of the image in video is enhanced to improve the moving object detection and tracking in the video file sequence as shown in figure 8.

Figure 8. Segmented image

Figure 8 clearly shows the result of segmentation based on multiple texture features and adaptive threshold-based values. The image texture feature extraction removes noise and distortions present in the image and filters the input image for segmentation as shown in figure 7. Next, texture-based segmentation is performed to provide the output of segmented image which is shown in above figure 8. Finally, moving objects are detected and tracked at various levels. Here, objects are detected that enter and exit the scene and tracking those objects are performed at different levels and positions with respect to time.

Table 1. Tabulation for segmentation accuracy

No. of video frames/s	Segmentation accuracy (%)								
	168VJ Clips video dataset			SBI dataset			Actions as Space-Time Shapes dataset		
	MTOS	ACM	AFABS	MTOS	ACM	AFABS	MTOS	ACM	AFABS
10	87.65	79.25	69.11	84.23	74.23	66.26	82.13	72.21	63.25
20	89.13	82.36	73.65	87.34	78.52	70.33	85.43	76.34	66.15
30	90.54	84.65	75.82	88.21	80.31	72.34	86.14	78.35	68.26
40	91.23	85.31	76.31	89.15	81.35	73.34	87.23	79.34	69.31
50	92.41	86.17	77.04	90.61	82.41	74.33	88.31	80.52	70.21
60	93.26	87.23	78.35	91.12	83.27	75.08	89.05	81.36	71.32
70	94.11	88.04	79.19	92.44	84.18	76.28	90.54	82.05	72.36
80	95.31	89.4	80.43	93.34	85.64	77.46	91.34	83.61	73.54
90	96.02	90.13	81.27	94.25	86.34	78.27	92.42	84.55	74.25
100	96.65	91.24	82.18	95.34	87.46	79.22	93.26	85.31	75.61

EXPERIMENTAL SETUP

An experimental evaluation of the MTOS technique is implemented in MATLAB to improve moving object detection and tracking. The proposed MTOS technique is simulated using three different datasets such as 168VJ Clips video dataset, Actions as space-time shapes dataset and Scene Background Initialization (SBI) dataset. These datasets consist of different video clips in various file sizes. The MTOS technique was used to improve the video quality, and experiments were conducted using *.avi* file format. The evaluation of MTOS technique is compared with existing ACMs developed in [1] and AFABS in [2], respectively. The performance of the proposed system is evaluated on the factors like segmentation accuracy, segmentation time, Peak signal to noise ratio (PSNR) and moving object detection rate.

RESULTS AND DISCUSSION

The MTOS technique is analyzed with the existing ACMs developed in [1] and AFABS in [2], respectively. The performance is carried out on the factors such as segmentation accuracy, segmentation time, peak signal-to-noise ratio (PSNR) and moving object detection rate.

Impact of segmentation accuracy

Segmentation accuracy is defined as the ratio of the number of objects being correctly segmented to the total number of video frames. The segmentation accuracy (SA) is measured as follows: -,

$$SA = \frac{Objects\ being\ correctly\ segmented}{No.of\ video\ frames} * 100 \quad (5)$$

When the segmentation accuracy has a higher value, we say that the method is more efficient.

Table 1 describes the segmentation accuracy of three different methods. Video frames ranging from 10 to 100 frames per second, are given as input to the proposed system. The MTOS technique performs object segmentation based on multiple texture features. Therefore, larger video files are efficiently segmented based on multiple texture features to provide maximum segmentation accuracy. It is observed that the proposed method gives 96.65% improved classification accuracy as well with increased numbers of video frames (say 100 frames/s) using 168VJ Clips video dataset. It can be clearly seen that the MTOS technique has 7% and 20% higher segmentation accuracy than ACMs in [1] and AFABS in [2], respectively. In addition, the proposed MTOS technique increases the segmentation accuracy by 10% and 22% using SBI dataset when compared to existing ACMs and AFABS method developed in [1] and [2] respectively. Similarly, the proposed MTOS technique improves the segmentation accuracy by 10% and 26% when compared to ACMs and AFABS method developed in [1] and [2], respectively using Actions as Space-Time Shapes dataset.

Impact of segmentation time

Segmentation time is defined as the amount of time taken to segment the video frames based on the texture feature. The segmentation, measured in terms of milliseconds (ms). Segmentation time is calculated as follows: -,

$$Segmentation\ time = No.of\ video\ frames * Time \quad (6)$$

Table 2. Tabulation for segmentation time

No. of video frames/s	Segmentation time (ms)								
	168VJ Clips video dataset			SBI dataset			Actions as Space-Time Shapes dataset		
	MTOS	ACM	AFABS	MTOS	ACM	AFABS	MTOS	ACM	AFABS
10	10.9	13.8	18.4	11.5	15.4	20.4	12.6	16.7	22.3
20	12.5	16.1	21.6	14.2	18.3	23.5	15.4	19.6	25.4
30	15.2	18.7	23.3	16.3	20.2	25.4	17.3	21.9	27.1
40	16.7	20.9	25.6	18.4	22.2	27.6	19.4	23.5	28.9
50	18.8	22.6	28.4	20.3	23.7	29.5	21.6	25.2	31.2
60	20.1	24.8	29.1	21.5	25.6	31.4	23.4	27.3	33.7
70	21.3	26.3	31.5	23.6	28.1	33.6	24.5	29.4	35.6
80	22.6	27.2	32.5	25.4	29.2	34.6	26.4	30.5	37.2
90	23.4	28.1	34.6	26.1	29.8	36.2	27.1	31.7	38.7
100	24.8	29.3	35.1	27.6	31.6	37.4	28.2	32.5	39.5

Table 2 describes the segmentation time for three different methods. The objective of the research work is to reduce the segmentation time. The proposed MTOS method uses adaptive threshold-based technique to segment the frames based on the texture features. The highest predominated pixel values are selected to segment the video frames, which resulted in the minimization of the segmentation time. From table 2, it can be clearly seen that the MTOS technique using 168VJ Clips video dataset has segmentation time of 19 % and 34% lesser than ACMs in [1] and AFABS in [2], respectively. Similarly, by using SBI dataset, the MTOS reduces the segmentation time by 17% and 33% when compared to the existing ACMs in [1] and AFABS in [2], respectively. Finally, the MTOS technique reduces the segmentation time by 17% and 33% using actions as space-time shapes dataset when compared to the existing ACMs developed in [1] and AFABS in [2], respectively.

Impact of PSNR

PSNR rate is defined as the ratio of reference video frame and distorted video frame being detected in a video file. Its value is mathematically computed from the formula given below.

$$PSNR = 10\log 10\ \frac{R^2}{MSE}. \tag{7}$$

$$MSE = \sum_{i=1}^{n}(V_i - V_i') \tag{8}$$

From (7), "PSNR" is evaluated with the maximum possible pixel value of the frame (R) (with size 255) with respect to mean squared error rate "MSE". From (8), "MSE" is the difference between the actual frame size "V_i" and the estimated frame size "Vi'" being detected.

Table 3. Tabulation for PSNR

No. of video frames/s	PSNR (db)								
	168VJ Clips video dataset			SBI dataset			Actions as Space-Time Shapes dataset		
	MTOS	ACM	AFABS	MTOS	ACM	AFABS	MTOS	ACM	AFABS
10	48.12	40.85	33.54	46.32	37.12	30.44	44.16	35.14	27.01
20	50.85	43.2	35.61	47.91	40.35	32.17	46.28	38.45	29.43
30	54.35	45.86	37.42	51.32	42.11	34.02	50.71	40.22	31.18
40	58.76	49.23	40.35	55.42	46.45	38.11	54.26	43.61	34.06
50	63.28	53.61	43.03	59.64	49.43	40.41	56.34	46.22	36.39
60	66.97	56.44	46.09	63.41	52.96	42.33	60.87	50.15	40.11
70	72.43	60.28	49.88	67.81	55.52	46.92	64.46	53.64	43.05
80	75.44	63.81	52.46	70.11	57.61	49.22	68.21	55.11	45.12
90	77.37	66.12	54.31	73.43	60.16	51.43	71.33	56.63	46.08
100	78.49	68.33	56.43	75.11	62.31	53.24	73.44	59.66	48.62

Table 3 illustrates PSNR based on different video frame sizes. A higher PSNR indicates that the reconstruction is of higher quality. The scalability of the proposed technique is evaluated by means of PSNR. For each frame, MSE rate is calculated. The minimum error rate provides higher PSNR rate. Higher PSNR rate is obtained by applying median filtering technique. As a result, error rates are reduced efficiently in MTOS technique. From the figure, it can be clearly seen that the MTOS technique using 168VJ Clips video dataset has 18% and 44% higher PSNR, than ACMs developed in [1] and AFABS in [2], respectively. Likewise, proposed MTOS technique improves the PSNR rate by 21% and 47% using SBI dataset when compared existing ACMs developed in [1] and AFABS in [2], respectively. Similarly, using Actions as Space-Time Shapes dataset, the PSNR rate is effectively improved by 23% and 56% when compared to start-of-the-art methods.

5.4 Impact of moving object detection rate

The moving object detection rate (MODR) is defined as the ratio of the objects being detected to the total number of video frames/s. The MODR, measured as a percentage (%) is expressed as follows: -,

$$MODR = \frac{No.of\ Object\ being\ detected}{No.of\ frames/second} * 100. \quad (9)$$

From (9), Moving Object Detection Rate ($MODR$) is described based on the number of video frames.

Table 4 illustrates the measure of moving object detection rate. From the figure, it can be clearly seen that the moving object detection rate is higher in the MTOS technique than that in the existing techniques ACMs developed in [1] and AFABS developed in [2]. This is because the segmentation was carried out based on the multiple texture features using an adaptive threshold-based technique. For each pixel value in the texture features, the threshold values were measured. If the pixel value of the texture is higher than the threshold, then it is set as the foreground object otherwise it is set as the background. This helps to easily identify the moving object from the background for efficient segmentation. Table 4 shows the object detection rate with respect to different number of video frames. By using 168VJ Clips video dataset, MTOS technique has 15% and 27%, higher detection rate, than ACMs developed in [1] and AFABS in [2], respectively. Similarly, MTOS increases the object detection rate using SBI dataset by 13% and 28% when compared to ACMs developed in [1] and AFABS in [2], respectively. Finally, using actions as space-time shapes dataset, the proposed MTOS method improves object detection rate by 13% and 29% when compared to start-of-the-art methods.

Table 4 Tabulation of moving object detection rate

No. of video frames/s	Moving object detection rate (%)								
	168VJ Clips video dataset			SBI dataset			Actions as Space-Time Shapes dataset		
	MTOS	ACM	AFABS	MTOS	ACM	AFABS	MTOS	ACM	AFABS
10	79.38	68.25	60.51	75.31	65	57.37	71.34	62.44	53.51
20	82.64	70.14	62.55	77.62	67.2	59.55	74.48	64.35	56.34
30	84.1	72.65	65.48	79.34	70.13	62.34	76.47	67.15	58.63
40	86.36	74.35	66.42	81.24	71.64	63.44	78.33	68.31	60.34
50	90.2	76.99	68.54	83.49	73.98	65.81	80.64	70.31	62.25
60	91.25	79.1	69.81	86.64	75.42	66.94	82.41	72.22	64.09
70	92.36	81.2	71.61	88.44	78.65	68.04	84.11	74.81	66.01
80	93.45	83.44	73.51	89.31	80.41	70.33	85.34	76.05	67.31
90	94.63	84.31	76.09	90.73	82.33	72.31	86.64	78.61	69.15
100	95.51	85.26	78.46	91.56	83.47	74.33	87.11	80.22	70.34

CONCLUSIONS AND FUTURE WORKS

An efficient novel technique called MTOS was developed to improve moving object detection and tracking. The proposed technique firsts locate the moving objects' boundaries in the video frames and then assigns similar labels to pixels with similar characteristics. Preprocessing is done to reduce the distortion and noise present in the video frames. Finally, segmentation is performed using an adaptive threshold-based segmentation to improve the segmentation accuracy with minimum time. Detection of moving regions is achieved by choosing threshold values to segment the moving object based on the multiple textures features. The experimental results revealed that the MTOS technique significantly improved the segmentation accuracy and reduced the segmentation time and PSNR. Compared to the existing state-of-the-art methods, the MTOS technique improved the objects segmentation for further task involved in moving object detection and tracking. Furthermore, new methods can be incorporated for classifying moving objects and an advanced kalman filter-based pattern matching technique can be combined for efficient moving objects detection and tracking.

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