

Detection and Tracking of a Moving Object using Canny Edge and Optical Flow Techniques

ABSTRACT

Aims: In the discipline of computer vision, detecting and tracking moving objects in a succession of video frames is a critical process. Image noise, complicated object motion and forms, and video real-time processing are some of the challenges faced by existing methods. Hence, they are computationally complex and susceptible to noise. This work utilized Canny Edge and Optical Flow (CE-OF) techniques for identifying and tracking moving objects in video files.

Methodology: Video sequence datasets in Avi and Mp4 format from MathWorks and YouTube were used to evaluate the developed CE-OF technique. The video clip's frames were sampled several times and the frame rate display was calculated. The original images were converted to grayscale, preprocessed, and CE-OP was applied to identify and track the moving object. The results of the CE-OF and optical flow techniques in terms of accuracy, precision, false acceptance rate, false rejection rate, and processing time were obtained and compared. The performance of the developed technique was evaluated using accuracy, precision, false acceptance rate (FAR), false rejection rate (FRR) and processing time. The results obtained were 94.12%, 92.86%, 25.00%, 25.00%, and 19.51s for Mp4; and 93.33%, 90.91%, 20.00%, 20.00%, and 44.11s for Avi video 1 format, respectively

Conclusion: The developed CE-OF is a better competition in terms of accuracy and time compared with well-known techniques in the literature. The CE-OF technique performed better compared with the conventional methods in detecting and tracking a moving object. Therefore, it can be adopted in the designing of intelligent surveillance systems.

Keywords: frame, object tracking, sampling, video sequence, canny edge, local optical flow, global optical flow, image noise

1 INTRODUCTION

Detection and tracking are closely connected processes since tracking normally begins with detecting objects, and it is frequently essential to identify an item again in consecutive image sequences to aid and validate tracking [2]. Image noise is one of the drawbacks with a traditional tracking system. To a significant degree, a reliable tracking system should be noise-tolerant. Desired visual qualities may be lost as a result of the blurring [6] [11]. Edge and color information-based block matching [1] is one of the many methods to increase matching accuracy. In the frames that are to be matched, edge detection is conducted initially [2] [3]. The blocks are then matched based on their similarities in terms of intensity, edge, and color [4]. Using the suggested approaches, preliminary findings showed that they worked better than the commonly used method based on intensity [5].

Optical flow is a measure of how far each image pixel moves between successive images and is used to assess local image motion. It can detect motion in the presence of camera movement or changing backgrounds. [3] [3]. Optical flow is a factor of the relative motion of moving objects that may be accounted for by tracking the movement of each pixel between frames. This consistency is required to differentiate the object from the background [5] [6] [7]. The Canny edge detector was used to identify the object's edges and traces in order to recognize it. It is the most popular and commonly used strategy for object identification because of its curve-let transformations [10] [11]. The Canny Edge and Optical Flow (CE-OF) approach combines Canny edge detection with optical flow techniques to identify and track moving objects in video datasets. CE-OF will be used to remove the object's boundary from the segmentation module and track the item. The success of subsequent operations is strongly dependent on this stage, and it is crucial that the recognized foreground pixels properly match the moving objects of interest. [12] [10]

It was suggested [6] [7] that identifying and tracking moving objects using a quick and resilient method. Edges that were extracted using optical flow and an edge detector are restored as lines, and the previous frame's background lines are removed from the new image [6] [8]. Each tracked object has a state for dealing with occlusion and interference—you can draw contours around it. The suggested approach performs well in outdoor settings, as seen by the testing findings. The gradient based optical flow and edges have proven to be well matched for accurate computation of velocity for detecting and tracking objects using this feature in 3D virtual reality [9] [10] [11].

Most edges can be detected by the edge detector and refined by the tracker, which also decreases the effect of noise or blurriness. In addition, the extracted edges are virtually thin and suitable for most applications [10]. A gradient image is a representation of the variations between adjacent pixels in a picture. Only using gradient images to extract edges will result in noisy and broken edges. Two-stage edge extraction with contextual filter edge detector and multiscale edge tracker is presented in this technique to tackle the difficulties [12]. With six wavelet basis functions, comparisons with other approaches demonstrate that the proposed methodology extracts better edges than existing wavelet-based edge detectors and Canny detection extractions. It has the benefit that if the beginning points are lost or blended together in the coarser pictures, the edge tracking will not be successful. By first finding edges in fine pictures and then tracing them in coarser images, we can extract more acceptable edges, reduce the impact of noise and blur, and eliminate broken-edge issues [9].

2 RELATED WORKS

The detector has been tested on various databases, including a tough video test set that has a broad range of camera positions, motion, and backdrop imbalances (including rotating backgrounds). The researchers found that oriented histograms of differential optical flow gave the best results. Histogram of Oriented Gradient appearance descriptors are used in conjunction with motion-based descriptors [13]. A sparse optical-flow technique was used in

order to estimate the mobility of these locations [14]. However, the approaches aren't very strong and are not able to deal with moving objects in the video being occluded. Predicting the estimated instantaneous velocities of the objects using adaptive filters and neural networks was utilized. [13] used optical flow to detect mobility in the body. When objects and the observer move in relation to one another in space, optical flow can be generated, and it can provide valuable information about how quickly an object's spatial arrangement changes. Image segmentation is made easier by optical flow discontinuities.

Motion detection techniques based on temporal difference and optical flow fields were developed by [16]. It adapts well to a changing environment. First, two successive gray pictures are used to create an absolute differential image. A low-pass filter is applied to the image to convert it into a binary image. Three Frame Differential Method combined with Canny Edge Detection [17] is described. It eliminates the ghosting effect and defeats the empty phenomena and edge deletion concerns of the traditional three-frame differential technique. A bright light source and visible shadows will impair the picture, as would a dynamic backdrop. There's a new automated bandwidth adjustment technique based on canny edge detection [18]. When the object changes, the canny operator calculates the diagonal distances between the diagonal edge points. Compared to traditional Mean Shift algorithms, this approach is more efficient and has a better adaptive effect.

An optical flow vector is generated using the Horn-Schunck method for moving object identification in [14]. For this reason, it is more susceptible to noise and ineffective under occlusion circumstances since it requires smoothness in the flow throughout the whole frame. The FAR was 0.2226, the accuracy was 0.7881, the precision was 0.7744, and the occlusion rate was 26.06. Researchers [15] have proposed a new way to detect and track moving objects in video. Their simulation was based on about 400 moving objects from the film Gravity. Using the suggested approach, 374 accurate detections were made, yielding a 93.5 percent accuracy rate. There was no difference in performance between the suggested technique and rivals. For video surveillance [20] presented a unique method of object detection. A two-dimensional discrete cosine transform (2DCT) is used in video compression to reduce storage needs. A Bayesian rule is used to classify foreground and background feature points in object detection. Videos may be compressed and objects can be localized using the suggested technique. [11] developed an object detection approach that includes both velocity estimates and classification by speed. We utilized a clustering basis technique (k-mean) to recognize objects, then eliminated noise from erroneous objects and estimated velocity. As the object detection is efficient, the computation of velocity is limited to the identified item, requiring less computing time. A video-based method for vehicle detection has been developed [21].

Fragmentation, morphological operations, and vehicle counting were conducted on traffic video pictures. One hundred and eighty-eight out of fifteen pieces of traffic footage with varying backgrounds from across the world were successfully identified by the system. The proposed method yielded an accuracy of 91.02%. [22] propose the use of entropy-based Canny operator with the local and global optical flow (LGOF) technique. This is a unique data fusion methodology. The proposed method yielded the highest recognition rate of 93% out of 100,000 tested experiments conducted by researchers at ETH Zurich in Switzerland. Researcher [23] suggested optical flow-based object tracking. The system automatically switches between algorithms based on the conditions. Individual items in each frame are identified once the incoming video is split into frame sequences. The most appropriate optical flow algorithm is determined for tracking the passage of objects based on different forms of contextual inputs, such as traffic and wind patterns. The results show that the optical flow-based technique was efficient in object movement tracking.

Vehicle identification, tracking and counting was performed using the gaussian mixture model with optical flow [24]. Several image processing techniques were used in order to recognize and track moving cars from movies taken by a stationary camera. Moving vehicles were counted and identified with an accuracy of about 97 %. Because of ambient noise and

background complexity as well as light variations, it was determined that most approaches used for the identification of moving objects are exceedingly difficult to achieve real-time performance. Also, most flow computation methods are computationally complex and highly sensitive to noise. The application of an efficient edge detection technique can be used to overcome these issues. Hence, this research will apply canny edge segmentation and optical flow techniques to enhance the detection and tracking of moving objects.

3 METHODOLOGY

In this study, the CE-OF technique was used to detect and track moving objects. The detailed annotation of the block diagram of the CE-OF method for detecting and tracking objects within a video sequence is shown in Fig. 1. The data acquisition stage, frame rate display, pre-processing stage, background subtraction stage, segmentation, tracking, and evaluation stages comprise the block diagram's structure. Video sequence datasets were obtained from a common internet source. The video clip's frames were sampled several times. These procedures were carried out in order to detect any minor movement in the video stream. Following that, the frame rate display was calculated, and the original image was converted to grayscale. They had all been pre-processed in the same manner. The images were then cleaned to remove any unwanted noise and to improve the results of subsequent processing. Using the background subtraction method, we were able to determine whether there was a total or a total lack of change in the video. For edge detection and extraction of the image's border, Canny edge segmentation was used. In the final stage of the process, an optical flow technique was used to track the item.

3.1 Acquisition of Video Sequence file

The first steps in the moving object recognition and tracking process were carried out after obtaining a video sequence file from an online database and video data from the MathWorks toolbox. This project made use of a variety of video formats (Mp4 and Avi).

3.2 Frame Display

The average update rate of the input signals was computed and presented in the frame rate display block, which was calculated and displayed. If you've heard of object representation, this is what you're looking for. This was done to enable detection for any slight movement that might occurs in the video sequence. The blocks were used to check the video frame rate of the simulation to control the specified number of video frames.

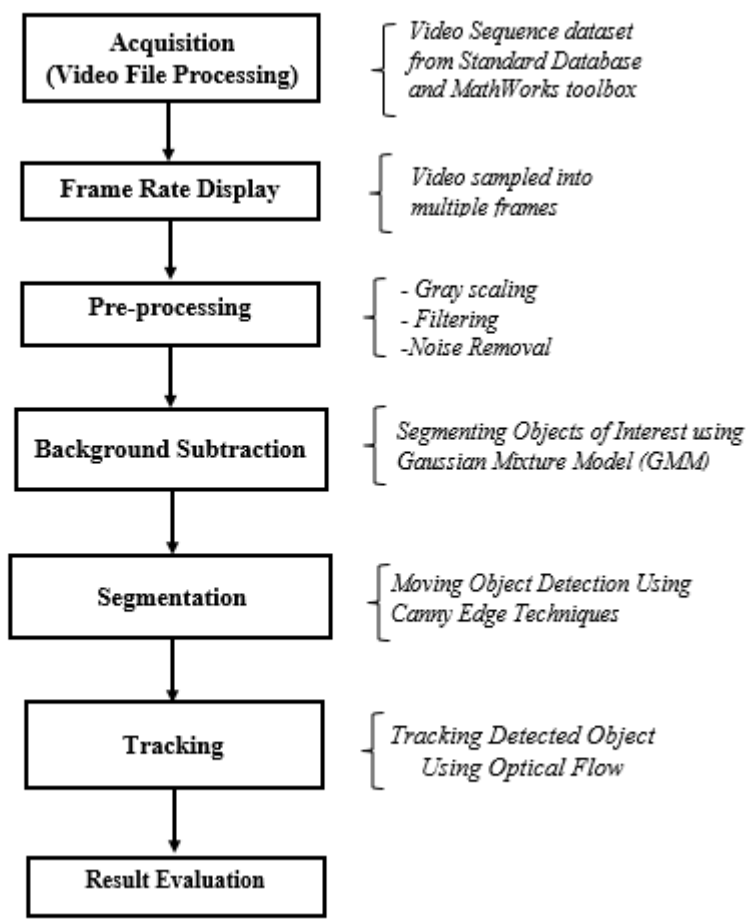


Fig. 1: The Structure of the Moving Object Detection System
3.3 Pre-processing

The frame rate display block calculates and displays the average update rate of the input signals. This is what you're looking for if you've heard of object representation. This was done to detect any minor movement that may have occurred in the video sequence. The blocks were used to control the number of video frames by checking the simulation's video frame rate.

3.3.1 Conversion to Gray Scale

After the frames have been captured, each frame must go through the same processing chain as the previous frame. The first step is gray-scaling. It is a digital image in which each pixel represents a single sample of data. Most images of this type are composed of grayscale shades ranging from black at the lowest intensity to white at the highest. In theory, the samples could be displayed as shades of any color, or even labeled with multiple colors for varying intensities. This allows for the recording of 256 intensities, typically on a non-linear scale for grayscale images intended for visual display.

3.3.2 Noise Reduction

Noise reduction is a necessary preprocessing step to ensure accurate object detection and tracking. This is also significant because the Canny edge detector employs a filter based on

the first derivative of a Gaussian, which is susceptible to noise present in raw unprocessed image data. Thus, the raw image is first convolved with a Gaussian filter. As a result, the original is slightly blurred but not significantly affected by a single noisy pixel.

3.4 Background Subtraction

Background subtraction detects moving objects in a video frame that differ significantly from a background model. Background subtraction is a simple technique that involves subtracting the observed image from the estimated image and thresholding the result to generate the objects of interest. The locations of the objects of interest are indicated by areas of the image plane where there is a significant difference between the observed and estimated images. The Gaussian Mixture Model (GMM) was used in the study to segment objects of interest. A pixel in the current frame was checked against the background model using this method by comparing it to every Gaussian in the model until the same Gaussian was found. If the same Gaussian is found, the Gaussian's mean and variance are updated; otherwise, a new Gaussian with a mean equal to the current pixel color and some initial variance is introduced into the mixture. Each pixel is classified according to whether the matched distribution represents the background process.

3.5 Canny Edge for Object Detection

The Canny technique was used to detect edges in a picture by looking for local maxima in the gradient. The Canny method was used to detect the background picture's borders in the absence of moving objects. Canny's edge detector is a powerful tool that determines the squared gradient magnitude. There is a lot of math involved in the optimization process. A Gaussian low-pass filter was used to smooth the image, and edges were identified as local maxima of gradient magnitude that exceeded a threshold. The edge detector's reduced noise sensitivity is a direct result of the low-pass filtering performed before computing gradients. The threshold local peak detection method is known as non-maximum suppression.

3.6 Optical Flow for Tracking Object

Tracking an item over time is accomplished by keeping track of its location in each frame of the movie. Every time the item was tracked, the tracker displayed the entire picture area that the object was occupying at the time. To track the item in the video sequence in each frame, an optical flow estimation method was used. The algorithm's optical flow estimation begins as soon as an item is detected.

In a visual image, optical flow refers to the apparent mobility of objects, surfaces, and edges caused by an observer's relative motion (an eye or a camera). It can be used to see how frames change as a result of motion over a specific time interval. To generate dense flow fields, the flow vector of each pixel must be calculated while the brightness remains constant.

Real-world three-dimensional items are simplified and accelerated by converting them to a two-dimensional (2D+time) scenario. To characterize the image, a 2D dynamic brightness function of place and time is used (x, y, t). As long as there was no change in brightness intensity along the motion field in the vicinity of a displaced pixel, the following equation (1) was used:

$$I(x, y, t) = I(x + \delta x, y + \delta y, t + \delta t) \quad (1)$$

Using Taylor series for the right-hand part of equation (1); equation (2) is obtained:

$$I(x + \delta x, y + \delta y, t + \delta t) = I(x, y, t) + \frac{\partial I}{\partial x} \delta x + \frac{\partial I}{\partial y} \delta y + \frac{\partial I}{\partial t} \delta t . . . \quad (2)$$

From equation (1) and equation (2), after modifications equation (3) is produced

$$I_x \cdot v_x + I_y \cdot v_y = -I_t \quad (3)$$

or equation (4) in formal vector representation.

$$\nabla I \cdot \vec{v} = -I_t \quad (4)$$

Where I is the spatial gradient of brightness intensity and is the image pixel's optical flow (velocity vector), the time derivative of brightness intensity. Equation (4), also known as the 2D Motion Constraint Equation, is the most important for optical flow calculation. This computation is always performed in the pixel's vicinity, either algebraically or geometrically. The model generates binary feature images by thresholding and performing morphological closing operations on the motion vectors.

3.7 Implementation for Object Detection and Tracking

For the implementation, we utilized the MATLAB R2018a version of the program. A graphical user interface was required (GUI). The input video was initially divided into frames. Using GMM to separate the background from the preprocessed frames The Canny Edge method was used to identify moving objects, and an optical flow algorithm based on contextual features of trained video sets was used to track discovered objects.

3.8 Evaluation Measures

The CE-OF techniques for detecting and tracking moving objects will be evaluated in terms of accuracy, false alarm rate, false rejection rate, precision, and processing time. The value of the performance metrics will be determined using a confusion matrix. The following words are included: TP, FP, FN, and TN.

True positives (TP) are foregrounds that have been detected successfully, whereas false negatives (FN) are foregrounds that have not been detected (FN). When an item is detected incorrectly, it is referred to as a "false positive" (FP). The true negative (TN), as the name implies, are the items that are not mistakenly identified as the backdrop. The false alarm rate (FAR), precision, and accuracy are some of the performance indicators derived from these words as equation 5-8.

$$\text{False Acceptance Rate} = \frac{\text{FP}}{\text{TN} + \text{FP}} \quad (5)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (6)$$

$$\text{False Rejection Rate} = \frac{\text{FN}}{\text{FN} + \text{TP}} \quad (7)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (8)$$

4 RESULTS AND DISCUSSION

4.1 The Experiment

The experiment for this study was carried out on a computer equipped with an Intel (R) Core (TM) i5-2540M CPU running at 2.60 GHz and 6.00 GB of RAM. In this study, two videos in two different formats (Mp4 and Avi) were used to evaluate the techniques. The software is written in MATLAB R2018a. This chapter presents the experimental results. Based on the CE-OF method and the traditional optical flow method, an extensive experiment was conducted on the acquired videos with some people as moving objects. Fig. 2 graphically displays the simulation results for each video, as well as the input videos and the actual number of people detected. The segmented result is labeled (a) in the figure, while the moving object in the binary image is labeled (b). The graphical representation of the

performance of the method considered in this study demonstrates that the CE-OF technique can detect moving people accurately and provide the correct number of moving people in the video. However, the traditional optical flow method has some cases of occlusion, and two objects are counted as one, resulting in a small difference between the actual and detected number of people. The use of a canny edge in conjunction with an optical flow technique reduces occlusions and improves the detection and tracking of moving objects.

4.2 Result for Video 1

Tables 1 and 2 show the optical flow and CE-OF performance, respectively. Video 1 has 13 moving objects in Mp4 format and 10 moving objects in Avi format, according to the results in Table 1. Optical flow detected 15 and 14 objects, respectively, in Mp4 and Avi formats.

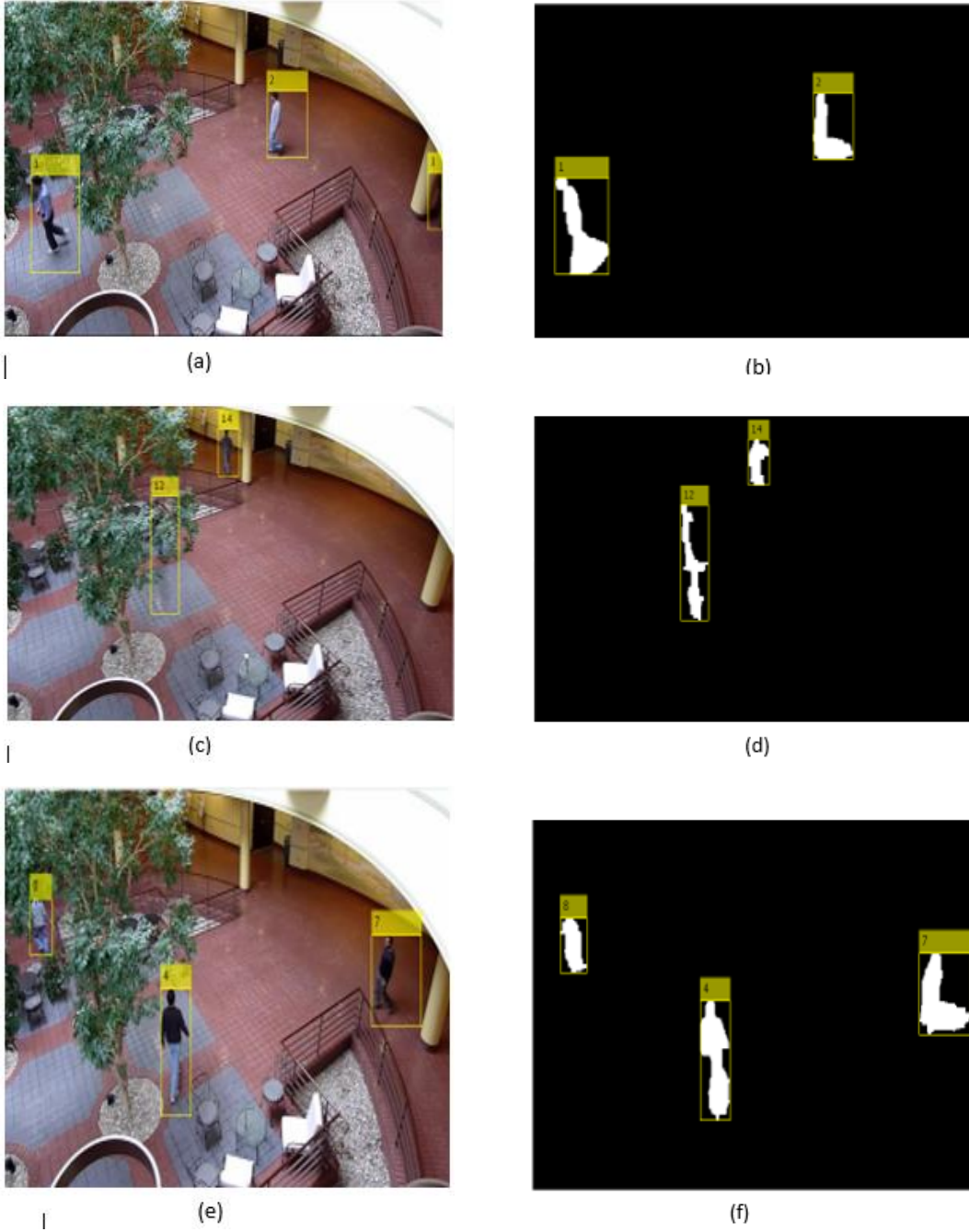


Fig. 2: Depiction of Tracking of Images (a), (c) and (e) and the Simulation Results of the Tracked Images are in (b), (d) and (f) each video graphically by the CE-OF technique.

Table 1: Optical Flow and CE-OF Performance for Video 1

Technique Used	Optical Flow		CE-OF	
	Mp4	Avi	Mp4	Avi
Video Type	Mp4	Avi	Mp4	Avi
Total moving Object	13	10	13	10
Object Detected	15	14	17	15
Correct Object (TP)	12	9	13	10
Misclassified Correct Object (FN)	1	1	0	0
False Static Object (TN)	1	3	3	4
Misclassified False Object (FP)	1	1	1	1
Accuracy (%)	86.67	85.71	94.12	93.33
Precision (%)	92.31	90.00	92.86	90.91
FAR (%)	50.00	25.00	25.00	20.00
FRR (%)	7.69	10.00	25.00	20.00

Table 2: Optical Flow and CE-OF Performance for video 2

Technique Used	Optical Flow		CE-OF	
	Mp4	Avi	Mp4	Avi
Video Type	Mp4	Avi	Mp4	Avi
Total moving Object	12	9	12	9
Object Detected	14	12	16	14
Correct Object (TP)	11	8	12	9
Misclassified Correct Object (FN)	1	1	0	0
False Static Object (TN)	1	2	4	4
Misclassified False Object (FP)	1	1	1	1
Accuracy	85.71	83.33	94.12	92.86
Precision	91.67	88.89	92.31	90.00
FAR	50.00	33.33	20.00	20.00
FRR	8.33	11.11	20.00	20.00

For video in Mp4 format, the optical flow technique correctly detected 12 moving objects, misclassified 1 correctly detected object, detected 1 false static object, and misclassified 1 misclassified object. Similarly, for video in Avi format, the optical flow technique correctly detected 9 moving objects, misclassified 1 correctly detected object, detected 3 false static objects, and misclassified 1 misclassified object. Furthermore, for the Mp4 and Avi formats, CE-OF detected 17 and 15 objects, respectively. In a video in Mp4 format, the CE-OF technique correctly detected 13 moving objects, incorrectly detected 3 static objects, and misclassified 1 object. Similarly, for video in Avi format, the CE-OF technique correctly detected 10 moving objects, incorrectly detected 4 static objects, and misclassified 1 false object.

Moreover, as shown in Tables 1 and 2, the optical flow technique achieved an accuracy of 86.67%, a precision of 92.31%, a FAR of 50.0% and a FRR of 7.69% for video in Mp4 format. Similarly, the optical flow technique achieved an accuracy of 85.71%, a precision of 90.00%, a FAR of 25.0% and a FRR of 10.0% for video in Avi format. Moreover, the CE-OF technique achieved an accuracy of 94.12%, a precision of 92.86%, a FAR of 25.0% and a FRR of 25.00% for video in Mp4 format. Similarly, the CE-OF technique achieved an accuracy of 93.33%, a precision of 90.91%, a FAR of 20.0% and a FRR of 20.0% for video in Avi format.

4.3 Result for Video 2

According to the results in Table 2, video 2 contains 12 moving objects in Mp4 format and 9 moving objects in Avi format. Optical flow detected 14 and 12 objects, respectively, in Mp4 and Avi formats. For video in Mp4 format, the optical flow technique correctly detected 11 moving objects, misclassified 1 correctly detected object, detected 1 false static object, and misclassified 1 misclassified object. Similarly, for video in Avi format, the optical flow technique correctly detected 8 moving objects, misclassified 1 correctly detected object, detected 2 false static objects, and misclassified 1 misclassified object. Furthermore, for the Mp4 and Avi formats, CE-OF detected 16 and 14 objects, respectively. The CE-OF technique correctly detected 12 moving objects, incorrectly detected 4 static objects, and misclassified 1 object in Mp4 video. Similarly, for video in Avi format, the CE-OF technique correctly detected 9 moving objects, incorrectly detected 4 static objects, and misclassified 1 false object.

Moreover, as shown in Table 2, the optical flow technique achieved an accuracy of 85.71%, a precision of 91.67%, a FAR of 50.0% and a FRR of 8.33% for video in Mp4 format. Similarly, the optical flow technique achieved an accuracy of 83.33%, a precision of 88.89%, a FAR of 33.3% and a FRR of 11.1% for video in Avi format. Moreover, the CE-OF technique achieved an accuracy of 94.12%, a precision of 92.31%, a FAR of 20.0% and a FRR of 20.00% for video in Mp4 format. Similarly, the CE-OF technique achieved an accuracy of 92.86%, a precision of 90.00%, a FAR of 20.0% and a FRR of 20.0% for video in Avi format.

4.4 The Processing Time

The processing time achieved by both the optical flow and the CE-OF techniques is shown in Table 3. The CE-OF technique achieves a process time of 19.51s and 44.11s for Mp4 and Avi video formats, respectively, according to the table results, while the optical flow technique achieves a process time of 23.25s and 57.78s for Mp4 and Avi video formats, respectively, using the first video. Furthermore, using the second video, the CE-OF technique achieves process times of 21.65 s and 48.19 s for Mp4 and Avi video formats, respectively, whereas the optical flow technique achieves process times of 27.62 s and 59.36 s for Mp4 and Avi video formats, respectively. The results show that using canny edge in conjunction with optical flow reduces the processing time for detecting and tracking moving objects.

Table 3: The Processing Time

Video Format	Mp4			Avi		
	Techniques	Optical (Seconds)	Flow CE-OF (Seconds)	Optical (Seconds)	Flow CE-OF (Seconds)	CE-OF (Seconds)
Video 1		23.25	19.51	57.78		44.11
Video 2		27.62	21.65	59.36		48.19

4.5 Results Discussion

The results obtained by the techniques under investigation demonstrated that both the CE-OF technique and the standard optical flow technique were effective in detecting and tracking moving objects. The technique's graphical representation of the simulation serves as proof of the techniques' efficiency in segmenting and tracking the moving object. The binary representation of moving objects demonstrates that the shadows of the people moving in the video were also included in the segmented image. This was improved with CE-OF techniques, but it still needs to be improved further. Fig. 3 depicts the processing time achieved by each technique based on different video formats. The use of canny edges in conjunction with the optical flow technique ensures faster detection and tracking of moving objects due to a shorter process time when compared to the standard optical flow technique. The avi video format takes longer to process than the mp4 video format. This is due to the fact that the Avi video format has higher quality, size, and lossless compression than the mp4 format. This is consistent with [16] forensic analysis of video file formats, which concluded that Avi video requires extensive processing due to its large size and high quality. Furthermore, [17] confirmed that different video files have different processing times, and that the larger the file and the higher the quality, the longer the processing time. As a result of the results obtained in this study, CE-OF has a faster processing time than standard optical flow.

Figures 4–7 show a graph depicting the performance of the techniques under consideration in this study based on performance metrics. According to the graphs, the CE-OF technique improved accuracy, precision, FAR, and FRR. Fig. 5 depicts the video format accuracies achieved by CE-OF and the standard optical flow technique. The CE-OF technique resulted in an increase of 8.41%, 9.53%, 7.45%, and 7.62%.

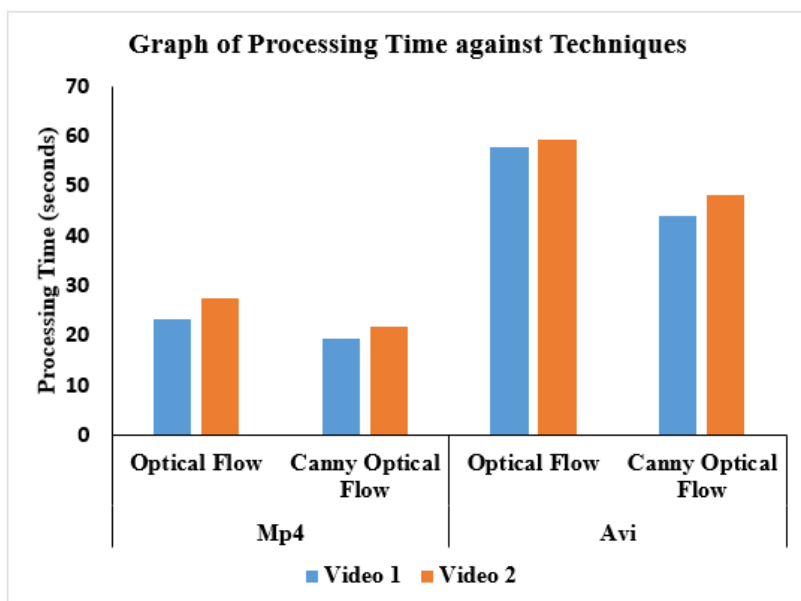


Fig. 3: Bar Chart of Processing time against each technique

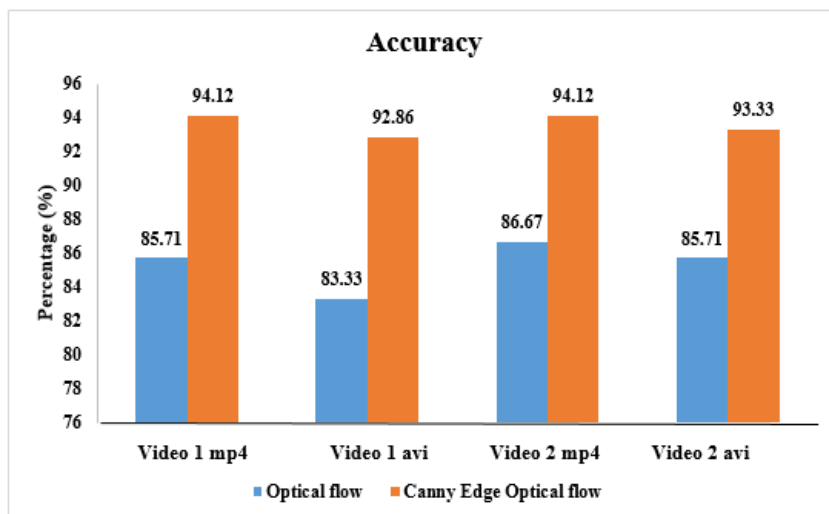


Fig. 4: Bar Chart Showing the accuracy of the Techniques

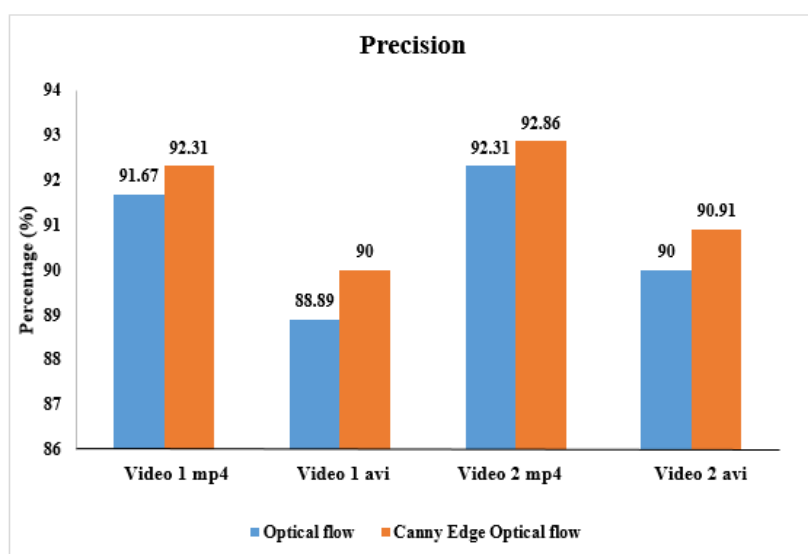


Fig. 5: Bar Chart Showing the Precision of the Techniques

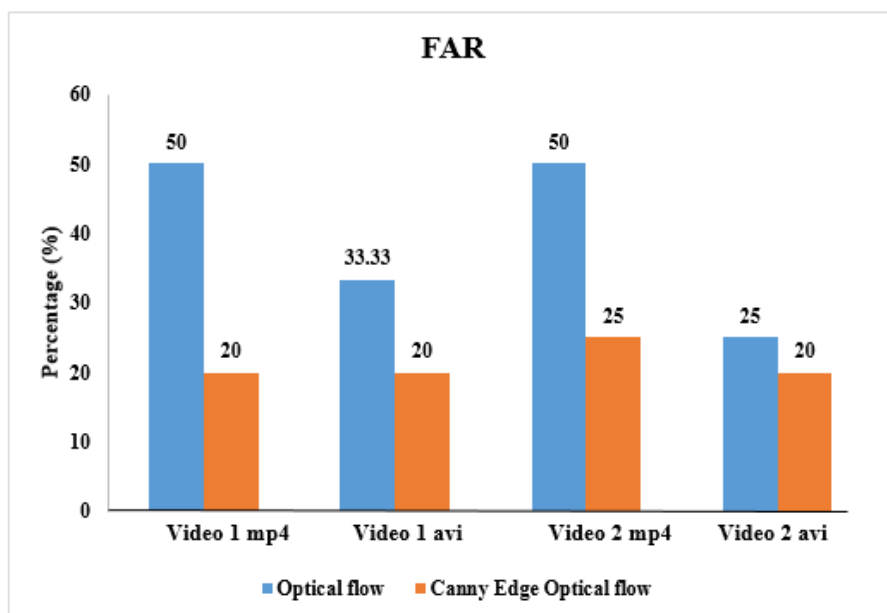


Fig. 6: Bar Chart Showing the FAR of the Techniques

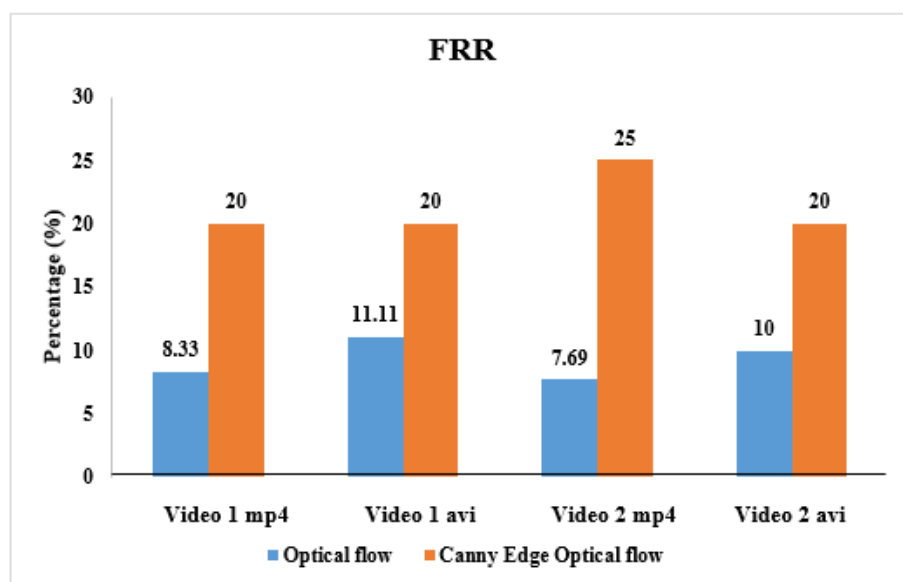


Fig. 7: Bar Chart Showing the FRR of the Techniques

For Video1.mp4, Video2.mp4, Video1.avi, and Video2.avi, use the standard optical flow technique. It was also discovered that the video-avi format performed better than the other two techniques in terms of accuracy. The CE-OF technique, on the other hand, outperformed the standard optical flow technique. The improved accuracy is due to the use of the canny edge technique, which suppresses noise while retaining edge information for easy tracking using the optical flow technique. The accuracy implies that the proposed solution in this study ensures the accurate detection of moving objects. The obtained results support the assertions of [4] and [18], which state that accurate edge estimation combined with the use of optical flow can improve the accuracy of tracking moving objects.

Fig. 6 shows the precision gained by CE-OF and the typical optical flow technique in terms of video format. For Video1.mp4, Video2.mp4, Video1.avi, and Video2.avi, the CE-OF

technique provided a minor gain in precision of 0.64 %, 1.11 %, 0.55 %, and 0.91 % over the traditional optical flow technique. The results suggest that using canny edge approaches has little effect on the performance of the optical flow technique. In addition, Fig. 7 displays the FAR obtained by CE-OF and the normal optical flow technique in terms of video format. For Video1.mp4, Video2.mp4, Video1.avi, and Video2.avi, the CE-OF technique reduced FAR by 30.0 %, 13.33 %, 25.0 %, and 5.0 %, respectively, compared to the traditional optical flow technique. The results showed that using the CE-OF approach resulted in a higher FAR. This is consistent with the findings of [19], who claimed that edge-based optical flow approaches give improved speed and accuracy while having a low false acceptance rate. Fig. 7 also shows the FRR achieved by CE-OF and the typical optical flow approach in terms of video format. The CE-OF technique outperformed the normal optical flow technique by 11.67%, 8.89%, 17.31%, and 10.0% for Video1.mp4, Video2.mp4, Video1.avi, and Video2.avi, respectively. The results showed that using canny edge with the optical flow technique has a negative influence on the FRR when compared to using the regular optical flow approach. This usual optical flow approach resulted in a higher FRR. This is most likely due to the CE-OF approach incorrectly rejecting moving object shadow edges. This is consistent with [20], who claimed that edge-based optical flow approaches can suffer from poor FRR due to occlusions and incorrectly labeled flow. According to the findings of this investigation, the CE-OF technique is more accurate and precise, with less FAR and processing time than the typical optical flow technique. The created approach, on the other hand, has a greater FRR. The difficulties raised by the increasing FRR will be addressed in the future.

4.6 Statistical Evaluation

The results obtained by the procedures examined in this study reveal quantitative variation; nonetheless, it is necessary to determine whether the difference between the techniques is substantial. As a result, an inferential statistical analysis was performed using a paired-sample t-test to compare the accuracy, precision, FAR, and FRR between CE-OF and the standard optical flow. The test was carried out to establish the level of relevance in the execution of the developed technique. Table 4 displays the findings of the SPSS analysis. At a 5% level of significance, the paired sampling t-test was done on the null hypothesis (H_0) that there is no significant difference between optical flow and the CE-OF technique, versus the alternative that there is a significant difference between optical flow and the CE-OF technique (H_1). The hypothesis is defined as follows:

Table 4: Summary of t-test results for optical flow and the CE-OF approach

Parameter	t	Degree of Freedom (<i>df</i>)	p-value	Comment
Accuracy	17.395	3	0.000	Significant
Precision	6.275	3	0.008	Significant
FAR	-3.243	3	0.048	Significant
FRR	6.399	3	0.008	Significant

H_0 : There is no discernible distinction between optical flow and the CE-OF approach.

H_1 : The CE-OF method and optical flow have substantial differences.

The p-values for accuracy, precision, FAR, and FRR in Table 4 are 0.000, 0.008, 0.048, and 0.008, respectively. The p-value is a measure of statistical significance. The significance test of the accuracy, precision, FAR, and FRR at a 95% confidence level revealed a significant difference between the optical flow and CE-OF techniques. As a result, the alternate theory is accepted. The t-test result confirms that CE-OF outperforms optical flow in terms of accuracy, precision, and FAR. In terms of FRR, however, optical flow outperformed the CE-OF approach.

4.7 Comparison with other state-of-the-art methods

The CE-OF technique developed in this work was compared with other known methods in the literature including optical flow using Horn-Schunck algorithm proposed by [14], Canny edge detection algorithm developed by [15], Two-dimensional discrete cosine transforms (2D DCT) proposed by [16], Morphological approach with Black Top-Hat Transform proposed by [17], and Local and global optical flow (LGOF) proposed by [18]. Table 5 shows the results of a comparison of the created methodology with other state-of-the-art technologies. The table presents the results, which show that the developed techniques are well matched with existing techniques in term of accuracy and processing time.

Table 5: Comparison results of the developed technique with other state-of-the-art methods

Author	Method	Accuracy (Time)
Developed technique	CE-OF Algorithm	94.12% (19.51s)
Tang et al. (2019)	Local and global optical flow (LGOF)	93.0% (N/A)
Pawar et al. (2017)	Morphological approach with Black Top-Hat Transform	91.00% (N/A)
Pawar et al. (2017)	Morphological approach with Black Top-Hat Transform	91.00% (N/A)
Kalirajan and Sudha (2015)	Two-dimensional discrete cosine transforms (2D DCT)	90.03% (N/A)
Karamiani and Farajzadeh (2014)	Canny edge detection algorithm	93.5% (60s)
Jansari and Parmar (2013)	optical flow using Horn-Schunck algorithm	78.81% (N/A)

5 CONCLUSIONS

In this research, a Canny edge-based optical flow technique was applied for the detection and tracking of moving objects. Results show that in terms of accuracy, precision, FAR, and processing time, the developed technique outperformed the optical flow technique. The developed technique tends to provide an effective way towards improving the performance of detecting and tracking moving objects in surveillance systems. The developed CEOF can be adopted for accurate detection and tracking of objects in intelligent visual surveillance systems that can assist the human operators in detecting unusual events in the video sequence and responding to them rapidly. Also, it could be adopted for various applications in computer vision, such as video surveillance, video compression, vision-based control, human-computer interfaces, robotics, medical imaging, and augmented reality. Future work can be carried out by investigating how to reduce the FRR associated with the developed technique and by eliminating the shadow effect of moving objects.

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