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# Improve Multi-Object Detection and Tracking for an Automated Traffic Surveillance System

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***Abstract***— *Multi-Object Detection and Tracking (MODT) are essential in many application fields. Still, many enhancements in the speed of detection and tracking were required to overcome the challenges during implementation. This paper presents a new algorithm system for (MODT) to improve the execution time to be robust in real-time applications. A background subtraction detection algorithm with a Kalman filter was used to track and predict the object position and speed parameters. To improve the processing time, its needs to reduce some frames in a way that does not affect the detection accuracy too much and instead use the prediction and the estimated value obtained based on the Kalman filter for the tracked object. This work uses a single video camera to show how effectively to compute and detect multiple objects concurrently; it is applied for daytime preprocessing in an automated traffic surveillance system.*
*Preliminary testing findings show that the suggested algorithm for this vehicle monitoring system is feasible and effective. It illustrates that using the suggested algorithm with a single video camera can simultaneously watch, detect, and track several vehicles and improve execution time. Simulation results on the built system demonstrate that the proposed system reduced the execution time to approximately 41.5% compared to the standard background subtraction algorithm. Results indicate the proposed algorithm has an approximate error for the position and speed of detected and tracked objects compared with the standard background subtraction algorithm.*

***Index Terms***— *multi-object detection, tracking, background subtraction, Kalman filter, morphological.*

## I. INTRODUCTION

Surveillance, detecting, and locating technologies have become more prevalent in many modern applications in recent decades. Security and traffic surveillance systems, medical applications, automated driving systems, and so on are examples of these uses. Numerous studies and papers have also been published using various tactics and strategies to achieve an efficient real-time system. With the development of surveillance systems and the growth in closed circuit television (CCTV) cameras, it has become challenging for many employees in control centers to operate efficiently throughout the day while controlling many cameras simultaneously. As a result, effective detection and tracking technologies that operate in real-time were necessary. It has applications in the early identification of foreign species, violent crime, and other areas, as in [1], [2]

The use of visual sources such as cameras in video processing applications is continuously growing. A video visual sequence may be used to analyze and identify moving object position, speed, and direction. By sampling the continuous video at the desired sample rate, the video read from a camera is saved and transformed into frames, an essential step for object recognition and tracking. Frame differencing employs comparing two video frames and checking for an apparent change in the pixels to discover the change in the series of frames. When determining an item's location as an output,

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differencing comes in handy when the object's template is located and determined using this extracted position as in [1], [3].

Picture morphology is a technique for making image content highly apparent, i.e., accurately detecting the object's area inside the image region. This Image Morphology technique stretches and shrinks the object area according to the requirements. The technique of dilating (growing) the picture area by adding equivalent additional pixel values is known as image dilation. Image dilation and erosion are two forms of image morphology. Image dilation is the expansion of an image, whereas image erosion is the shrinking or decrease of an image. On the other hand, picture erosion reduces an image's size by deleting unwanted pixels, as in studies [4], [5].

Before the Morphology process, it should use the threshold approach to turn the frame-differenced picture into a binary image. Here, it should take a specific pixel value as the threshold value, with pixels below this threshold regarded as zero and pixels over this threshold considered one. The threshold was determined so that the image's information was not lost. Template matching is a crucial approach in object tracking; it simply extracts the objects from the early frames as rectangular templates, which are then matched with subsequent frames to track the item in the video as in research[6], [7]. The tracking module receives the created template from each frame and begins tracking the object using the input reference template. This module uses template matching to search the scene acquired by the video Camera for the input template. A new template is dynamically constructed and utilized if an item is lost during tracking because of its look. This dynamic development of such templates aids in accurately tracking the item as in [8], [ 9].

The paper was divided into sections: The second section will describe the related work and research contributions. Section three will cover the methodology and the equations used with the standard and the suggested algorithm's conceptual foundation and fundamental concepts. Section four, which illustrates the proposed method, will be thoroughly examined. Section five is devoted to the proposed algorithm's experiment findings and testing, as well as their comparison with the results of the existing algorithm to evaluate its performance, effectiveness, and efficiency. The final section part shows the importance of the proposed algorithm with ways that can be used to make more improvements to the systems proposed.

## II. RELATED WORK

An increasing number of video processing applications use cameras as their video inputs. All moving items in a scene can be identified simultaneously, but those items cannot be tracked simultaneously. However, for effective tracking, it can only focus on one object. While detecting and tracking objects, a variety of challenges or difficulties develop. The obstacles in object detection and tracking are caused by a loss of information, image noise, intricate object shapes, varying lighting in scenes, the shadows of moving objects, real-time tracking, and other variables as in[10], 11].

References [12], [13] proposed a method to extract motion information from video data using the Fast Principle Component Purist (FPCP). The Fast Principle Component Purist (FPCP) develops a brand-new algorithm for identifying moving objects in video footage (FPCP). The technique consists of three primary components: (1) modeling the backdrop and extracting the foreground; (2) smoothing, filtering, and recognizing moving objects inside the video frame; and (3) tracking and predicting the behavior of discovered objects. A highly effective ideal filter was employed to filter out the noise morphologically. When identifying objects and their regions in space, Blob analysis is performed to smooth things out, and then the Kalman Filter is employed to keep tabs on the recognized item. After that, it passed to the median filter to eliminate the noise using a high-performance optimum filter. Kalman Filter keeps tabs on the discovered item.

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Airports, ports, major motorways, government buildings, and other vital sites often have a video surveillance system installed to act as "thousands of eyes" and aid in the battle against crime [9]. The studies [4] evaluated three different camera setups in a parking lot and compared them using the Gaussian Mixture Model technique and two saliency-based algorithms.

Foreground/Background Separation methods that decompose the low-order matrix have recently seen a lot of success; therefore, a new real-time incremental technique was presented based on the Low Rank and Total Variation (T.V.) model to remove many types of noise simultaneously. The adaptive modeling technique may automatically eliminate noise and detect the foreground, whether actual or internet films are utilized as in [14].

Since its inception, evaluating multi-object tracking (MOT) systems has been challenging. Previous measurements have overvalued both detection and association. Higher order tracking accuracy (HOTA) is a new (MOT) assessment metric to overcome this issue; it integrates the importance of correct detection, association, and localization into a single, cohesive measure [8]. Simple Online and Real-time Tracking (SORT) aims to efficiently track many objects in real-time using the most basic yet effective methods. In [15], the researchers added visual cues to (SORT's) performance to make the algorithm more practical. The improvement allows the algorithm to keep tabs on objects even after those objects have been obscured for longer, reducing the need for identity shifts.

The work in [16] provides a real-time multiple-object tracking system based on a modified version of the DeepSort algorithm. The update addresses the object initialization process, and its reasoning is to consider an object monitored if it is identified in a sequence of prior frames. The improved DeepSort is combined with You Only Lock One (YOLO) detection algorithms. Concrete and multi-dimensional examination of the framework's performance is undertaken in real-time monitoring of automobiles and people in various traffic movies using datasets and real-world footage.

Researchers in [17] extract valuable information with high speed and accuracy through an efficient approach for detecting and tracking multiple objects, calculating critical detection, and tracking performance characteristics such as training and learning efficiency, as well as the influence of training sample sizes, inspecting some problems to assist the algorithm, giving good results and stable performance training. Also, several Deep Learning Networks (DLN) detection models were tested on the NVidia Jetson (TX2) Platform, and the suggested approach was also implemented in [17]. The suggested method in [18] employed an effective Kalman filtering algorithm to track moving objects in video frames. The video clips were translated into morphological procedures depending on the number of frames using the region growth model. After differentiating the items, the probability-based grasshopper method optimized parameters using Kalman filtering.

In [1], Features, such as the number of items, velocity, acceleration, deceleration, and the path of the objects, are also revealed by the movement direction and how it enters and departs the zone of interest. Image analysis may also be used to infer these traits. The reach in [2] has techniques that combine principal component analysis with deep learning networks to maximize the benefits of both approaches to build a real-time intelligent identification and tracking system.

Reference [20] studied a novel and end-to-end trainable (MOT) architecture that extends Center-Net by adding a (SOT) branch for tracking objects in parallel with the existing branch for object detection, allowing the (MOT) task to benefit from the solid discriminative power of (SOT) methods effectively and efficiently. Unlike most previous (SOT) approaches, which learn to identify the target object from its local backdrops, the new (SOT) branch trains a distinct (SOT) model per target to live to distinguish the target from its surrounding targets, allocating the unique discrimination to (SOT) models. Furthermore, like the detection branch, the (SOT) branch interprets objects as points, allowing for fast online learning even when several targets are handled concurrently [19]. The use of visual characteristics enhanced the (SORT) algorithm. As a result of this improvement, fewer identity flips occurred while tracking objects across longer occlusions was included by moving much of the

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computational complexity to an offline pre-training step, where a deep association metric is learned on a massive human re-identification dataset.

The study in [21] presents a new technique to enhance the adaptive background mixing model. Update equations were reexamined, and new ones were used in various processes. Because of this, the proposed system learns more quickly and correctly, adapts to new conditions, and maintains its effectiveness over time. The study also discovered a method for detecting shadows. In [22], the suggested background model is built on computational color space. Studies of video-based object recognition and tracking have been conducted. Organized the many tracking approaches into several categories and described a few more prominent ones from each in depth.

A new algorithm system must be presented to make Multi-Object Detection and Tracking (MODT) more suitable for real-time contexts. A background subtraction detection technique used a Kalman filter to track and predict the object's position and speed characteristics. When the detector is not actively searching for a new object, it is necessary to reduce the number of frames being processed in a way that does not negatively impact the detection accuracy to reduce the overall processing time required. It is done by substituting the prediction and the estimated value obtained from the Kalman filter for the tracked object.

A movie is a collection of pictures that have been appropriately sequenced. This video is sampled to create a dataset from the series of frame samples. For subsequent item recognition and tracking, these frames are employed. In this work, use stationary camera videos that have been elevated more. A high level of picture description is needed to identify the moving item and convey the precise trajectory. However, employ low-and high-quality videos to check the proposed algorithm's performance. The primary goal of this research is to develop a more advanced system for detecting and tracking moving objects with less execution time and reasonable accuracy. When applied to linear problems, the Kalman filter gives a sequential, unbiased, and lowest error variance estimate, all while assuming that the statistics of the system and measurement errors are known. The ability of the Kalman filter to statistically create flow-dependent error covariance is its primary strength when used for oceanic problems. The main contribution of this work is:

1 The proposed system is faster at detecting and following multiple objects.
2 Some real-time detection and tracking applications are possible with this algorithm.
3 Exhibit solid performance despite the presence of noise in a few frames.

## III. THE PROPOSED METHODOLOGY

The Stationary Camera videos, which are stationary in the region of interest, produce picture sequences. By sampling the video acquired with the Camera at a specific sampling rate, input pictures are retrieved directly.

After sampling, background subtraction is carried out. Then, thresholding techniques converted the results into binary image sequences. The binary picture is created by performing a thresholding operation on a colored image. The intensity levels of the item are what determine the thresholding. The actual structure of the items is obtained by morphologically operating the binary picture in which it is acquired. As a result, the items are discovered and organized. It constructs the templates after recognizing the objects using the first image sequences. These templates track the objects' trajectories by matching them to the following visual sequences. Calculate an item's velocity by finding the distance between the pixels of the centroid of an object in successive picture sequences. Image trajectory data is then utilized to determine the object's movement direction. This information will be used instead of the eliminated frame to help the Kalman filter estimate the object's new position. The equations used for Morphological processes as in [23], [24]:

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$$P * D = (P \oplus D) \oplus D \tag{1}$$

Where:

P = a matrix that includes moving object information obtained through threshold segmentation [7]

$$D = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} \tag{2}$$

The input space vector for the Kalman filter:

$$X \;= [u, v, u', v'] \tag{3}$$

Where (u & v, u' &v') are the object's center position with their rate of change.
The prediction equations as given in [25]:

$$X_t = AX_{t-1} + B_u \tag{4}$$

$$S_t = AS_{t-1}A^T + Q \tag{5}$$

Where ($X_t$ )is the input space vector for the Kalman filter at a time (t),($X_{t+1}$ ) is the input space vector for the Kalman filter at a time (t+1), (A) is the matrix of state transitions, (B) is the coverts control input, and (Q) is the covariance of the process noise.
Correction: The updated measurement formulae are provided as given in [25]

$$K_t = S_{t-1}H^T(HS_{t-1}H^T + R)^{-1} \tag{6}$$

$$X_{t+1} = X_t + K_t(Y_t - HX_t) \tag{7}$$

$$S_{t+1} = (I - K_tH)S_t \tag{8}$$

Where; (K) is Kalman gain, (S) is estimate uncertainty, (R) is measurement error covariance, and (H) is observation matrix. The prediction of the following state ($S_{t+1}$) is accomplished by incorporating the actual measurement with a prior estimate of ($S_{t-1}$).
This proposed method depends on the background subtraction detection technique and Kalman filter; the detection technique subtracts two consequence frames to find the moving objects in the frame and then determines the position and velocity of each object in the frame. Kalman filter takes the value of the object position and velocity from the background subtraction detector to use them to predict and estimate the object position and velocity depending on the motion state model; the Hungarian method was used to find the optimal object position and speed from the detector and Kalman filter values. Multiple Object Tracking (MOT) takes a long time because the background subtracted detector requires a long time to complete the detection, especially when there are many objects in video frames or high video resolution, so to improve the execution time, it's required to reduce reliant on the background-subtracted detector by reducing the number of frames whenever there is no new object detection in the incoming frame and depend on Kalman filter value for prediction and estimation objects position and speed. Multiple object detection and tracking processes in the system are suggested here, as illustrated in the proposed algorithm model flow chart *Fig. 1*. It is, indeed:

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Step 1: Enter the video, and a series of frames will be created by sampling it. The next block uses a sample of this image sequence.
Step 2: Initialize the trackers and check the New Frame (N.F.) flag value. If one uses the object detector, else bypass the object detector.
Step 3 Object detection: Object detection uses the background model to subtract the image background, then the image morphology process.
Step 4: A counter is used to count the identified items. And set the new object flag to one when finding a new object with the current frame. Else, set the flag to zero.
Step 5: Assign detections to track: Cost is reduced by assigning currently-played tracks to object detections in the current frame. The cost is determined by calculating the Hungarian of a detection matching a track.
Step 6: Update assigns to track: Update each assigned tracked object with the corresponding detection value, which will help Kalman filter to correct the location estimate. It calls the correct method of vision.
Step 7: Delete the hidden object after a certain age: Delete each object that disappears from the incoming sequence frame after a certain age.
Step 8: Create a track for each new object: Unassigned detections can be used to create new tracks. Consider any unassigned detection to be the beginning of a new track. Use other indicators like size, location, or appearance to eliminate false positives.
Step 9: Show the result: It is now possible to identify and visualize the output of the Tacked results using the center of gravity and the graph plot. Initial recognition of the centroid is followed by detecting and visualizing the various motion characteristics.

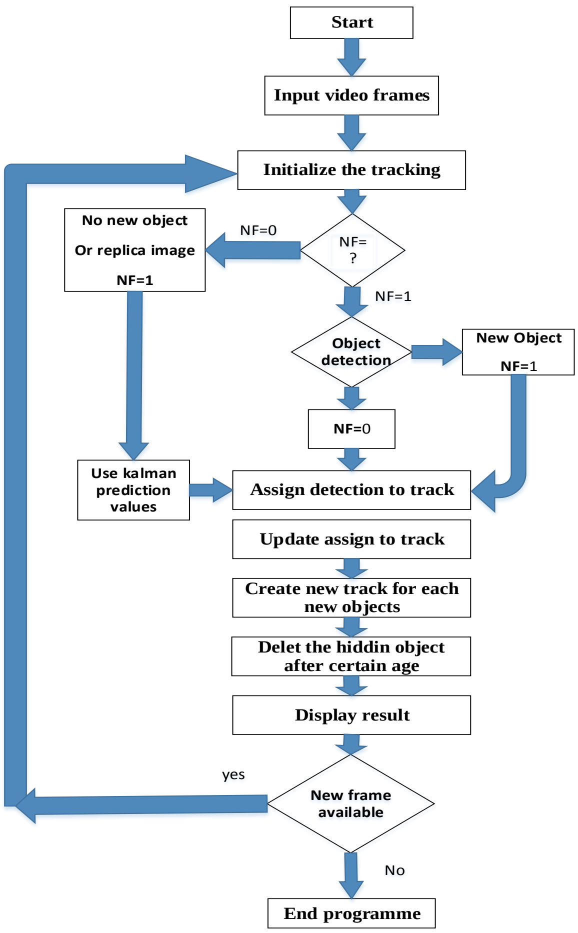


FIG. 1. THE PROPOSED ALGORITHM MODEL FLOW CHART.

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## IV. RESULT AND DISCUSSION

The suggested algorithm accurately locates moving objects and maintains tracking them when objects appear in the video frame sequence. The proposed algorithm (P.A.) and standard algorithm (S.A.) are done in MATLAB version (2018b), using Dell laptop core (i7), (2.5GHz CPU) speed, and (8 G.B. RAM) with (4GB GPU AMD) Radeon graph processor. The tested videos are recorded at 30 frames per second with 320x240 pixel frames. The recorded videos are sampled at the chosen sample rate. The last three videos are in Table I and have different resolutions to see and illustrate the resolution effect on the system performance.

The proposed work has utilized video record data in formats like (MP4, MOV, and AVI). After evaluating the suggested algorithm's effectiveness, successful outcomes have been attained in various article settings on outdoor, low-traffic, and congested traffic.

Different types of videos were used to test the proposed algorithm. Some have many objects per frame (high density), and others are low objects per frame (low density); the last three videos are the same but have different resolutions to see the resolution's effectiveness on the execution time. It is also clear that not only when the number of frames is high, the execution time is high, but when the number of objects per frame (high density), the video resolution, and the light reflection will cause a high execution time. Table I. illustrates the proposed algorithm performance for different videos to improve the proposed algorithm results over the standard one.

TABLE I. EXECUTION TIME REQUIRED AND FRAME NUMBER FOR THE STANDARD AND THE PROPOSED ALGORITHM FOR DIFFERENT VIDEO IMPLEMENTED.

| No. | Input Video | Number of frames | P.A.* execution time in second | S.A.** execution time in second | P.A.* frame rate frame/s | S.A.** frame rate frame/s |
|---|---|---|---|---|---|---|
| 1 | Video 1 | 810 | 60 | 125.59 | 13.5 | 6.45 |
| 2 | Video 2 | 367 | 18 | 51.18 | 20.38 | 7.17 |
| 3 | Video 3 | 1135 | 78.11 | 252 | 14.53 | 4.5 |
| 4 | Video 5 | 531 | 23.6 | 61.69 | 22.5 | 8.607 |
| 5 | highway | 1700 | 39.1235 | 63.7926 | 43.45 | 26.65 |
| 6 | sample11-1280*720 | 335 | 119.8411 | 184.5440 | 2.79 | 1.81 |
| 7 | Sam*ple12-960*540 | 335 | 44.8619 | 87.0228 | 7.46 | 3.85 |
| 8 | sample13-640*360 | 335 | 18.9638 | 25.8994 | 17.66 | 12.93 |
| | ***Average number | 693.5 | | | 17.784 | 8.995 |

*PA=the proposed algorithm

**SA=Standard algorithm

*** Average number = total number of items/ number of videos (8)

The frame rate comparison between the proposed algorithm and the standard in the last two columns of Table I. shows that the proposed has a good frame rate process for online implementation. In contrast, the standard has a low frame rate in many videos that fail in online implementation.

The video frame is shown in *Fig. 2*; for outdoor cars moving objects, similar sequence frames are used as input for this system for tracking moving objects, which use them to execute operations like morphology, template matching, image subtraction, etc. The detection of moving objects in the series frames is also shown in *Fig. 2*; It shows videos (1 and 2) with tracking enclosed boxes for each object,

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(a and d) new algorithms, (b and e) for the standard subtracting algorithm, (c and f) foreground mask. A frame differencing approach is used to detect an item. Frame differencing takes two consecutive frames as input and produces the difference between those frames in the form of a binary image, as demonstrated in the approach. White areas are regarded as an object in a binary picture. The bounding box enclosing the moving item identified is shown in *Fig. 2*; and is utilized to represent the item in the video, which helps with object tracking.

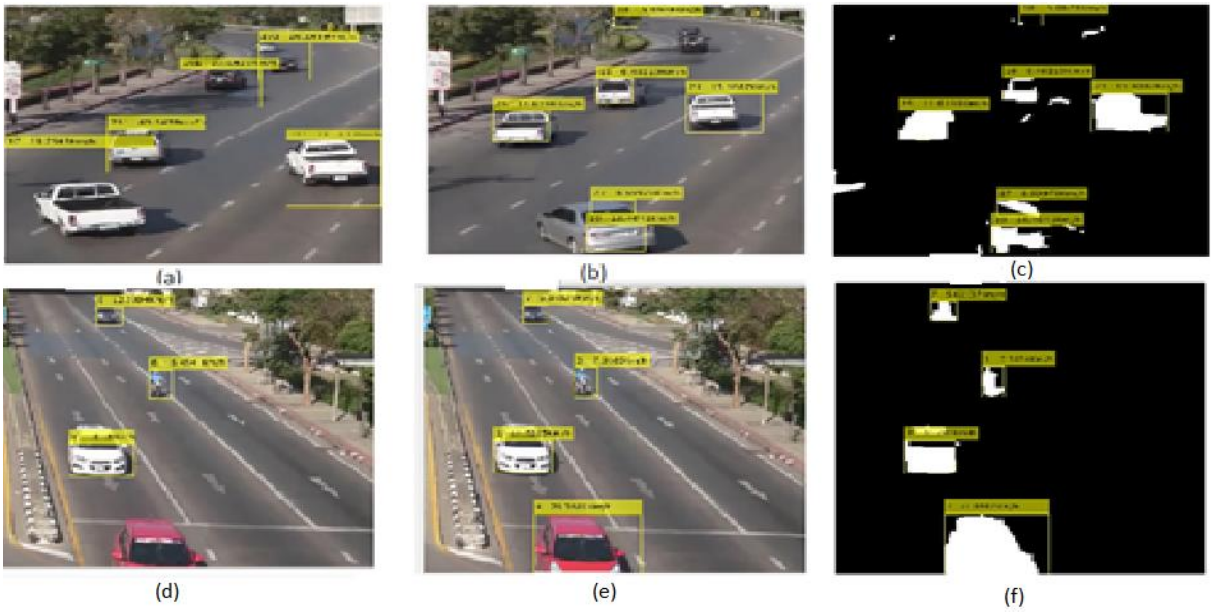


FIG. 2. VIDEOS (1 & 2) WITH TRACKING ENCLOSED BOX FOR EACH OBJECT (a & d) NEW ALGORITHM (b & e) STANDARD SUBTRACTION ALGORITHM (c & f) FOREGROUND MASK.

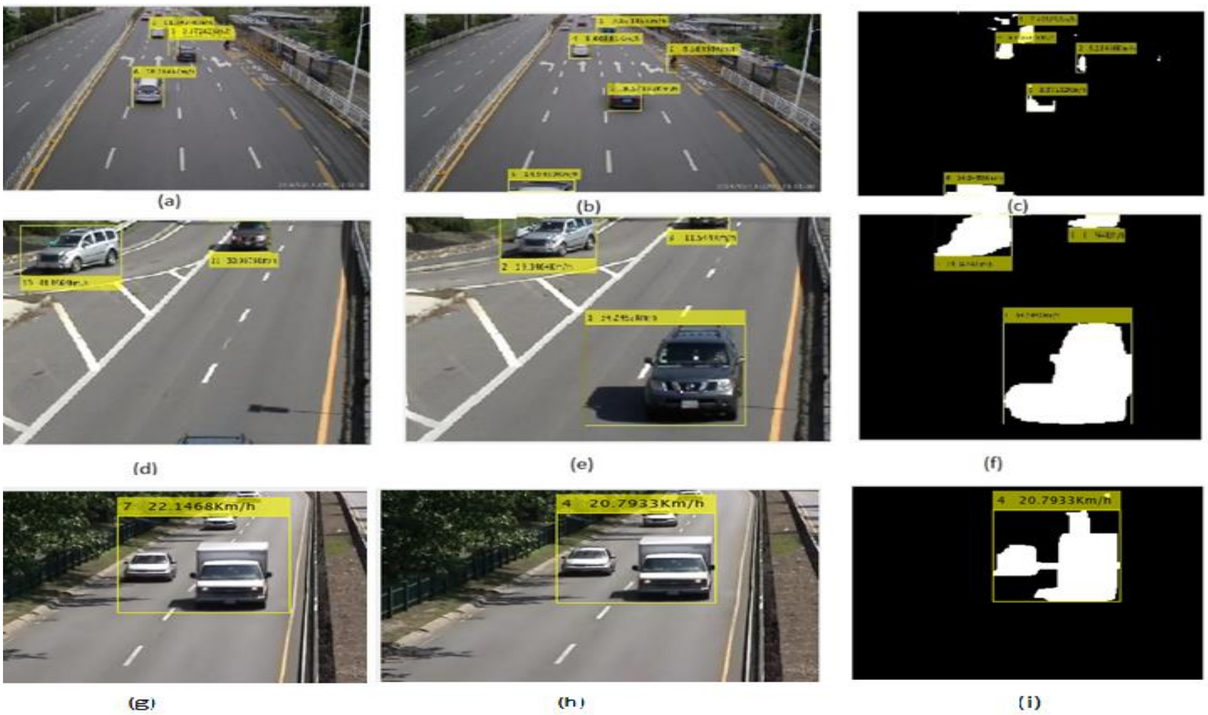


FIG. 3. VIDEOS (3, 5, & HIGHWAY) WITH TRACKING ENCLOSED BOX FOR EACH OBJECT (a, d, & g) NEW ALGORITHM (b, e, & h) STANDARD SUBTRACTION ALGORITHHIM (c, f, & i) FORGROUND MASK.

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*Fig. 3* for cars moving objects but for videos (3, 5, and highway) with tracking enclosed boxes for each object (a, d, and g), new algorithm (b, e, and h) standard subtracting algorithm (c, f and i) foreground mask. Pixel velocity is determined by measuring the separation between an object's Centroid points across many time frames.

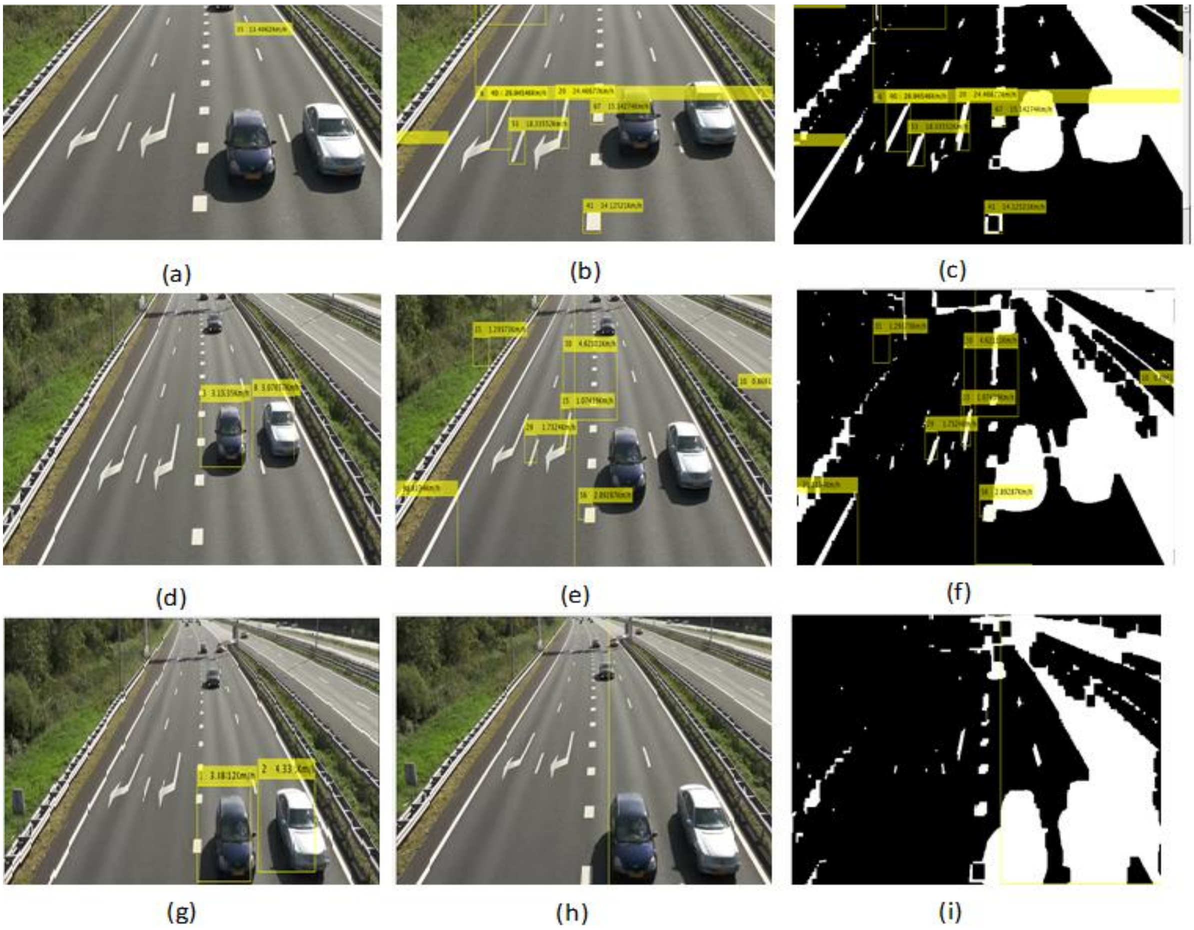


FIG. 4. VIDEOS (SAMPLES 11, 12 & 13) WITH TRACKING ENCLOSED BOXES FOR EACH OBJECT (a, d, & g), NEW ALGORITHM (b, e, & h), STANDARD SUBTRACTING ALGORITHM (c, f, & i) FOREGROUND MASK.

*Fig. 4* show the proposed algorithm and the standard subtract algorithm for three videos, each with a different resolution. The video sample11 with 1280*720 resolution, the video sample12 had 960*540 resolution, and the video sample13 had 640*360 resolution. The result shows the high effect of the video with high resolution on the algorithm frame rate while not improving the system tracking because the background subtraction depends on the threshold of the stretched area from the frame for each object.

In the last move, sample 13, the proposed algorithm distinguishes between the two cars by enclosing each car with an individual box. In contrast, the standard subtracting algorithm enclosed both cars with one box because the proposed algorithm depends less on the detection value, which may have a light scattering that affects detection values as appear in the background subtraction *Fig. 4* (C, f, and i).

## V. CONCLUSIONS

Objects are recognized and tracked in the above-described system utilizing video processing algorithms, which are far more efficient than standard algorithms systems. The system is designed to reduce the reliance on the detector because it takes much computation

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time compared with the tracker execution time. The new algorithm improves the total processing execution time compared with the standard background subtraction algorithm, as illustrated in the result Table I. Show that the (P.A) has a higher frame rate than the (S.A). Further video processing using the Kalman filter can minimize noise and improve the observed object's track. However, there is still some deviation in the average accuracy of the detector and tracker .For further work to improve the accuracy required need to use a more accurate state space model for the detected objects within the frames in the Kalman filter or use other intelligent detection algorithms instead of background subtraction algorithm to improve detection and tracking accuracy.in addition, it can use an aspect or practical filter to reduce the effects of light scattering.

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