VIDEO-BASED TRAFFIC SURVEILLANCE WITH BACKGROUND SUBTRACTION FOR OBJECT DETECTION AND FEATURE EXTRACTION

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Abstract
Video surveillance systems depend on the capability to find out moving objects in the video stream that is an appropriate information extraction step in a broad range of computer vision applications. Still the identification of objects from vehicles and tracking of several vehicles exist in the similar video based traffic surveillance turns out to be main issue since minimum feature extraction for the duration of detection phase. In this research work present new background subtraction technique to assess the functioning of objects detection as well as identifies objects from video series. This process lets us to emphasize features (for example, region splitting or merging) that are particular of the technique being utilized. There are three phases for instance background subtraction, vehicle detection. For the duration of Background subtraction techniques, proposes a method for motion detection which integrates various inventive methods. For instance, research method stores, for each pixel, a set of values considered in the precedent at the similar location or in the adjacent. It afterward contrasts this set to the present pixel value with the intention of identifying whether that pixel be in the background, and acclimatizes the model by selecting haphazardly that values to substitute from the background model. Additionally take out significant characteristics for instance symmetry, edge, headlight, brightness, and appearance, day and night time got from Improved Particle Swarm Optimization (IPSO), to evaluate the presented technique; experimentations are performed dependent upon situations from diverse kinds of vehicles. Video-based traffic surveillance using a fuzzy hybrid information inference mechanism (FHIIM). Outcomes point to that the research system shows better performance beneath congested conditions.
Keywords: Traffic monitoring, congested condition, traffic surveillance, vehicle detection, vehicle tracking, feature extraction, Background Subtraction, Principal Component Analysis (PCA).

1. INTRODUCTION

Video surveillance systems depend on the capability to identify moving objects in the video stream that is an appropriate information extraction step in a broad range of computer vision applications. Every image is split by automatic image analysis methods. This has to be accomplished in a consistent and efficient manner with the purpose of coping with unrestrained environments, non stationary background as well as diverse object motion patterns. Additionally, diverse kinds of objects are physically taken for example, persons, vehicles or groups of people.

Manual video surveillance includes investigation of the video content by a human. Such systems are presently broadly utilized. Semi-autonomous video surveillance includes certain kind of video processing however with important human interference. Classic instances are systems which carry out simple motion detection. Simply in the existence of important motion the video is recorded and forward for investigation by a human proficient. By a fully-autonomous system

[1], just input is the video sequence considered at the scene where surveillance is carried out. In that type of a system there is no human interference and the system performs the low-level jobs, such as motion detection and tracking, and in addition, high-level decision making jobs similar to abnormal event detection as well as gesture recognition. Video surveillance system which holds automated objects classification as well as object tracking. Examining of video for long period by human machinist is not practical and not feasible. Mechanical motion detection that could give assault human attention [2].There is various kinds of applications in video surveillance such as access control, person identification, and anomaly detection. Intelligent visual surveillance (IVS) points to an automated visual monitoring process which includes investigation and interpretation of object conducts, in addition to object detection and tracking, to recognize the visual happenings of the scene [2].

Presently, various contributions have been presented and fruitfully illustrated for foreground identification and tracking. On the other hand, these techniques want to resolve the problems like radical changes as well as target drift encountered throughout tracking process. Major challenge in motion tracking technique is to guesstimate object motion as more precisely and effectively as possible. Moving object detection is a significant facet in any surveillance applications for instance video analysis, video communication, traffic control, medical imaging, and military service [3]. Typically, video frames comprise foreground and background information, wherein the feature points in the area of interest are the foreground information and the rest of the feature points are taken to be background information.

Generally, video surveillance system includes two main building blocks for example motion detection as well as motion estimation. Object detection is the primary step as it is unswervingly inclined by the background information. As there is substantial unrelated and redundant information in the video across space and time, the video data want to be compressed at the past in video surveillance applications [4]. Compression could be attained by reducing the spatial and temporal redundancies exist in the video. In past days, the video data is compressed either by minimizing the size of the frame or by frame skipping with little deprivation in video quality [5]. The 2D orthogonal transforms as well as motion compensation methods are included in present video coding standards to eliminate the spatial as well as temporal redundancies. In the research technique, 2D discrete cosine transform is utilized for video compression as of its uppermost energy compaction. The motion detection as well as motion guesstimation are the two main building blocks of video surveillance system [6].

In motion detection, the moving object is detected by taking out the modifications in object boundaries while, in motion estimation, the motion vectors are calculated to guesstimate the locations of moving objects [7]. The best possible motion vector is discovered by identifying the displacement of coordinates of the finest match in a reference frame for the block in a present frame [8]. Optical flow vector is computed by Horn-Schunck algorithm for moving object detection [9]. The RLOF contains superb long-term feature tracking performance, however its computational complexity is high when comparing to KLT [10].

Nonstationary backgrounds and elucidation modifications are bottleneck issues in the background subtraction technique [11]. In actual fact, the universal restraints of optical flow based techniques are despoiled that brings about tracking error beneath cluttered environments. In lot of the background subtraction techniques, the object trackers are inclined by the background information that results in false detection. Additionally, an efficient classifier is wanted to differentiate the target in cluttered environments [12]. In this background subtraction, to guesstimate the traffic flow or traffic density on a road, loop detectors or supersonic wave detectors were utilized by road engineers. Now days, traffic management systems alternatively use image and video processing methods to take out the similar information from surveillance video of roads. According to visual surveillance applications, identification by background subtraction is a general technique for distinguishing moving objects from the stationary parts of the video frames. Background subtraction includes computing a reference image, subtracting this reference from every new frame, and after that using a threshold to the outcome. Even though lot of surveillance techniques are proposed, for vehicle detection and tracking, still there are two main issues happens in jam-packed situation ,mainly within tunnels . In surveillance system, the camera's low angle position denotes that vehicles are simply linked visually in images. In order to reach detection accurateness the adjacent vehicles need to be detached. In addition, in congestion the background reformation is more significant because of the cover of vehicles. The cause for this problem is that lot of techniques presumes a static background, and therefore one requires bringing up to date the background model for dynamic backgrounds. The update of the background model is one among the main confronts for background subtraction techniques. The subsequent step in the video analysis is tracking that could be merely described as the formation of temporal correspondence amongst identified objects from frame to frame. This process gives temporal detection of the segmented areas and produces cohesive information regarding the objects in the observed area for instance trajectory, speed and direction. The outcome generated by tracking step is usually utilized to hold and improve motion segmentation, object classification and high level activity examination.

Lot of the previous work concentrates primarily on using a general object identification method to vehicle detection and vehicle tracking techniques; there is extremely small study on identifying vehicles via particular vehicle facets for instance windshields or headlights. The main work of the presented system should performed via three main steps are background subtraction, object detection and vehicle detection. This paper presented an efficient method for keeping up to date a background model adaptively in dynamic scenes. Background model works in a different way in carrying out novel or fading objects in the background, devoid of the necessity to consider them openly. Besides to being sooner, our technique shows an attractive asymmetry in that a ghoul is included to the background model very rapidly than an object which stops moving. For the duration of vehicle detection stage, occluded vehicles is fragmented dependent upon their inter information. Third, tracking vehicle is performed by research work in three steps that is to say: feature extraction by Improved Particle Swarm Optimization (IPSO) algorithm and Fuzzy Hybrid Information Inference Mechanism (FHIIM), here compensation is raised while the comparison outcome is different.

2. RELATED WORK

Morris & Trivedi [13] propose a Learning, modeling, and classification of vehicle track patterns from live video. The purpose is to get better the classification pattern of moving objects or vehicles. The highway monitoring module precisely categorizes vehicles into eight diverse kinds and gathers traffic flow statistics by leveraging tracking information. These data are endlessly collected to sustain every day highway models which are utilized to classify traffic flow in real time. The path modeling block is a common investigation tool which studies the usual motions taken place in a scene in an unsupervised manner. The spatiotemporal motion features of these motion paths are encoded by a Hidden Markov Model (HMM). Wu et al [14] virtual line group based technique utilizing luminance as well as chrominance information and the spatiotemporal information of the virtual line group is presented as a development for it. The virtual line group comprises four neighboring virtual detection lines. The enhanced technique as well basis on the technique of background subtraction to identify vehicles on every detection line as the original algorithm which is, subtracting the background from the present frame, afterward contrasting the dissimilarities with the threshold to examine if there exists a vehicle. However the enhanced technique brings in two-level detection to do this, specifically, it first performs the initial level detection using luminance information as the original algorithm performs, in case it chooses there is no vehicle it would alter the luminance threshold in relation to the pixels' colors obtained by utilizing the chrominance information to perform the second level detection. Afterward it enhances the outcome utilizing the spatiotemporal information of the virtual line group.

Generally, headlights identification is carried out by template matching (the template comprises a circular bright area bounded by a dark background). After that headlights are coupled together utilizing distance or else symmetry information. On the other hand, these techniques are inclined to provide so much false positives and ignore some vehicles. Rashid et.al [15] proposes a Detection and classification of vehicles from a video utilizing time-spatial image; it is the addition of the detection as well as categorization of vehicles. Propose a new detection and classification technique which applies an investigation of Time-Spatial Image (TSI) go from at virtual line on the frames of a video with the intention that the dependencies of pixel intensities of still and moving objects of the video might be minimized. Primarily, the TSI is fragmented to add up the amount of vehicles those cross the virtual line. Afterward, a feature-based classification method is presented to categorize these vehicles. The classification method uses the shape of the segmented areas of the TSI in addition to that of suitable frames of a video to take out some facets of the moving objects.

3. PROPOSED METHODOLOGY

In this research, a new traffic analysis of Video-based Traffic Surveillance framework is proposed at diverse levels for instance background subtraction, vehicle detection as well as vehicle tracking. The presented work primarily carries out preprocessing through Background subtraction, after that takes out vehicle facets for instance symmetry, edge, headlights, brightness, and appearance, day and night time obtained utilizing Improved Particle Swarm Optimization (IPSO) framework at tracking phase. It solves issues for instance headlight consequences. Subsequently utilizes a FHIIM to find out the tracked vehicles. Tracking technique is usually applied to get better the vehicle detection accurateness and taking out more vehicle parameters. Vehicle detection stage, presented system identifies candidate's vehicles. The number steps ought to be performed in presented framework is illustrated in Figure 1.

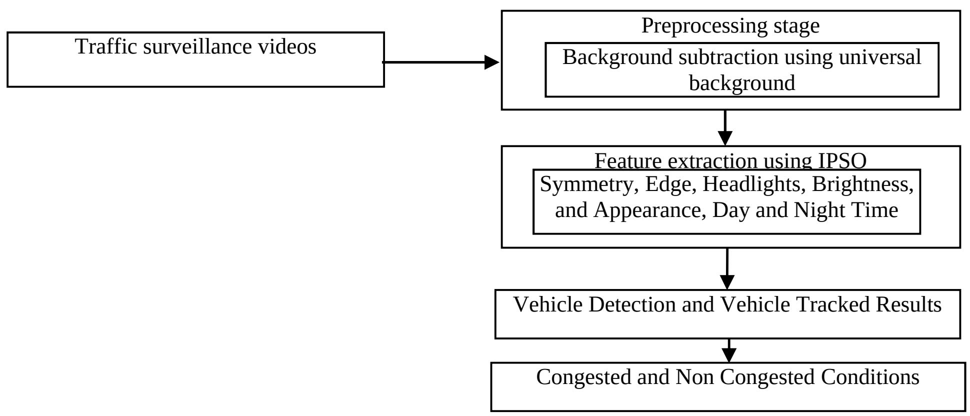

Figure 1: Entire architecture of proposed system

3.1. Background subtraction

Background model is one among the very helpful techniques for change detection. Background modeling is utilized in the subsequent video surveillance systems. Categorize a novel pixel value regarding its direct neighbourhood in the selected color space, in an attempt to evade the consequence of any outliers. This inspires us to model every background pixel with a group of examples in place of with an explicit pixel model. A novel value is contrasted to background samples and has to be close to certain sample values rather than most of all values. The fundamental thought is that it is more consistent to guesstimate the statistical distribution of a background pixel with a little amount of close values than with a huge amount of samples. Alternatively, in case one believes the values of the model, it is critical to choose background pixel samples cautiously. Officially, let us indicate by $v(x)$ the value in a specified Euclidean color space considered by the pixel placed at x in the image, and by v_i a background sample value with an index i. Every background pixel x is modeled by a group of N background sample values

$$M(x) = \{v_1, \dots v_N\} \tag{1}$$

considered in earlier frames. At the present, disregard the idea of time; this is talked about afterwards. In order to categorize a pixel value $v(x)$ in relation to its equivalent model

$M(x)$, contrast it to the *closest* values within the set of samples by describing a sphere $S_R(v(x))$ of radius R centered on $v(x)$. The pixel value $v(x)$ is after that categorized as background in case the cardinality, represented#, of the set intersection of this sphere and the set of model samples M(x) is greater than or equivalent to a specified threshold $\#_{min}$. More officially, match up with $\#_{min}$,

$$\#\left\{S_R\big(v(x)\big)\cap\{v_1,\dots v_N\}\right\} \qquad (2)$$

In relation to equation 2, the categorization of a pixel value $v(x)$entails the calculation of N distances amid $v(x)$ and model samples, and of N comparison with a thresholded Euclidean distance R. This procedure is demonstrated in Figure 2.

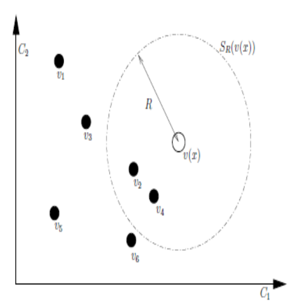

Figure. 2. Comparison of a pixel value with a set of samples in a two dimensional Euclidean color space (C1, C2). To classify v(x), count the number of samples of M(x) intersecting the sphere of radius R centered on v(x).

reminder that, as are merely involved in identifying a a small number of matches, the segmentation procedure of a pixel could be stopped just the once $\#_{min}$ matches are identified. Since could effortlessly be seen, the accurateness of this model is found by two parameters: the radius *R* of the sphere as well as the minimal cardinality $\#_{min}$. Experimentations illustrated that a unique radius R of 20 (for monochromatic images) as well as a cardinality of 2 are suitable. Require to neither acclimatize these parameters for the period of the background subtraction nor do require to modify them for diverse pixel locations inside the image. Reminder that as the amount of samples N and $\#_{min}$are selected to be set and because they inspire on the identical decision, the sensitivity of the model could be regulated utilizing the subsequent ratio,

$$\frac{\#_{min}}{N} \qquad (3)$$

However in all comparative analysis maintained these values unaffected. Officially, presume that $t = 0$ indexes the first frame as well as that NG(x) is a spatial neighborhood of a pixel location x, so,

$$M^0(x) = \{v^0(y|y \in N_G(x))\} \qquad (4)$$

here locations y are selected haphazardly in relation to a uniform law. Notice that it is probable for a specified $v^0(y)$ to be chosen a number of times. On the other hand, this is not a problem in case one grants that values in the neighbourhood are outstanding sample candidates.

IPSO (Improved Particle swarm optimization) for Feature extraction

Present a technique for secluding moving objects from an input image. Initially, moving-edge extraction is utilized to get the moving characteristics of vehicles. The significant characteristics extracted from vehicle traffic are symmetry, edge; headlight, brightness, and appearance, day and night time are utilized to achieve the moving characteristics of vehicles. After that, associated component labeling is utilized to recognize the shapes of objects. Lastly, every labeled object is confirmed dependent upon its characteristics taken out from IPSO algorithm and it as well decreases the calculation loading by using associated component labeling. Particle Swarm Optimization (PSO) exposed its rapid search speed in numerous difficult optimization and search issues. On the other hand, PSO can frequently effortlessly drop into local optima best feature extraction outcome for background subtracted images since the particles can rapidly come nearer to the most excellent particle features. With the intention of overcoming the difficulty of PSO ,in this work presents a novel enhanced particle swarm optimization technique to resolve the issue of global features extraction outcome by including novel mutation parameter .The included Cauchy mutation takes out most excellent video-based traffic surveillance characteristics for instance symmetry, edge, headlight, brightness, appearance, day and night time from background model outcomes ,with the intention that the mutated particle creates finest taken out feature outcomes and gets better the outcomes of other particles to obtain most excellent feature extraction points. Every particle in PSO contains a position and a velocity. From complete features of video traffic samples PSO take out finest features dependent upon the position identified by all background subtracted images particles in the search process. For a probable solution of finest feature extraction outcomes is signified by a particle which regulates its position and velocity in relation to Equation (5) and (6):

$$BSIV_i^{(t+1)} = w * BSIV_i^{(t)} + FLC_1 * rand\ 1() * \left(F_i - BSI_i^{(t)} \right) + FGC_2 * rand\ 2() * \left(F_g - BSI_i^{(t)} \right) \quad (5)$$

$$BSI_i^{(t+1)} = BSI_i^{(t)} + BSIV_i^{(t+1)} \quad (6)$$

here BSI_i and $BSIV_i$ are the position and velocity of background subtracted images (Particles) i, F_i and F_g are preceding finest extracted features for the i^{th} particle and the global best particle identified by all particles up to now correspondingly, and w is known as an inertia factor, and $rand1()$ and $rand2()$ are two random numbers separately produced inside the range of [0,1], and FLC_1 and FGC_2 are two learning factors that manage the influence of the local feature extraction as well as global feature extraction outcomes. In this study, a novel improved PSO (IPSO) is presented. Cauchy mutation can obtain the finest position of Background Subtracted Image (BSI) samples of vehicles beyond the local optima. In case the searching adjacent of the universal finest features of BSI of vehicles will be included in every generation of PSO algorithm, it will aid to enlarge outcome to finest feature extraction position to the enhanced feature extraction positions. This could be achieved by containing a Cauchy mutation on the universal finest feature extraction outcomes for each BSI images in each generation. The one-dimensional Cauchy density function centered at the origin is described by:

$$f(BSI) = \frac{1}{\pi} \frac{t}{t^2 + BSI^2}, -\infty < BSI < +\infty \quad (7)$$

here $t > 0$ is a scale parameter . The Cauchy distributed function is,

$$f_t(BSI) = \frac{1}{2} + \frac{1}{\pi} arctan\left(\frac{BSI}{t}\right) \quad (8)$$

In this research Cauchy distribution work of every feature for instance symmetry, edge, headlight, brightness, and appearance, day and night time dependent upon the state given below:

3.1.1. Headlight and brightness features

A headlight is designed by a disk and is anticipated to all pixels of the camera image. For this reason, the size of an average headlight in pixel units is pre-calculated for every camera's pixels. Headlight could be anticipated dependent upon the vehicles standards, and the average size of a headlight as well as its average height (in meter unit). The primary step contains identifying the bright regions in the image by searching connected pixels ('blobs') which increase the ratio V/S (Value on Saturation). This is attained by the non-linear luminance equation of the color channels (R,G,B),

$$L = \frac{1}{2}(\max(R, G, B) + \min(R, G, B)) \quad (9)$$

3.1.2. Appearance features

Appearance feature is merely identified while the confidence value of a candidate vehicle is less. The outward show of features of level is anticipated dependent upon the parameters of headlight diameter (HD), headlights separation distance (HSD) is computed from dissimilarity amid left and right position

$$\mathrm{HSD} = |\mathrm{HL} - \mathrm{HR}|) \quad (10)$$

All of them in pixel coordinate. For every pair candidate, square image size of $(\mathrm{HD} + \mathrm{HSD})^2$ for image column as well as row.

3.1.3. Day and night time features

Day-time vehicle identification is tricky initially since there is no sturdy feature for instance headlight and the vehicles are underneath a variety of elucidations. Employed an alike process as for night-time features investigation. Images of cars are physically gathered, and the mean image and the 'eigen images' are computed.

3.1.4. Edge features

Edge features are got by employing a Sobel operator to the image. On the other hand, the edges generated by lane marks and road marks might contain an effect on the shapes of vehicle edges. Consequently, the edges of a background image are considered to decrease the noise. In case local Background subtracted images samples fulfills the above stated state these features are taken out from specific samples otherwise additional iteration is carried out, to take out finest features. The cause for utilizing a mutation operator is to augment the likelihood of evading from a local optimal feature extraction outcomes for BSI samples. In case local Background subtracted images samples fulfills the above stated condition these characteristics are taken out from specific samples otherwise additional iteration is carried out, to take out finest features. The cause for utilizing a mutation operator is to augment the likelihood of evading from a local optimal feature extraction outcomes for BSI samples. The Cauchy mutation operator utilized in IPSO is defined in this manner,

$$W(j) = \left(\sum_{j=1}^{PSI} BSIV[j][i]\right) \Big/ PSI \quad (11)$$

here BSIV[j][i] is called the i^{th} velocity vector of the j^{th} particle in the population, PSI is known as the population size of BSI samples. W(i) is called a weight vector within $[-\mathrm{W}_{\mathrm{max}}, \mathrm{W}_{\mathrm{max}}]$, and $\mathrm{W}_{\mathrm{max}}$ is fixed to 1.

$$\mathrm{F}'_{\mathrm{g}}(\mathrm{i}) = \mathrm{F}_{\mathrm{g}}(\mathrm{i}) + \mathrm{W}(\mathrm{i}) * \mathrm{NF}(\mathrm{BSI}_{\mathrm{MIN}}, \mathrm{BSI}_{\mathrm{MAX}}) \quad (12)$$

Here NF is called a Cauchy distributed function with the scale parameter $\mathrm{t} = 1$, and $\mathrm{NF}(\mathrm{BSI}_{\mathrm{MIN}}, \mathrm{BSI}_{\mathrm{MAX}})$ is known as a random number within $[\mathrm{BSI}_{\mathrm{MIN}}, \mathrm{BSI}_{\mathrm{MAX}}]$ that is a described domain of a test function. Novel procedure was designed for concurrently tracking numerous vehicles, mainly underneath congested states. Primarily, the novel positions of the tracked objects are gauged utilizing a feature extraction and dimensionality reduction technique. Secondly, the FHIIM method is utilized to confirm the tracking outcomes and to choose whether to recompense for the errors. The taken out feature outcomes from IPSO and minimized feature extraction outcomes are utilized in FHIIM, it contrasts the dissimilar values of features into the histograms values, since histogram comparison thinks all features in the tracked areas. High scores would be attained in case the search outcomes match the preceding tracking outcomes. The whole process of the FHIIM techniques procedure is alike to previous work [16], excluding as opposed to two features think about a variety of diverse features; it ought to be taken out from IPSO.

4. EXPERIMENTAL RESULTS

In our research, the performance of the presented system was assessed utilizing traffic surveillance videos. This investigation and the comparison are talked about in depth. Two situations were assessed in the experimentation, specifically Chien-Kuo Bridge in Taipei City in the daytime and nighttime utilizing camera 19 and Mu-Cha Tunnel on Highway 3 utilizing camera 27. There were a lot of confronts in both situations. The cameras were extremely older, and the resolution was not extremely obvious in either situation. Consequently, the overlapping of vehicles was a severe issue in the images. These situations were all assessed by utilizing a Windows XP platform with an Intel Core 2 2.14-GHz central processing unit as well as 2-GB random access memory. The size of image was 320 × 240, the sampling rate of the sequence was 30 frame/s, and the processing time ranged from 17 to 23 ms. Experimentations were carried out in six environment conditions. In the quantitative assessments of the presented system, the Recall and Precision specified in

$$Recall = \frac{T_p}{(T_p + F_n)} \quad (13)$$

$$Precision = \frac{T_p}{(T_p + F_p)} \quad (14)$$

here

$T_p = True\ positives$ signify the amount of appropriately identified vehicles

$F_p = False\ positives$ amount of falsely identified vehicles

$F_n = False\ negatives$ amount of missing vehicles, correspondingly

They were utilized to assess the information retrieval performance. Third performance index was utilized to make a fair comparison, that is to say the Accuracy utilizing (15).

$$Accuracy = \frac{T_p}{(T_p + F_p + F_n)} \quad (15)$$

On the other hand, it is hard to get outcome images for testing false positives and false negatives; consequently, we tested the performance dependent upon the balance of incomplete counting and additional counting. For each testing experiment the error was updated each 5 min, and the average error (AE) was identified as described by utilizing equation (16)

$$AE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E}{M}\right| \times 100\% \quad (16)$$

Here E is called the error distinction amid system counting and manual counting, M is called the value for manual counting, and N is the data number.

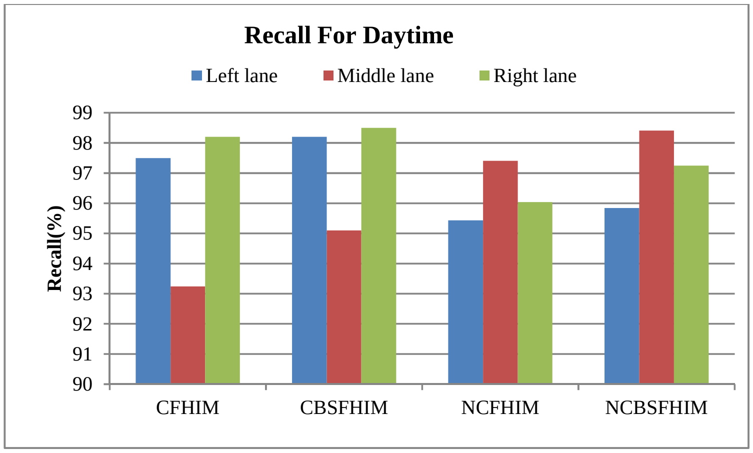

Figure 3: Recall value of congested and non congested at day time

Figure 3 gauge the recall value of congested and non congested traffic analysis outcomes of FHIM and Background Subtraction with FHIM (BSFHIM) system underneath left ,center and right lane states at day .

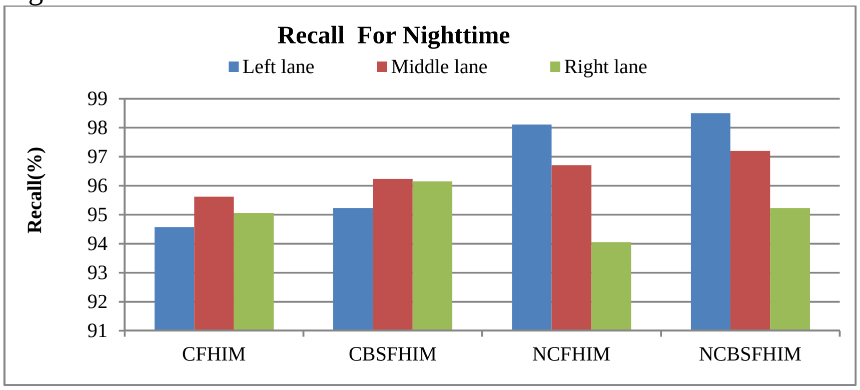

Figure 4: Recall value of congested and non congested at Night time

Figure 4 gauges the Recall value of jam-packed and non jam-packed traffic analysis outcomes of FHIM and BSFHIM system underneath left, center and right lane conditions at nocturnal Matched up to day, recall value of night time will be higher value. Figure 5 measure the recall value of jam-packed and non jam-packed traffic analysis outcomes of FHIM and BSFHIM system underneath left ,center and right lane conditions at tunnel time ,it demonstrates that best average recall values while contrasted to day as well as nocturnal. Table 1 illustrates the precision values of jam-packed and non jam-packed traffic analysis outcomes of FHIM and BSFHIM system underneath left, center and right lane conditions at day. The values are tabularized; it demonstrates that precision values of day time are higher while contrasting to night time as well as tunnel time.

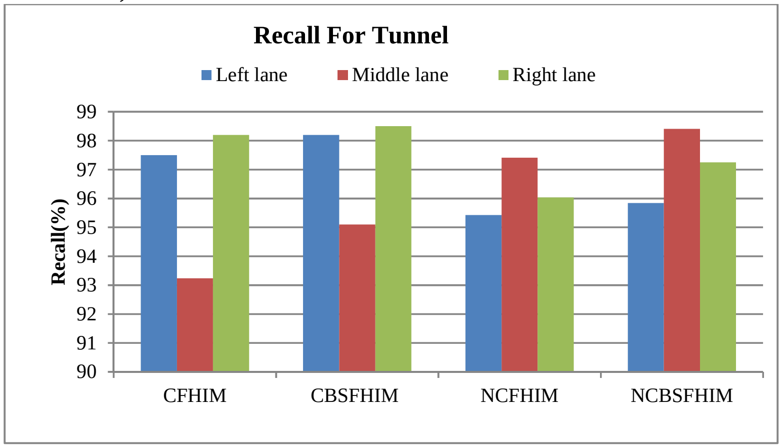

Figure 5: Recall value of congested and non congested at tunnel

Table 1: Precision value of congested and non congested at Daytime

Precision value /Day time	Left lane	Middle lane	Right lane
CFHIM	89.56	97.2	96.88
CBSFHIM	90.25	98.52	97.25
NCFHIM	91.42	91.54	88.54
NCBSFHIM	92.85	92.89	91.25

Table 2 gauges the precision value of jam-packed and non jam-packed traffic analysis outcomes of FHIM and EFHIM system underneath left, center and right lane conditions at nocturnal. Contrasted to day and night time, precision values of night would be reasonable. The values are tabularized in Table 2.

Table 2: Precision value of congested and non congested at Night time

Precision value /Night time	Left lane	Middle lane	Right lane
CFHIM	92.46	92.74	90.44
CBSFHIM	93.45	93.87	91.63
NCFHIM	92.86	90.67	97.5
NCBSFHIM	93.5	91.78	98.12

Table 3 gauges the precision value of jam-packed and non jam-packed traffic analysis outcomes of FHIM and BSFHIM system underneath left, center and right lane conditions at tunnel time. Contrasted to day and night time, precision values of tunnel time would be low. The values are tabularized in Table 3.

Table 3: Precision value of congested and non congested at tunnel

Precision value /Tunnel	Left lane	Middle lane	Right lane
CFHIM	91.42	91.54	88.58
CBSFHIM	91.34	93.2	90.23
NCFHIM	91.23	95.9	92.4
NCBSFHIM	92.28	96.4	93.9

5. CONCLUSION

In this research, a robust algorithm is presented to identify and follow the moving object in video surveillance utilizing background subtraction technique. In this paper presented a general sample-based background subtraction technique. In the research work make sure the spatial reliability of the background model by letting samples to disperse amid neighbouring pixel models. Road traffic jamming is a central issue in the majority of developing areas. Lot of the researches are presented to surmount the issue of vehicle detection and vehicle tracking .In this research study the issue of road traffic jamming in high congestion in developing areas. Initially, the background is effortlessly kept up to date by utilizing selective averaging technique, while a little range update is utilized underneath jam-packed situations. Second significant features of the Background subtraction images attained by Improved Particle Swarm Optimization (IPSO).Because headlight, brightness, day and night time features are greatly have an effect on the traffic analysis outcomes. Lastly use these presented techniques into FHIIM it is called as Enhanced FHIM for tracked vehicles. Lastly, while tracking errors did come into view, error compensation is utilized to get better the tracking quality. Dependent upon the experimentation outcomes, it is obvious that Enhanced FHIM performed fine underneath usual congested conditions, and it is as well offered excellent performance underneath jam-packed conditions within a tunnel.

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