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A Novel Framework for Moving Object Tracking in Video Surveillance

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Abstract: Video Object segmentation is more vital for video compression principles for identification, event analysis, understanding and manipulation of moving object in videos. Moving object segmentation techniques is used to separate a video file into different frames for video surveillance, traffic surveillance criminal pattern identification and so on. Recently, most of the research works has been conducted for video object segmentation and detection though video object segmentation based on features like shape, texture, intensity was not efficiently performed. Besides, Efficient Threshold Filtered Video Object Detection and Tracking framework is designed for video object tracking of moving video objects in video sequence.

Keywords: ETFVODT, AFABS, AEMM

I. INTRODUCTION

ETFVODT framework technique is used to segment the video object based on their features like shape, texture, intensity and to improve the video object detection accuracy of moving objects in video sequence. Initially ETFVODT framework takes the video file as input and then separate the video frames based on shape, texture, intensity to improve accuracy of objects, then filtering technique is applied for tracking the video objects in video sequence. ETFVODT framework, Filtering technique is used to improve the video quality and to reduce the mean square error rate of video image. Finally, ETFVODT framework effectively performs the video objects detection task by applying the Thresholding technique which in turn improves the video object detection accuracy. The proposed ETFVODT framework is used video images obtained from Internet Archive 501(c) (3) for conducting experimental work. The performance of ETFVODT framework is tested with the following parameters such as object segmentation accuracy, Peak Signal to Noise Ratio, object tracking accuracy, Mean Square Error and object detection accuracy of moving video object frames.

A. Video Object Segmentation And Detection Techniques In Video Surveillance

Moving object detection from video sequences is a primary step in many visual surveillance applications such as object tracking, human action recognition, high level behavior understanding etc. Surveillance and monitoring systems involve the segmentation of all moving objects in a video sequence. Moving object detection aims to identify objects of interest in the video stream by using their visual and motion properties. It plays a significant role because it reduces the amount of information to be processed by higher processing levels, object tracking, classification or recognition and locates the position of the targets.

1) *Neighborhood Supported Model Level Fuzzy Aggregation for Moving Object Segmentation:* Pojala Chiranjeevi and Somnath Sengupta (2014) developed an Advanced Fuzzy Aggregation based Background Subtraction (AFABS) for Moving Object Segmentation. AFABS approach was introduced a fuzzy aggregation based background subtraction algorithm for moving object detection. AFABS approach utilizes a set of fuzzy aggregated multi-feature similarity measures applied on multiple models equivalent to multimodal backgrounds. Fuzzy aggregation based background subtraction algorithm was developed with a neighborhood-supported model initialization strategy for faster convergence. A model level fuzzy aggregation measure driven background model maintenance provides more robustness. Similarity functions were estimated between the consequent elements of the current feature vector and the model feature vectors. Concepts from Sugeno and Choquet integrals were integrated in Fuzzy aggregation based background subtraction algorithm to evaluate fuzzy similarities from the ordered similarity function values for each model. Model updating and the foreground/ background classification decision depends on the set of fuzzy integrals. The AFABS approach eliminates explicit offline training to initialize background model. The feature space employs a mixture of intensity and statistical texture characteristics for object localization and robustness. Multi-feature based background subtraction techniques require efficient fusion of the information provided by the individual features. Information fusion is the process of integrating these features into a single datum and the fusion was attained by means of aggregation operators which are mathematical functions. The aggregation operators require various type of parameterization to express additional information about the features that take part in the aggregation process. In AFABS, each pixel is modeled

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with a feature vector, composed of intensity and ST (Statistical Texture) features, a combination of pixel and region-based features, to inherit the advantages of both types of features. By providing significance value to each feature and fusing those via a fuzzy integral, correlations or interactions among the features can be measured. In AFABS approach, multiple models were created for each pixel where the models are initialized with neighborhood support therefore faster convergence of the background model to the background variations was achieved. Model level fuzzy similarity, determined between each model and the current by the fuzzy integral, represents the amount of matching between those, and the model is updated consequently. AFABS approach was designed a fuzzy aggregation based background subtraction algorithm for moving object detection. The fuzzy aggregation based background subtraction algorithm includes of five steps as follows, model initialization, background models selection, fuzzy integral calculation for all the models, background model updating, and the foreground detection. Model initialization is the first and the most essential step of background subtraction. In model initialization scheme, models at the pixel are initialized with the feature vectors from the neighborhood pixels. Because, the neighboring pixels share their feature vectors for their model initialization, the possible spatial background variations are integrated into the model in the beginning itself, resulting in faster convergence of the background model by adapting to those variations. AFABS model initialization provides lesser false positives than the initialization scheme without neighborhood support by reason of faster convergence of the former by using neighborhood support.The probability of a model feature vector produced from the background processes is directly associated to its weight. When the weight is larger, the higher the probability of the model was being generated by background process. In the current frame, the same set of features was estimated at the corresponding pixel to form the current feature vector. After that the similarity functions were estimated between the corresponding elements of the current feature vector and the model feature vector. The fuzzy integral for each model was determined with the help of ordered similarity function values and the membership values of all the features.The Advanced Fuzzy Aggregation Based Background Subtraction approach was used fuzzy aggregation for object localization and robustness using intensity and texture features. However, the object segmentation was not effectively performed in AFABS approach.

2) *Self-Crossing Detection and Location for Parametric Active Contours:* Arie Nakhmani and Allen Tannenbaum (2012) designed two algorithms, the first algorithm was for a self-crossing detection and the second was for the computation of crossing locations. Self-Crossing Detection algorithm was designed for detecting active contour self-crossing depends on the concept of turning number. In Self-Crossing Detection algorithm, the detection was achieved by exploring the entire net change of a given contour's angle without point sorting and plane sweeping. In addition, 4-Connected Line Interpolation algorithm was intended for locating crossings with angle considerations and plotting the 4-connected lines between the discrete contour points. The designed Self-Crossing Detection and 4-Connected Line Interpolation algorithms were employed for any parametric active contour model. The Self-Crossing Detection algorithm executes without computing the crossing segments and crossing point for all snake iterations. The 4-Connected Line Interpolation algorithm effectively addresses the troubles of crossing localization. 4-Connected Line Interpolation algorithm gives 4-connected segments i.e. each snake point has two neighbours from the left, right, top or down which in turn helps to entirely remove the false negatives without a significant increase in false positives. The crossing points are calculated only if a self-crossing is recognized. The self-crossing was recognized by way of investigating the suitable segments for crossing. Self Crossing Detection for Parametric Active Contours method was introduced for tracking objects in real world video sequences with help of Sobolev active contours. However, the object detection accuracy remained unsolved in this method.
3) *Automatic Estimation of Multiple Motion Fields from Video Sequences Using a Region Matching Based Approach:* Manya V. Afonso, et al., (2014) introduced an automatic method to extract object trajectories from the video sequence and to compute the vector fields without user interference. Initially, Automatic method recognizes the active regions by way of background subtraction and determines the centroids of all 8-connected neighboring active regions. After that, Automatic method estimates the displacement at each centroid by means of region matching to calculate the motion fields. Then, Automatic method present a motion correspondence step to cluster matching points into trajectories with the support of determined centroids of moving objects and their linked velocity fields for the entire sequence. Automatic method depicts the segmentation and feature extraction processes in Video Sequences. At first, Automatic method accomplishes background subtraction for recognizing the active regions in a frame and then computes the velocity fields at the centroid of each active region with the help of region matching algorithm. The result of these steps is a series of vectors having the spatial coordinates of the centroids of the active regions beyond the whole set of frames and also the corresponding velocity fields.Automatic Estimation of Multiple Motion was developed to automatically detect the multiple motion of object. Though, object segmentation based on shape, texture, intensity is remained unaddressed in this method.

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II. ENHANCED THRESHOLD FILTERED VIDEO OBJECT DETECTION AND TRACKING (ETFVODT) FRAMEWORK

The structure of Enhanced Threshold Filtered Video Object Detection and Tracking (ETFVODT) framework is detailed described in this section. All moving objects in a video sequence have to be segmented properly for facilitating efficient surveillance and monitoring. Thus, video object segmentation is considered to be one of the most significant processes because it has higher influential rate during the working of the other modules.

The key objective of applying video segmentation to the moving objects in a video sequence is that it signifies and identifies the region of interest (RO) from video stream with the aid of their visual and motion properties. Simultaneously, it is also important as video segmentation in moving objects plays a vital role by minimizing the information (i.e. size) to be processed at the later stages, like object tracking, classification of the ROI, segmentation of ROI and locating the target position (target ROI).

The goal of ETFVODT framework is to efficiently segment the vide objects based on their features like shape, texture, intensity and to perform the video object detection by using Thresholding and filtering techniques. At first, The ETFVODT framework is employed filtering technique for improving the video quality and reducing the noise frame. ETFVODT framework is performs the video object segmentation and tracking with the assist of filtering techniques. Subsequently, Threshold technique is used in TFVOD framework to perform efficient moving object detection. In ETFVODT framework, the thresholding technique is accomplished with the support of Gaussian-based Neighbourhood Intensity Proportion (GNIP). The architecture diagram of Improved Threshold Filtered Video Object Detection and Tracking framework is demonstrated in Figure 2.0.

As shown in Figure 2.0, initially ETFVODT framework takes the video file as input. The video file is partitioned into number of video frames. All the video frames acquired in ETFVODT framework do not have identical characteristics such as quality, brightness or contrast. With the objective of obtaining good quality video images without lacking the quality, brightness or contrast, preprocessing has to be accomplished for each input video file. Then, filtering techniques are applied on the video frames for performing video object segmentation and tracking. ETFVODT framework is effectively removes the noise video frame and improves the video quality with the help of filtering technique. ETFVODT framework is performs the object segmentation task based on their features like shape, texture, intensity which in turn improves object segmentation accuracy. With the aids of segmented object, ETFVODT framework is performs effective object tracking which results in improved the object tracking accuracy. Finally, ETFVODT framework is performs effective moving object detection with the support of tracked moving objects by applying thresholding techniques.

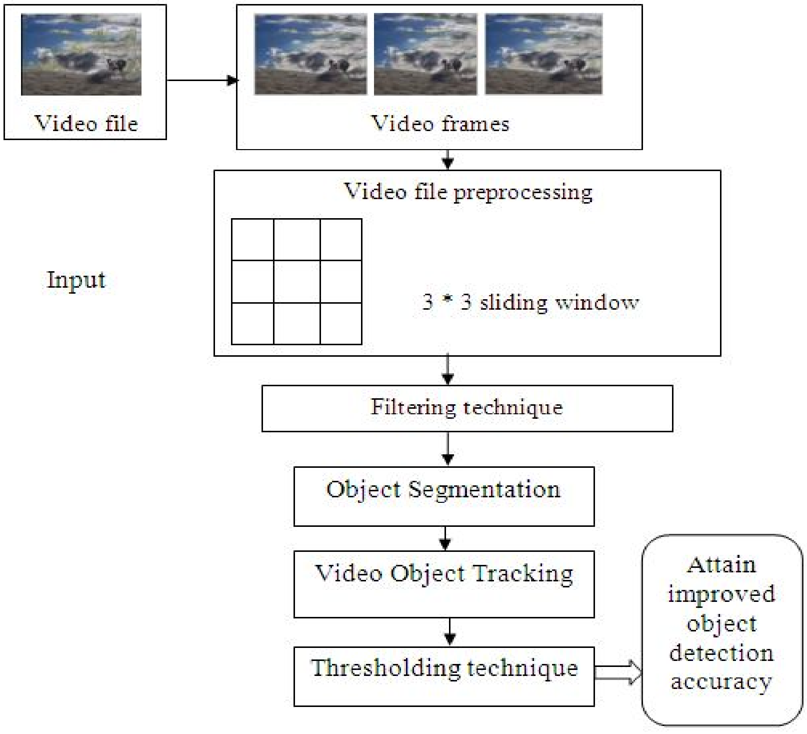


Figure 2.0 Architecture diagram of ETFVODT framework

A. Video File Preprocessing

The first step in the design ETFVODT framework is video file preprocessing. When an input video file is given, the video file 'VF_i' is partitioned into number of video frames. All video frames in video sequence do not give same characteristics such as quality, brightness or contrast. In order to obtain high quality video images without lacking the quality, brightness or contrast, video preprocessing has to be accomplished for each input video file. Generally, several frames in video will not be of good quality, perfect size or with good brightness and contrast.

The proposed ETFVODT framework is employs Un-symmetric Trimmed Median Filter to reduce the noise and so that the preprocessed video frames is used for further process. Let us consider the video frames 'f_i' with the proposed ETFVODT framework de-noised using a 3 * 3 sliding window (i.e. the selected window in the proposed MF-ELT method has three dimensions as it is a RGB image) and is mathematically formulated as given below,

$$VF_i \rightarrow f_1, f_2, \ldots, f_n \tag{1}$$

From (1), the input video file 'VF_i' is divide into 'n' frames as the input video file cannot undergo pre-processing without obtaining frames. With the assist of obtained frames 3 *3 sliding window for de-noising is formulated as follows,

$$VF_i = \sum_{i=1}^{n} f_i \ (3 * 3) \tag{2}$$

From (2), the frame 'VF_i' accomplishes de-noising by using '$3 * 3$' sliding window. Subsequently, the video frames are subjected to the noise detection during the video preprocessing stage. The detection or non-detection of noise in the video frames is determined by using the threshold factor 'α' that lies between '$0 \ to \ 255$' inside the selected sliding window '$3 * 3$'.

If the pixel values of the video frames are either '0' or '255', then it is remain unchanged. Conversely, if the pixel values are greater than '255', then it is said to be highly noisy pixels or if it lies between '$0 \ and \ 255$' it is said to possess noise according to the values acquired. Then, the median value is computed for the remaining pixels. This median value is employed to replace the noisy pixels and is formulated as follows for a given '$M_{columns} * N_{rows}$' of frame 'f_i',

$$M3D[M * N] = median \left\{ \frac{M_{columns} N_{rows}}{Total\ video\ frames} \right\} \tag{3}$$

From (3), the median value for a 3 dimension '$M3D[]$' is replaces noisy pixels along with the number of row and columns which posses the noisy pixels with respect to the overall size of video frames.

B. Filtering Technique for Video Object Segmentation and Tracking

The second step performed in design of ETFVODT framework is video object segmentation and tracking. Proposed ETFVODT framework is performs the video object segmentation and tracking tasks by using filtering technique. After obtaining the high quality image, video objects are efficiently segmented based on their characteristics like quality, brightness or contrast which in turn improves the object segmentation accuracy. With the help of segmented video objects, ETFVODT framework is effectively tracks the moving objects by using filtering technique which in turn improves the object tracking accuracy. In ETFVODT framework, initially Filtering technique is computes the Bayes Sequential Estimation i.e. posterior and prior function for tracking of multiple objects in a video sequence (i.e. videos) with the objective of reducing the peak signal to noise ratio (i.e. PSNR). Each particle 'V_i^j' evolves consistent with the state space model and yields an approximation of the prior function as given below.

$$Prob\,(V_i) = \frac{1}{n} \sum_{i,j=1}^{n} (V_i - V_i^j) \tag{4}$$

After that, the prior function using Color Histogram-based Particle Filter is obtained, the posterior function for each particle is determined for each particle at time 'T' as given below,

$$Prob\,(V_i \mid a_{1 \rightarrow n}) = \sum_{i=1}^{n} W_T^i \,(V_i - V_T^i) \tag{5}$$

From (4) and (5), the prior function and posterior function for each particle based on the weight of each particle 'W_T^i' is obtained.

The likelihood model (i.e. prior and posterior function) helps in enhancing the object tracking accuracy by using filtering technique. The algorithm description of video object tracking using filtering technique is shown in below Figure 2.1.
From the Figure 2.1, video object tracking algorithm using filtering technique is performs three steps as follows. For each video sequence, the initial step estimates the likelihood function of color histogram. After that, second and third step computes the particle prior and posterior function respectively which in turn increases the object tracking accuracy.

Input: video sequence '$V_i = V_1, V_2, \dots, V_n$',
Output: Improved video object tracking accuracy
Step 1: Begin Step 2: For each video sequence 'V_i' Step 3: Evaluate likelihood function of the color histogram Step 4: Measure particle prior function using (4) Step 5: Measure particle posterior function using (5) Step 6: End for Step 7: End

Figure 2.1 Video Object Tracking Algorithm Using Filtering Technique

III. EXPERIMENTAL RESULTS

The proposed Improved Threshold Filtered Video Object Detection and Tracking (ETFVODT) framework is implemented using MATLAB. The video files used for conducing experimental work is obtained from Internet Archive 501(c) (3), a non-profit organization. The Internet Archive consists of texts, audio, moving images, and software as well as archived web pages.

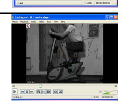
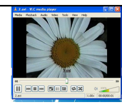
Name	Video file information		
	Video frames	Resolution	Size (KB)
Blossom.avi		216 * 192	349.5
Sample.avi		256 * 240	113.6
Vehicle.avi		510 * 420	323.7
Atheltic.avi		854 * 480	905.3
Person.avi		320 * 240	936.2
Flower.avi		350 * 240	454.5
Rose.avi		458 * 213	635.2

Table 3.1 Video File Information

The video file information illustrated in Table 3.1 includes the name of the video file, resolution of the video files and their size respectively for estimating the performance of ETFVODT framework. Experimental evaluation using ETFVODT framework is conducted on different factors such as object segmentation accuracy, Peak Signal to Noise Ratio, object tracking accuracy, Mean Square Error and object detection accuracy with respect to different videos and video frames. The video employed for object segmentation and tracking using ETFVODT framework is demonstrated below Table 3.1 with detailed information.

The performance of ETFVODT framework is compared against with exiting three methods namely, Self Crossing Detection for Parametric Active Contours (SCD-PAC)) by Arie Nakhmani and Allen Tannenbaum (2012), Automatic Estimation of Multiple Motion (AEMM) by Manya V. Afonso, et al., (2014) and Advanced Fuzzy Aggregation Based Background Subtraction (AFABS) by Pojala Chiranjeevi and Somnath Sengupta (2014).

A. *Measurement of Object Tracking Accuracy*

The object tracking accuracy using ETFVODT framework is defined as the ratio of objects being tracked to the total number of frame / second. The object tracking accuracy is measured in terms of percentage (%) and formulated as below

$$\text{object tracking accuracy} = \frac{OT}{\text{Number of frames/second}} * 100 \qquad (9)$$

From (9), 'OT' refers the objects being correctly tracked. When the object tracking accuracy is higher, more efficient the method is said to be.

Number of frames/second	Object Tracking Accuracy (%)			
	ETFVODT	AFABS	SCD-PAC	AEMM
10	80	75	73	70
20	85	79	77	74
30	88	83	82	79
40	82	76	75	72
50	87	81	80	78
60	90	84	83	80
70	92	87	85	84

Table 3.2 Tabulation for Object Tracking Accuracy

The result analysis of object tracking accuracy with respect to different number of frames being sent per second in the range of 10 to 70 is shown in Table 3.2. From the Table, it is illustrative that the object tracking accuracy using ETFVODT framework is higher as compared to other existing methods.

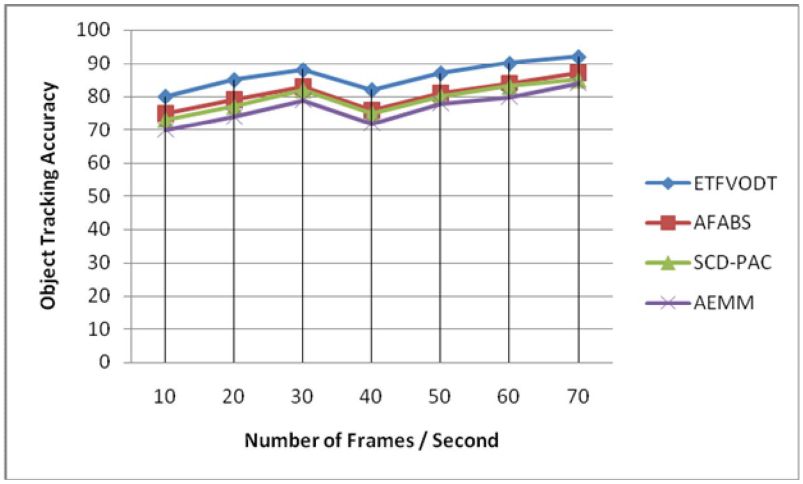


Figure 3.3 Measurement of Object Tracking Accuracy

Figure 3.3 depicts the Object tracking accuracy with respect to different number of frames being sent per second in the range of 10 to 70. From the results shown in the Figure, it is observed that the Object tracking accuracy using ETFVODT framework is comparatively higher when compared to AFABS by Pojala Chiranjeevi and Somnath Sengupta (2014), SCD-PAC by Arie Nakhmani and Allen Tannenbaum (2012), AEMM by Manya V. Afonso, et al., (2014) respectively. This is because of the application of filtering technique in ETFVODT framework which efficiently tracks the moving objects in video sequences. Therefore, object tracking accuracy using ETFVODT framework is improved by 6% as compared to AFABS by Pojala Chiranjeevi and Somnath Sengupta (2014) and 8% as compared to SCD-PAC method by Arie Nakhmani and Allen Tannenbaum (2012) respectively. In addition, ETFVODT framework is improves the object tracking accuracy by 11% as compared to AEMM method by Manya V. Afonso, et al., (2014).

B. Measurement of Peak Signal to Noise Ratio

In ETFVODT framework, Peak Signal-to-Noise Ratio computes the ratio between the reference video frame and the distorted video frame being detected in a video file. When higher the PSNR, the closer the distorted video frame is to the original. Thus, higher PSNR value relates with higher quality image (i.e. detected image) and is mathematically formulated as given below,

$$MSE = \sum_{i=1}^{n}(V_i - V_i') \qquad (7)$$

$$PSNR = 10 \log 10 \frac{R^2}{MSE} \qquad (8)$$

From (7), the mean square error 'MSE' is defined as the difference between the actual frame size 'V_i' and the estimated frame size 'V_i'' being detected. From (8), the peak signal-to-noise ratio '$PSNR$' is calculated using the unsigned integer data type (with size 255) with respect to mean square error rate 'MSE' respectively.

In the experimental setup, the size of video file ranges from 100 KB to 1000 KB. The results of Peak Signal-to-Noise Ratio using four different methods are listed in
Table 3.4. From the Table, it is illustrative that the Peak Signal-to-Noise Ratio using ETFVODT framework provides better results as compared to the other existing methods.

Size of video file (KB)	Peak Signal to Noise Ratio (%)			
	ETFVODT	AFABS	SCD-PAC	AEMM
113.6	29.34	23.69	19.65	15.11
323.7	34.17	27.63	24.87	19.59
349.5	40.19	31.25	29.33	23.78
454.5	43.11	35.87	31.82	27.17
635.2	45.37	39.65	34.43	31.10
905.3	49.87	43.12	37. 51	35.97
936.2	51.24	47.66	40. 28	39.98

Table 3.4 Tabulation for Peak Signal to Noise Ratio

The proposed ETFVODT framework provides better performances as compared to the AFABS by Pojala Chiranjeevi and Somnath Sengupta (2014), SCD-PAC by Arie Nakhmani and Allen Tannenbaum (2012), AEMM by Manya V. Afonso, et al., (2014) respectively. This is because of the application of Filtering technique in ETFVODT framework. Filtering technique is used Bayes Sequential Estimation that measures posterior and prior function for tracking of multiple objects in a video sequence and significantly reduces the Peak Signal to Noise Ratio. Therefore, Peak Signal to Noise Ratio using ETFVODT framework is reduced by 16% as compared to AFABS by Pojala Chiranjeevi and Somnath Sengupta (2014) and 26% as compared to SCD-PAC method by Arie Nakhmani and Allen Tannenbaum (2012) respectively.
In addition, ETFVODT framework is reduced the Peak Signal to Noise Ratio by 36% as compared to AEMM method by Manya V. Afonso, et al., (2014).

IV. CONCLUSION

In this article an enhanced novel framework is renowned as Improved Threshold Filtered Video Object Detection and Tracking (ETFVODT) for efficient video object segmentation and detecting the moving objects in video frames. The ETFVODT technique is significantly used for object segmentation accuracy by way of reducing the PSNR with the help of filtering technique. he main objective of ETFVODT framework is to improve the object segmentation accuracy based on their features. From the experiments conducted for ETFVODT framework, it is observed that of video object segmentation accuracy and detection accuracy for diverse video samples presents more accurate results when compared to state- of-the-art works. The experimental results illustrate that ETFVODT framework provides better performance with an improvement of object segmentation accuracy by 20% and the object detection accuracy by 25% when compared to state-of-the-art works.

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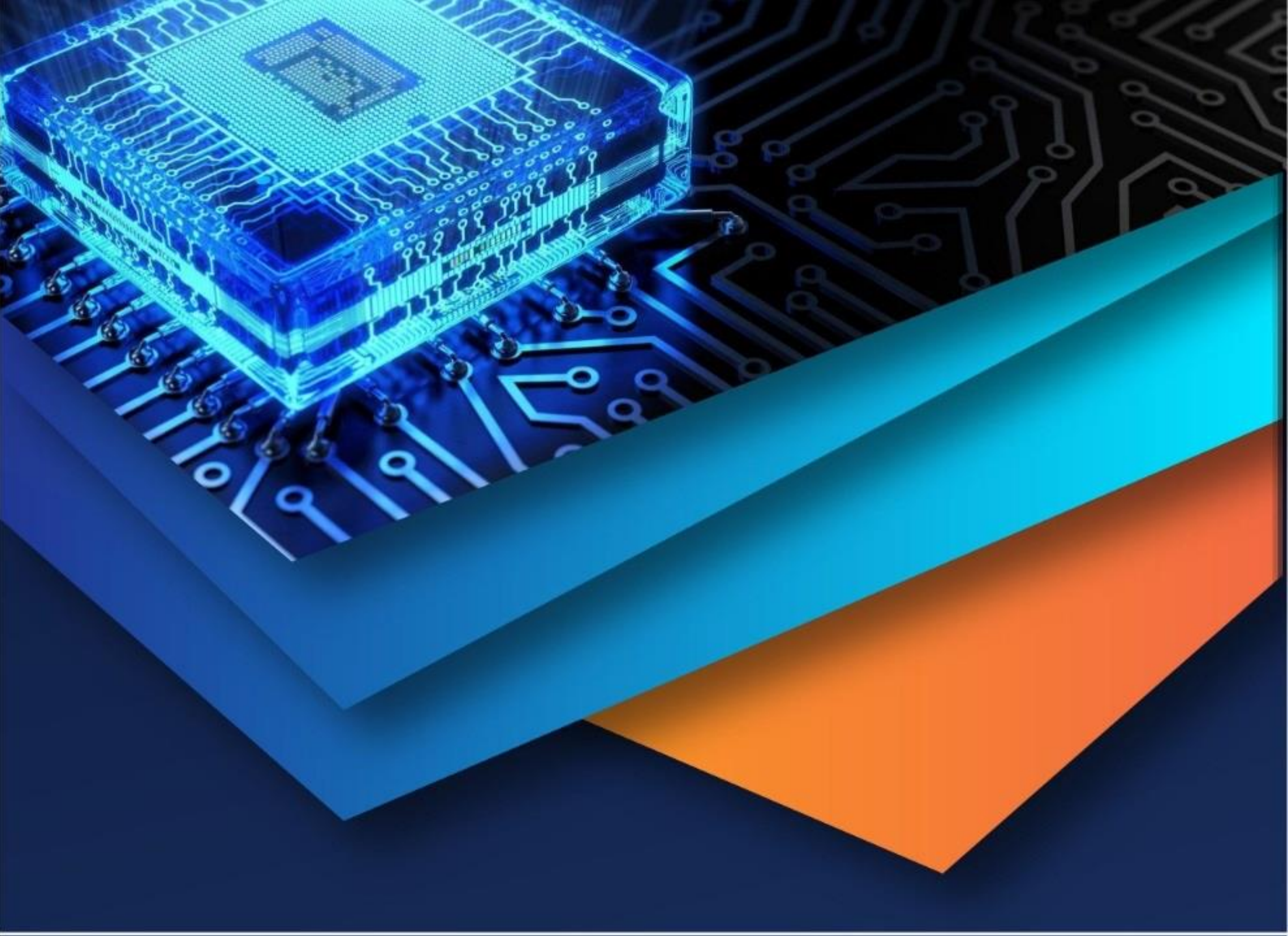

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