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Video-Based Traffic Surveillance with Feature Extraction and Dimensionality Reduction

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Abstract: There has been a highly hopeful advancement in image interpretation and sequencing through computer vision and therefore video camera has come to be a very essential sensor for applications such as economic traffic monitoring and surveillance. But extraction of features from high dimensional database is lesser during detection stage. This makes detection and tracking of multiple vehicles existing in same video based traffic surveillance a huge issue. This study is intended to overcome such issues of vehicles detection and tracking of multiple vehicles that are present in front of camera. The major contributions of proposed approach include background subtraction, vehicle detection and vehicle tracking. In background subtraction methods, models are employed to implement over background intensities in order to overcome minor changes in environment. Vehicle tracking stages have been conducted in two stages in which first stage is concerned with extraction of significant features like symmetry, edge, headlight, brightness and appearance during day and night time as got from Improved Particle Swarm Optimization (IPSO) algorithm then followed by dimensionality reduction of features by means of Hybrid Principal Component Analysis (HPCA). The second stage is involved with Fuzzy Hybrid Information Inference Mechanism (FHIIM) for determining tracked vehicles as reported in previous work. In vehicle detection stage, candidate vehicles resulting from background subtraction have been detected. The proposed approach has been evaluated by performing experiments with case studies of vehicles. Experimental results have shown that the proposed system performs better even during the situations of congestion.

Key words: Traffic monitoring, congested condition, traffic surveillance, vehicle detection, vehicle tracking, feature extraction, Improved Particle Swarm Optimization (IPSO), background subtraction, Principal Component Analysis (PCA), Fuzzy Hybrid Information Inference Mechanism (FHIIM)

INTRODUCTION

Presently, road management authorities have been facing issues related to saturation of transport's capacity across the globe. With increasing trend in car and vehicles users on roads, this problem is going to increase exponentially until no action is taken. There is also a fast growth in usage of vehicles for transport along with the improvement seen in quality of life. Nonetheless, an increase use of vehicles results in traffic problems. In addition, traffic network extension becomes tedious in several cities. Therefore, correct management of present road traffic will be the suitable solution. This can be made possible only through optimization in traffic lights, rapidity in responding to traffic incidents, scheduling of vehicles itineraries in a better way as anticipated by several traffic managers. Through implementation of these required factors, traffic flow could be sufficiently enhanced such that congestion, travel times and environmental effects will be minimized. In lieu of limiting congestion, research on different intelligent transportation systems has gained popularity. Traffic monitoring with the help of vision-based traffic surveillance is one among the commonly known techniques for which extensive and up-to-date surveys are been provided (Zhang *et al*., 2011; Buch *et al*., 2011).

In last few decades, road engineers employed loop detectors or supersonic wave detectors for estimating traffic flow or traffic density on a road. But, now, traffic management systems make use of image and video processing techniques for the extraction of same information from surveillance video of roads or junctions. Generally, the background subtraction is a widely-used detection approach to assist visual

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surveillance applications in distinguishing the mobile objects from the static portions of the video frames. The steps that are included in background subtraction are the calculation of a reference image, subtraction of this reference from each new frame and then application of a threshold to the result. Despite the availability of several new surveillance techniques for vehicle detection and tracking, there are two significant issues that generally come up during traffic congestion specifically inside tunnels. Low angle position of surveillance camera especially shows that vehicles are connected easily in images visually. Disconnection of adjacent vehicles is necessary for gaining detection accuracy. Since, the vehicles take up most space, the background renovation tends to become much crucial during the time of congestion management. Assuming a static background by most of the traffic management methods is the major reason behind this setback and so it becomes necessary for the background model to be updated for dynamic backgrounds. But, updating background model is one among the significant challenges for background subtraction techniques. Once background subtraction is completed, video tracking is the subsequent step which can be defined simply as the creation of temporal correspondence between detected objects on a frame to frame basis. The result of temporal identification of the segmented regions from this process can be used for the generation of cohesive information about the objects in the area monitored including trajectory, speed and direction. Usually, output is generated by tracking step will be utilized for supporting and enhancing motion segmentation, object classification and higher level activity analysis. Modeling of vehicle detection observed in many of the vehicle detection study generally adheres to a wire-frame model where windshield plays a part of the model (Kim and Malik, 2003). Detection of windshield area on the basis of color feature as a form of preprocessing has been conducted for detecting and counting people inside the vehicle (Philip *et al*., 2004). Several research works focused chiefly on the application of a general object detection technique for vehicle detection and tracking techniques while only less research on vehicle detection with the help of certain vehicle features like windshields or headlights has been studied. Three important steps that are hugely involved in new system of traffic management are the background subtraction of vehicle detection and vehicle tracking. An efficient scheme for the updating of an adaptive background model in the case of dynamic scenes is also introduced. Vehicles obstructed are segmented during the stage of vehicle detection in accordance with their inter information. Here in this research, vehicle tracking is performed in three stages that are known as feature extraction by Improved Particle Swarm Optimization (IPSO) algorithm, dimensionality reduction of features by means of Hybrid Principal Component Analysis (PCA) and compensation through Fuzzy Hybrid Information Inference Mechanism (FHIIM) in case of dissimilarity existing in the comparison result.

Literature review: There have been several approaches for computation of a background model of the camera images in addition to continuous updating of the model. Differences seem to raise due to the foreground objects, during comparison of the current camera frame with the background. Pixel modeling utilizing a mixture of Gaussians has been introduced by Staufer and Grimson (1999). Multiple background models have been compared systematically in the work which have been discussed by Piccardi (2004). Because of the variations in dynamic scenes as obtained from lighting and extraneous events, these kind of simple motion detectors which are based on a complicated environment model are highly sensitive. Wender and Dietmayer (2008) demonstrated the vehicle tracking pattern of learning, modeling and classification obtained from live video. The enhancement of classification pattern of mobile objects or vehicles has the goal of different vehicle tracking models. Both the detection and classification of vehicles in many techniques by employing different filters have been introduced by Gupte *et al*. (2002). During the time of vehicle identification, Kalman filter method and background subtraction method had been extensively used for easy traffic flow.

Cucchiara *et al*. (2000) have used template matching where the template is observed as a circular bright region that is surrounded by a dark background for headlights detection. In this technique, headlights are paired together by employing the distance or symmetry data. But, many false positives and missing of vehicles are the chief disadvantages of these methods. Wu *et al*. (2007) studied a virtual line group based algorithm that uses luminance, chrominance and spatiotemporal information of the virtual line group as it advances the temple matching method. Four neighboring virtual detection lines have also been incorporated in the virtual line group. Another enhanced algorithm based on background subtraction method has been introduced for the identification of vehicles on every detection line. Detection of occurrence of the vehicle can be done through the subtraction of the background from the current frame which is then followed by comparison between the differences with threshold. Then, the enhanced algorithm comprising of two-level detection have been developed where the first level of detection made use of luminance information. If the first level detection guaranteed no occurrence of vehicle, luminance threshold will be changed according to the pixel's colors as obtained by exploiting the chrominance information for conducting the second level detection. Result optimization can be carried out further by making use of the spatiotemporal information of the virtual line group. For the case of acoustic vehicle classification which is based on alpha-stable statistical modeling, Kornaropoulos and Tsakalides (2009) introduced a new K Nearest Neighbor (KNN) classifier by means of which the vehicles classification can be done with ease and accuracy.

MATERIALS AND METHODS

A new technique of traffic analysis of video-based traffic surveillance framework is proposed in this work with various stages namely background subtraction, vehicle detection and vehicle tracking. The initial stage of the proposed work is a preprocessing step supported by background subtraction. Subsequently at the tracking stage, Improved Particle Swarm Optimization (IPSO) framework have been applied for the extraction of vehicle features like symmetry, edge, headlights, brightness, appearance and day and night time. At last, dimensionality reduction for the extracted features is carried out by means of Hybrid Principal Component Analysis (HPCA) for the resolution of headlight effects. Decision on tracked vehicles is then performed utilizing a FHIIM. Tracking algorithm is usually helpful for enhancing the vehicle detection accuracy in addition to the extraction of more number of vehicle parameters. Detection of candidate's vehicles is conducted during the vehicle detection stage in the system proposed. Figure 1 indicates the entire architecture of the proposed system.

For changing detection method, background model is one among the largely useful techniques. As an example, background modeling is used in the subsequent video surveillance systems. Building of the background model at the start of a video sequence is the initial step for the detection of mobile objects making use of background subtraction. Selective averaging method has been utilized in this work for the purpose of constructing the initial background model given by Wang *et al.* (2007):

$$ILB_N(x, y) = \frac{\sum_{f=1}^{N} I_f(x, y)}{N} \quad (1)$$

where, $ILB_N(x, y)$ denotes the intensity level of background model of pixels (x, y), if (x, y) specifies the intensity level of normal images of pixels (x, y) at the frame

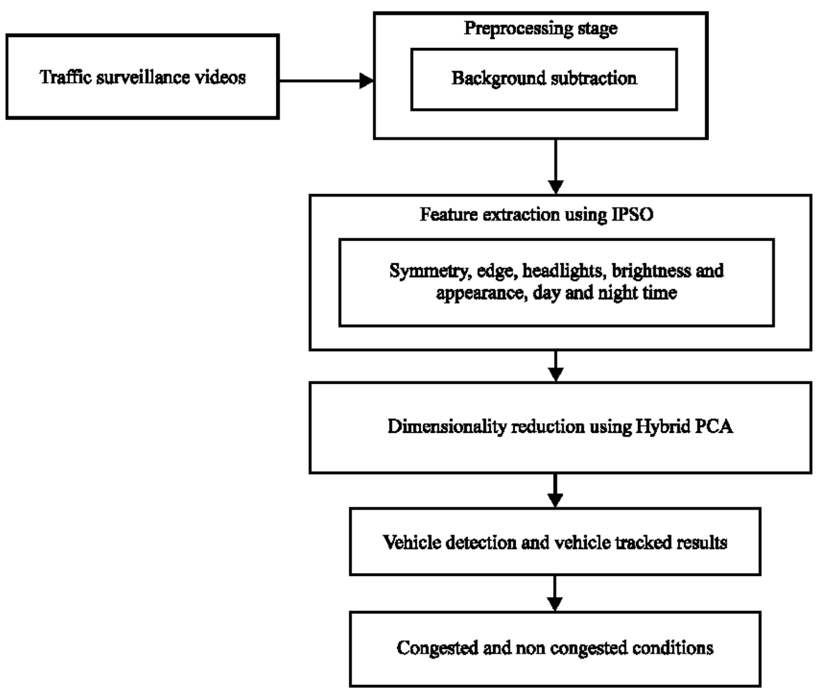

Fig. 1: Entire architecture of proposed system

till the fth level and N indicates the number of frames that are necessary for the construction of the background model. After finding the initial background model, the difference observed between the current frame and the background model is then computed:

$$D_t(x, y) = |I_t(x, y) - ILB_{t-1}(x, y)| \tag{2}$$

Where:

$ILB_{t-1}(x, y)$ = The intensity level of background model of pixels t
$I_t(x, y)$ = The intensity of pixel (x, y) in the current frame at time t

The difference $D_t(x, y)$ is further compared with an adaptive threshold Th_{ad} for foreground background pixel classification which is followed by the computation for Th_{ad} (Ng and Delp, 2010). Th_{ad} is generally received through iteration making use of the histogram of the difference frame $D_t(x, y)$ to take the frame-to-frame changes in the background into account. In case $D_t(x, y)<Th_{2d}$, the pixel is considered as a background pixel while if $D_t(x, y)>Th_{2d}$, it is classified however as a foreground pixel:

$$(x,y) \subset \begin{cases} \text{Foreground if } D_t(x, y) \geq Th_{ad} \\ \text{Background if } D_t(x, y) < Th_{ad} \end{cases} \tag{3}$$

The background model has to be updated for each frame such that the background dynamics like illumination changes and waving tree leaves could be taken into consideration. Updation of the background model is done in the proposed work on a pixel-by-pixel basis. Here, every pixel has an adaptive learning rate known as $\alpha_{ad,t}(x, y)$ that is defined as:

$$ILB_N(x, y) = \alpha_{ad,t}(x, y) I_t(x, y) + (1 - \alpha_{ad,t}(x, y)) ILB_{t-1}(x, y) \tag{4}$$

where, $0 \leq \alpha_{ad,t}(x, y) \leq 1$. The learning rate $\alpha_{ad,t}(x, y)$ is dependent on two weighted parameters, α_1 and α_2 (it is to be noted that the subscript^t and (x, y) are left out for simplicity sake):

$$\alpha_{ad,t}(x, y) = w_1\alpha_1 + w_2\alpha_2 \tag{5}$$

where, w_1 and w_2 are the weights for α_1 and α_2, respectively and $w_1+w_2 \leq 1$. The first parameter α_1 depends on the magnitude of $D_t(x, y)$. A larger value for α_1 is assigned for a smaller $D_t(x, y)$:

$$a_1 = \begin{cases} e^{\frac{-1}{2}\frac{D_t(x,y)^2}{\alpha_1^2}} & \text{if } D_t(x, y) < Th_{ad} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

Here, σ_1 is $Th_{ad}/5$ is a function of Th_{ad} indicates that the portion of pixels having the smallest $D_t(x, y)$ possesses higher α_1. Pixels in the background are considered to be longer. Background pixels with more stability and reliability are taken into account. Stability and reliability is computed by the temporal background count C_{bg} and therefore:

$$a_2 = \begin{cases} e^{\frac{-1}{2}\frac{(C_{max} - C'_{bg})^2}{s_2^2}} & \text{if } C_{bg} < C_{min} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where, σ_1 = 15, C_{max} = 150 and C_{min} = 30 have been empirically determined and $C'_{bg} = \min(C_{max}, C_{bg})$. If a pixel remains as a background pixel for more than C_{min} frames, a non-zero α_2 is assigned to that pixel. The parameter α_2 increases with C_{bg} until C_{bg} is greater than C_{max}. Unimportant objects having small and repetitive motion like waving tree leaves and water ripples are reduced by the parameter since it would lead to fake alarms. This operates under the supposition that in case the pixel switches between foreground and background states often (which means that the pixel does not regain its background status for longer than C_{min} frames), then there are more chances for it to become a background pixel. The temporal background count C_{bg} is then reset to zero when the pixel is detected as a foreground pixel.

In order to prevent the updation of the foreground object as the background image, small range update with great caution should be conducted. After getting the absolute difference value between the background intensity and the average value $\alpha_{ad,t}(x, y)$ in every range, the background intensity is then updated for the smaller difference compared to the range. Otherwise there will be no updation on the background pixel.

Improved Particle Swarm Optimization (IPSO) for feature extraction: For extracting the mobile objects from input image, a method is being proposed in which initially the mobile features of vehicles are obtained through moving-edge extraction. Significant features that are extracted for gaining the moving features of vehicles from vehicle traffic consist of symmetry, edge; headlight, brightness and appearance, day and night time.

Connected component labeling is then used to detect the shape of the objects. Every labeled object is then verified on the basis of its features as it is extracted from IPSO algorithm and at last the computation overhead is minimized by employing connected component labeling. In several complex optimization and search problems, Particle Swarm Optimization (PSO) is been used has good search speed. In addition, several optimization problems can also be resolved for different applications (Parsopoulos *et al*., 2001). Since, the particles could rapidly get near to best particle features, PSO could frequently fall easily into local optima best feature extraction result for the cause of background subtracted images. But, the choice of best features extraction results tends to become hard globally in general PSO algorithm. This is because of the higher time expended for the completion of the evolution process. This work is involved with overcoming the problem with respective to PSO through the implementation of a novel improved PSO algorithm. This is achieved by the addition of a new mutation parameter for dealing with the problem of global features extraction results. Cauchy mutation is a newly realized technique that facilitates the extraction of best video-based traffic surveillance features like symmetry, edge, headlight, brightness and appearance and day and night time obtained from background model results. This consequently achieves the best extracted feature results that are generated by the mutated particle and the results of the remaining particles are also enhanced in order to obtain best feature extraction positions. In comparison with other algorithms that are evolutionary, PSO is also a population-based search algorithm that begins with an initial population. An initial population is taken as the number of images samples in addition to the background subtraction results known as particles (Hu *et al*., 2004). In PSO, every particle possesses a position and a velocity. From all the features of video traffic samples, PSO does extraction of best features on the basis of the position that is identified by all background subtracted images particles in the search procedure. The possible solution of best feature extraction results is denoted by a particle through adjustment of its position and velocity in accordance with Eq. 8 and 9:

$$\mathrm{BSIV}_i^{(t+1)} = w\times \mathrm{BSIV}_i^{(t)} + \mathrm{FLC}_1\times \mathrm{rand1}(\,)\times \left(F_i - \mathrm{BSI}_i^{(t)}\right) + \mathrm{FGC}_2\times \mathrm{rand2}(\,)\times\left(F_g - \mathrm{BSI}_i^{(t)}\right) \tag{8}$$

$$\mathrm{BSI}_i^{(t+1)} = \mathrm{BSI}_i^{(t)} + \mathrm{BSIV}_i^{(t+1)} \tag{9}$$

Where:

- BSI_1 and $BSIVI_1$ = The position and velocity of background subtracted images (Particles) i
- Fi and F_g = Previous best extracted features for the ith particle and the global best particle found by all particles so far, respectively and w is an inertia factor and rand1( ) and rand1( ) are two random numbers independently generated within the range of [0, 1]
- FLC_1 and FLC_2 = Two learning factors which control the influence of the local feature extraction and global feature extraction results

In the standard PSO, easy slippage into local optima feature extraction stayed as the significant problem in several optimization issues. Research on getting over such problem has been reported so far (Xie *et al*., 2002). While the particles in PSO get to converge rapidly, it tends to become the reason behind the PSO to be converged into local optima in order to obtain the best position seen no change in a local optimum. In case of all particles becoming identical, a better position is find out to replace between the best positions found so far is not again much convenient. A novel improved PSO referred to as IPSO is presented in this work where cauchy mutation is applied to obtain the best position of Background Subtracted Image (BSI) samples of vehicles out of the local optimal. Along with the generation of PSO algorithm, searching neighbors of the global best features of BSI of vehicles is integrated in every generation of PSO algorithm which is useful in expanding result to best feature extraction position corresponding to the better feature extraction positions. With the aid of Cauchy mutation over the global best feature extraction results, it is possible for each of BSI images in every generation. One-dimensional Cauchy density function that is centered at the origin is defined by:

$$f(\mathrm{BSI}) = \frac{1}{\pi}\frac{t}{t^2+\mathrm{BSI}^2},\ -\infty<\mathrm{BSI}<+\infty \tag{10}$$

where, t>0 refers to a scale parameter. The Cauchy distributed function is:

$$f_t(\mathrm{BSI}) = \frac{1}{2}+\frac{1}{p}\arctan\left(\frac{\mathrm{BSI}}{t}\right) \tag{11}$$

The vehicle features like symmetry, edge, headlight, brightness and appearance, day and night time are extracted in this work making use of Cauchy distribution function in accordance with certain conditions that follow.

Headlight and brightness features: The headlight modeling is conducted by use of disk is projected towards all pixels of the camera image. Therefore, the average size of the headlight in units of pixel is pre-calculated for all the camera's pixels. Headlight estimation is on the basis of the vehicles standards, the average size of a headlight and its average height that is represented in meter units. Detection of the bright areas in the image becomes the initial step that is conducted by detecting the connected pixels ('blobs') which increases the ratio V/S (Value on Saturation). With the assistance of the non-linear luminance equation of the color channels (R, G, B) the detection is performed making use of the relation given:

$$L = \frac{1}{2}\left(\max(R,G,B) + \min(R,G,B)\right) \tag{12}$$

Appearance features: Detection of appearance feature is feasible only for the case of low confidence value of a candidate vehicle. The estimation of the appearance of features of level is done based on the parameters consisting of Headlight Diameter (HD), Headlights Separation Distance (HSD). HSD is generally computed from the difference between left and right position all given in pixel coordinates:

$$HSD = |HL\text{-}HR| \tag{13}$$

For every pair candidate, square image size of $(HD+HSD)^2$ is considered for both image column and row.

Day and night time features: Detection of vehicles at day-time is considerably time-consuming since there will be no aid of strong feature like headlight. In addition, the vehicles are susceptible to many other illuminations. But, identical to the process as conducted for night-time features evaluation, the method is employed for day time features. Images of cars have been gathered manually which is then followed by the calculation of the mean image along with the 'eigen images'.

Edge features: Edge features are attained through the application of a Sobel operator to the image. Although, the edges generated by lane marks and road marks might create impact on the shapes of vehicle edges. Hence, the edges of a background image are taken into account for the purpose of reduction of the noise. In case of the above condition being satisfied by the local Background subtracted images samples, these features are extracted from specific samples or otherwise best feature is extracted by iterating further. For increasing the probability of getting rid of a local optimal feature extraction results for BSI samples, such kind of mutation operator is brought in to use. The Cauchy mutation operator utilized in IPSO is explained as:

$$W(j) = \frac{\left(\sum_{j=1}^{PSI} BSIV[j][i]\right)}{PSI} \tag{14}$$

where, BSIV[j][i] refers the ith velocity vector of the jth particle in the population, PSI indicates the population size of BSI samples. W(i) represents a weight vector within $[-W_{max}, W_{max}]$ and W_{max} is set to 1:

$$F_g'(i) = F_g(i) + W(i) \times NF(BSI_{MIN}, BSI_{MAX}) \tag{15}$$

where, NF is a Cauchy distributed function with the scale parameter t = 1 and $NF(BSI_{MIN}, BSI_{MAX})$ is a random number within (BSI_{MIN}, BSI_{MAX}) which is a defined domain of a test function.

Algorithm 1 (improved particle swarm optimization for feature extraction):

while iteration <= max-iterations do
begin
for each Background Subtracted Images (BSI) particle i do
begin
Calculate fitness value for each features (Eq. 10 and 11) and it can be compared to Eq. 12 and 13
if the fitness value of local BSI features (Eq. 10 and 11) than its best fitness value in history (Eq. 12 and 13)
then Update local feature extraction F_i
if the fitness value of entire BSI features (Eq. 10 and 11) is better than the best fitness value in history (Eq. 12 and 13)
then update global feature extraction F_g
Calculate BSI_i and $BSIV_i$ are the position and velocity of background subtracted images (Particles) i, according to Eq. 8 and 9
end
for j = 1 to the population size do
begin
Update W(j) according to Eq. 14
if fabs($W[j]>W_{max}$) then $W[j]>W_{max}$)
end
Mutate F_g according to Eq. 15 for N times
Select a best particle F_g^{best} from the N particles after having N mutations
if the fitness value of F_g^{best} is better than F_g
then $F_g = F_g^{best}$
end

Hybrid Principal Component Analysis (HPCA) for dimensionality reduction: Hybrid PCA neural network is developed by means of the combination of unsupervised Principal Component Analysis (PCA) and supervised Markov Logic Framework (MLF) neural networks to conduct forecasting. Dimensionality reduction of the extracted feature results obtained from IPSO algorithm is performed by PCA neural network. PCA neural network can also minimize the high dimensional extracted features

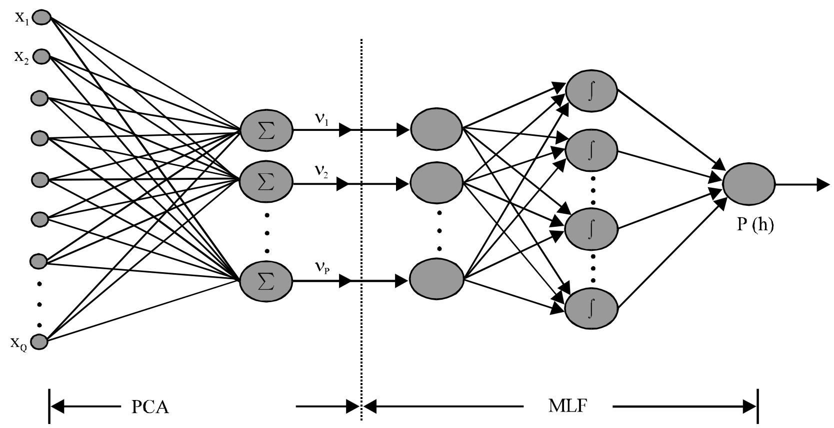

Fig. 2: Proposed hybrid PCA neural network

into low-dimensional extracted features which are then considered to be inputs of MLF neural network for the reduction of the training time of the original Background Subtracted Image (BSI) samples for the cause of video traffic evaluation. The goal of PCA neural network is finding a subset of features vectors P in a Q dimensional space ($Q \geq P$), so that these reduced feature vector results are saved in the input data as much as possible. The reduced feature Eigen vectors P that are associated with the P largest Eigen values of the $E(xx^t)$ where x represents the Q dimensional input samples result obtained from IPSO algorithm along with best features, i.e., $x = (x_1, x_2, \ldots, x_Q)^t$. The direction of the qth principal component will be in the direction of the qth Eigen vector, q = 1, 2, ..., Q. Symbol^t is treated as the training index. On the basis of the previous work for the updation of the weightings between the neurons of PCA network (Wang *et al*., 2012), this research also carries out update as given as:

$$\Delta w_p(t) = \eta(t) v_p(t) \left(x(t) - \sum_{pj=1}^{p} v_{pj}(t) w_{pj}(t) \right) \quad (16)$$

where, $\eta(t)$ represents a learning parameter for rate of dimensionality reduction and $v_{pi}^{(t)} = w_{pi}^{t}(t)^{x(t)}$ is taken as reduced dimensionality of features for the purpose of traffic analysis. Equation 15 is applied in order to train a neural network comprising of P linear neurons so that the first P principal components are found. Especially in Gorrell (2007), generalized Hebbian algorithm have been capable of making $w_p^{(t)}$, p = 1, 2, …, P, converge to the first P principal component directions in sequential order: $w_p^{(t)} \pm v_i$ where v_i refers to a normalized Eigen vector corresponding to the ith largest Eigen value of the correlation matrix. It is indicated that $w_{pj}^{(t)}$, p_j = 1, 2, …, P-1 have converged to v_{pj} (t), p_j = 1, 2, ..., P-1, correspondingly, then the maximal Eigen value λ_p and the respective normalized Eigen vector v_p of the correlation matrix of x_p, i.e., $C_p = E(x_p x^t_p)$ are exactly the pth Eigen value λ_p and the pth normalized Eigen vector v_p of the correlation matrix x_p, i.e., $C = E(xx^t)$, respectively. As a result, neuron p can be used to find the pth normalized Eigen vector of C. It is illustrated that $\eta(t)$ must be smaller than the reciprocal largest Eigen value of $E(xx^t)$ in order to assure the convergence of training a PCA neural network. In case the training process is convergent, w_p, p = 1, 2, …, P, converges to the pth Eigen vector of $E(xx^t)$. Figure 2 depicts the structure of hybrid PCA neural network.

For the purpose of tracking of multiple vehicles during conditions of congestion, new process has been evolved at the same time. This method measures the new positions of the tracked objects making use of a Feature Extraction and dimensionality reduction method. FHIIM method is then applied for verifying the tracking results such that the error compensation can also be determined. After the extraction and reduction of the feature results from IPSO, it will be used in FHIIM. Thereafter, the different values of features into the histograms values were compared, since histogram comparison takes all features in the tracked regions into consideration. Higher scores will be received due to the matching of the search results with the earlier tracking results. The whole procedure of FHIIM methods is identical to prior works (Wu *et al*., 2013) even though in place of two features being taken into consideration, various other features have been taken into account for being extracted from IPSO.

RESULTS AND DISCUSSION

In accordance with the experimental results, the performance of the proposed system has been assessed making use of the traffic surveillance videos. Detailed discussion over the analysis and the comparison has been conducted. The experimental analysis has been conducted employing camera 19 and camera 27 as per the two tested scenarios including Chien-Kuo Bridge in Taipei City in the daytime and nighttime and Mu-Cha Tunnel on Highway 3, respectively. In both the cases, there were several challenges to be met with. The cameras were way too old and the resolution is not at all clear in both the conditions. Therefore, the overlapping of vehicles tends to become a critical problem in the images. These scenarios were all tested utilizing a Windows XP platform with an Intel Core 2 2.14-GHz central processing unit and 2-GB random access memory. The size of image is 320×240, the sampling rate of the sequence is 30 frames/sec and the processing time range is from 17-23 msec. Experimental evaluations were performed in six environmental conditions. In the quantitative evaluations of the system proposed, the recall and precision are computed by:

$$\text{Recall} = \frac{T_p}{T_p + F_n} \tag{17}$$

$$\text{Precision} = \frac{T_p}{T_p + F_p} \tag{18}$$

Where:

T_p = True positives represent the number of correctly detected vehicles

F_p = False positives number of falsely detected vehicles

F_n = False negatives number of missing vehicles

Evaluation of the information retrieval performance has been done using recall and precision. The performance index called accuracy has also used to make afair comparison using the following Eq. 18:

$$\text{Accuracy} = \frac{T_p}{T_p + F_p + F_n} \tag{19}$$

However, the resultant images for analyzing false positives and false negatives were difficult to obtain and therefore the performance has assessed based on the balance of deficient counting and additional counting. For every testing experimentation, the error have been updated every 5 min and the Average Error (AE) have been determined as defined using Eq. 20:

$$\text{AE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E}{M}\right| \times 100\% \tag{20}$$

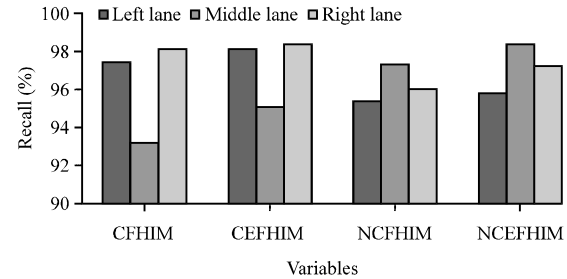

Fig. 3: Recall value of congested and non-congested at day time

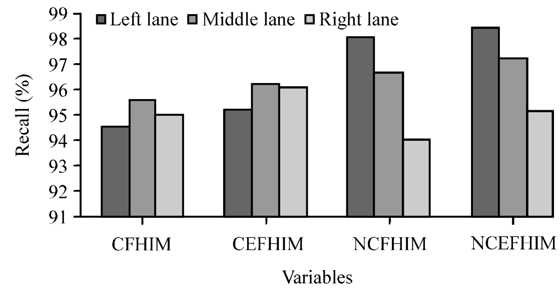

Fig. 4: Recall value of congested and non-congested at night time

Table 1: Recall value of congested and non-congested at day time

Recall value/Day time	Left lane	Middle lane	Right lane
CFHIIM	97.50	93.24	98.20
CEFHIIM	98.20	95.10	98.50
NCFHIIM	95.43	97.41	96.04
NCEFHIIM	95.84	98.41	97.25

Table 2: Recall value of congested and non-congested at night time

Recall value/Night time	Left lane	Middle lane	Right lane
CFHIIM	97.36	96.77	92.64
CEFHIIM	98.25	97.23	94.20
NCFHIIM	92.64	96.81	95.20
NCEFHIIM	93.64	97.23	96.82

Where:

E = The difference in error between system counting and manual counting

M = The value for manual counting and is the data number

The measured recall value of congested and non congested traffic analysis results of FHIIM and EFHIM system under left, middle and right lane conditions at day time has been shown in Fig. 3. The values are tabulated in Table 1. The determined recall value of congested and non congested traffic analysis results of FHIIM and EFHIIM system under left, middle and right lane conditions at night time is given in Fig. 4. Compared to day time, recall value of night time will have a higher value and the values are indicated in Table 2.

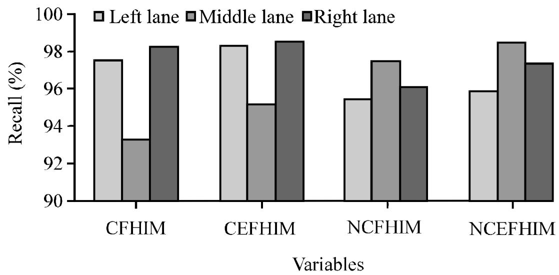

Fig. 5: Recall value of congested and non-congested traffic conditions at tunnel

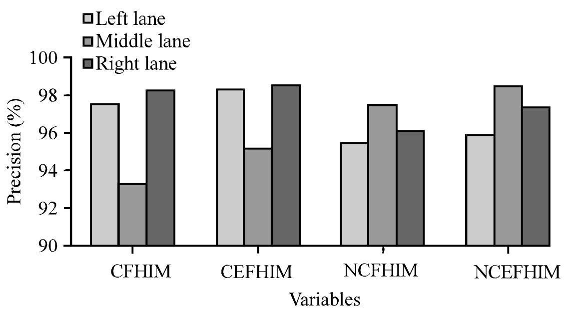

Fig. 6: Precision value of congested and non-congested at day time

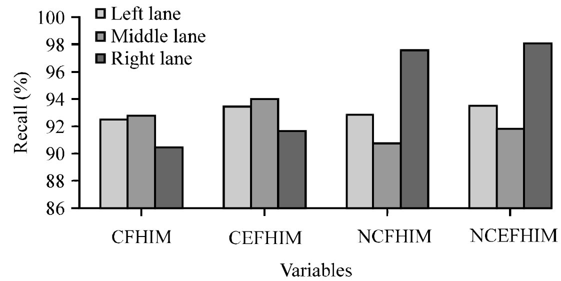

Fig. 7: Precision value of congested and non-congested at night time

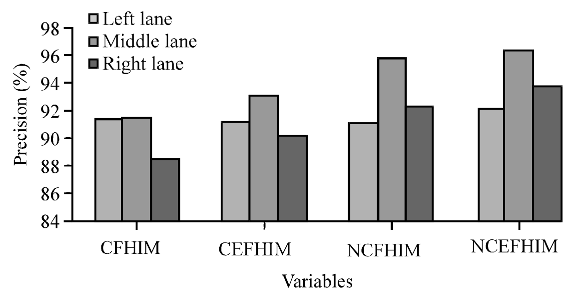

Fig. 8: Precision value of congested and non-congested traffic conditions at tunnel

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

Recall value/Tunnel	Left lane	Middle lane	Right lane
CFHIIM	94.57	95.62	95.06
CEFHIIM	95.23	96.23	96.15
NCFHIIM	98.11	96.71	94.06
NCEFHIIM	98.50	97.2	95.23

Table 4: Precision value of congested and non congested at day time

Recall value/Day time	Left lane	Middle lane	Right lane
CFHIIM	89.56	97.20	96.88
CEFHIIM	90.25	98.52	97.25
NCFHIIM	91.42	91.54	88.54
NCEFHIIM	92.85	92.89	91.25

Table 5: Recall value of congested and non congested at night time

Recall value/Night time	Left lane	Middle lane	Right lane
CFHIIM	92.46	92.74	90.44
CEFHIIM	93.45	93.87	91.63
NCFHIIM	92.86	90.67	97.50
NCEFHIIM	93.50	91.78	98.12

Table 6: Precision value of congested and non congested at tunnel

Recall value/Day time	Left lane	Middle lane	Right lane
CFHIIM	91.42	91.54	88.58
CEFHIIM	91.34	93.20	90.23
NCFHIIM	91.23	95.90	92.40
NCEFHIIM	92.28	96.40	93.90

The recall value measured for congested and non congested traffic analysis results of FHIM and EFHIM system under left, middle and right lane conditions at tunnel time is shown in Fig. 5 in which the best average recall values is found for comparingboth day and night time. Table 3 indicates the best recall values.

Figure 6 shows the precision values of congested and non congested traffic analysis results of FHIIM and EFHIIM system under left, middle and right lane conditions at day time. The values are tabulated in Table 4, it shows that precision values of day time are high when compare to both night time and tunnel time.

Figure 7 shows the precision value of congested and non congested traffic analysis results of FHIIM and EFHIIM system under left, middle and right lane conditions at night time. Compared to day time, precision values of night time will be less and high compare to tunnel. The values are tabulated in Table 5.

The precision value measured for congested and non congested traffic analysis results of FHIIM and EFHIIM system under left, middle and right lane conditions at tunnel time were represented in Fig. 8 and compared between day time and night time. It is also found from the values given in Table 6 that the precision values of tunnel time will be less.

CONCLUSION

With the road traffic congestion rising as one of the critical issues in many of developing countries, several studies have been presented in order to get over the problem of vehicle detection and tracking. The issue of road traffic congestion has been studied in this paper for providing a solution for the impact inflicted by highest congestion. The proposed methodology has been implemented with the support of two steps where in the first step, the background has been updated smoothly making use of selective averaging method whereas a small range update has been brought into use under congested situations in the second step. Vital features of the background subtracted images were got by means of Improved Particle Swarm Optimization (IPSO) and dimensionalities of those extracted features were reduced simultaneously through Hybrid Principal Component Analysis (HPCA).

Traffic analysis results are significantly impacted by the features like headlight, brightness, day and night time features. When every approach of the proposed method is employed into FHIIM, the resulting Enhanced FHIIM for vehicles tracking has been realized. The tracking quality has also been considerably improved through error compensation while the tracking errors occur. Experimental results suggest that Enhanced FHIIM performs well both under conditions of normal congestion and also under conditions within a congested tunnel.

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