An Efficient Location And Vehicle Tracking Scheme For Event Detection Using Its

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Abstract

The contribution of Intelligent Transportation Systems (ITS) has gained a significant importance in real-world by granting road-side communication and safety services. Road side event detection and vehicle tracking are facilitated with the information gained from the vehicles. Other than reliable transmission, efficient processing and analysis of the vehicle related information helps to improve the rate of accuracy in detecting events. This article introduces selective vehicle tracking and localization scheme (STLS) for processing transmitted information efficiently. This scheme is focused to reduce the errors in processing to classify events in road segments, irrespective of the density and physical attributes of the vehicles. The scheme exploits constraint based fuzzy normalization for preparing decisions and arriving at optimal solutions. The classification of events based on the physical attributes and constraints helps to reduce processing errors, improving the accuracy of event detection and vehicle tracking.

Keywords: *Event Detection, Fuzzy Logic, ITS, Localization*

I. INTRODUCTION

Intelligent transportation system (ITS) forms the fundamental element of road-side communication in real-world. The need for intelligent transport systems is mandatory to meet the user requirements in communication and information sharing. The autonomous vehicular communication is self-disciplined through the integration of on-board units (OBUs), road-side units (RSUs) and centralized network. OBUs are responsible for sensing and actuating messages from the vehicles to the neighbors or fixed infrastructures [1]. RSUs are fixed infrastructures that are capable of providing universal communication access and information privileges to the end-users with the help of wireless technologies and communication standards such as wireless access vehicular environment (WAVE), dedicated short range communication (DSRC), etc. The environment exhibits two types of communication namely: vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) [2]. The need for communication, information sharing apart from road-safety, traffic assistance, is used for vehicle monitoring and density observation in the recent years. The intelligence and cloud access features of the vehicles facilitate critical information sharing and environment monitoring. Information fetched from the vehicles is useful in determining the characteristics of the road segment and traffic in densely populated cities [3].

Road accidents, congestion, etc. are common due to the increasing population and un-realistic road conditions. ITS vehicles are interconnected to form a network that is capable of scaling long geographical distance. This helps to share information in a swift manner to the traffic processing centers [3]. Accident prevention, congestion de-touring, uncontrolled driving, emergency vehicle navigation, etc. are some of the advanced facilities that can be achieved by assimilating vehicles, communication technologies, and efficient analyzing techniques [4]. Observing and deriving such cases in a road-side communication helps to classify the events in city environment and traffic analysis. Classifying the events

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as normal or abnormal relies on the physical and extended attributes of the vehicles. The velocity, position, direction, etc. are the physical attributes and the derived characteristics such as density, handoff, are some of the extended attributes in vehicular communication. The attributes are processed using efficient algorithms and techniques for improving the accuracy in event detection and classification. More specifically, tracking and localization are prominent in estimating the road-side analysis with controlled error and better precision [5].

II. Related Works

By Bayesian Framework a new co-operative localization method (CLM) is proposed by Song et al. [6] used to measure the reliable and appropriate localization of vehicle in transportation intelligent application system. By using fusion method the angle is estimated for filtered global locating system data, the attitude angle and distance of inter-vehicle. The experimental output shows that efficiently enhanced the accurate localization of vehicle with the deliberation of attitude angle are linked with the distance of inter-vehicle and the GPS fusion.

A model based Linear Quadratic Gaussian (LQG) method with flexible Q matrix is presented in [7] to improve the efficient and methodically structure tracking director the way for target of the given vehicle successfully control the error detection and noise arise in the path planning algorithms and localization. The automatically structured regulator is used for tuning different speeds without more efforts. The simulation results shows that the proposed method is most efficient than the other conservative tracking methods.

Based on the particle filter an information fusion algorithm is proposed by Rabiee et al. [8] to obtain the lane level accuracy tracking by a GNSS denied surroundings. The fine scale and coarse scale signal capacity is used for angle positioning. From the recognized transmitters or RSUs the time of arrival is measured by the radio frequency signal and from an IMU gyroscope and acceleration is measured to form evaluation of a coarse position of the vehicle by the Kalman filter.

The appropriate angle of vehicle is identified using local inertial sensors and distance sensors. The integrate measurements of inertial sensor, neighboring vehicle information and distance sensors are estimated by a proposed new scheme [9]. By using RANSAC concept the graph matching model is introduced to match the near angle by LIDAr distance sensor using clustered objects.

The motion control of traced vehicles and dynamic modeling is proposed byZou et al. [10] is used to skid steering on hard terrain, under non-holonomic, horizontal controls. The non-holonomic mechanical systems obtain by the skew symmetry property, by the back stepping method the control methodology is estimated using modified proportional integral Derivation (PID) computed torque control.

Yin et al. [11] proposed a slope detection method by exploiting the longitudinal velocity and acceleration of the vehicle. The observed acceleration and velocity of the vehicle is used to verify the conditional analysis of the slope for feasibility. This method achieves better accuracy in detecting the road-side slope.

The authors in [12] induced support vector machines (SVM) for leveraging the accuracy of vehicle location estimation. With the help of global positioning system, navigation system and SVM with extended Kalman filtering (EKF) the accuracy of vehicle position and localization is achieved. This method achieves less cost through interracial sensors and less outage.

Collaborative tracking protocol (CTP)is designed by Derder et al. [13]that employs virtual RSUs for vehicle tracking and localization. A transferrable belief model is designed to reduce the network load and to improve the precision of localization. This protocol relies on the time updates and notifications in identifying the target.

III. Proposed Methodology

3.1 Selective Vehicle Tracking and Localization Scheme

STLS is designed with the communication considerations of vehicles communicated to internet. The intelligence of the vehicle communication systems is exploited for tracking and localization. In contrast to the conventional localization, this scheme ensures segment localization and path synchronization to

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identify physical changes in vehicle movement. A conventional vehicle movement is designed on the basis of Manhatan mobility model (MMM). The Following section provides a brief introduction to the proposed scheme with the network architecture.

The on-board unit (OBU) is configured with necessary sensors such as proximity and global positioning system (GPS). Proximity sensor is equipped in the license plate of the vehicle to identify collision/colliding circumstances. The GPS is used to share the position and location of the vehicle at any time instance. The functions of the sensors are administered by the OBU for transmitting location information. Similarly, the values of the proximity sensor are transmitted by the OBU while detecting multiple vehicles within the range. In Figure 1, the architecture of the ITS scenario with location and road segment consideration is illustrated.

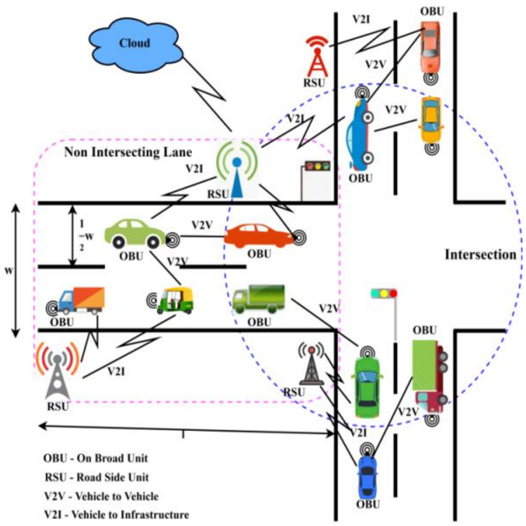

Fig. 1. ITS Architecture

The communication between the vehicles and infrastructure Units (RSUs) helps to transmit observed information to the traffic monitoring center (TMC). For localization and distributed information sharing and access, the vehicles are interconnected through internet/cloud. The vehicles moving under MMM have two probabilities in changing their direction of movement (i.e.) ½ in a straight/intersection-less lane and ¼ in an intersecting lane. The vehicle moves around a fixed road segment of with $'w'$ and length $'l'$ such that the dimension of the vehicles is$< \frac{1}{2} w \times l$. The placement of vehicle within half of the road width indicates that the vehicle in not exceeding its boundary. Let (x_a, y_a) and (x_b, y_b) represent the location co-ordinates of two vehicles "a" and "b". The distance D between the vehicles is estimated as

$$D = \sqrt{(x_b - x_a)^2 \, cos\theta + (y_b - y_a)^2 sin\theta} \qquad (1)$$

The distance follows geometric representation between the two vehicles, deviated by an angle θ. If $D < Range\ (a)$ or $Range\ (b)$, then proximity sensor measures the distance between the vehicle. If the safe distance limit (as per the traffic regulations of a country) between the vehicles is exceeded, then the chance of collisions is high. This results in an abnormal traffic event that can be detected at an earlier stage by monitoring the physical attributes of the vehicles. The physical attributes of the vehicles include its change in velocity (Δv), D and angle of deviation θ. The change in velocity and angle of deviation are estimated with certain reference points. Change in velocity is referred with respect to the current velocities if two or more vehicles; giving its displacement. In this localization and tracking scheme, the angle of deviation between two positions of a vehicle is computed with $(w \times l)$ as the reference point. Eq. (2) is used to estimate Δv and θ of a vehicle.

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$$\left.\begin{array}{c} \Delta v = \sqrt{v_a^2 - v_b^2 - 2v_a v_b cos\theta} \\ and \\ \theta = arc\cos\left[\frac{\Delta x_a + \Delta x_b + \Delta y_a + \Delta y_b}{\sqrt{\Delta x_a^2 + \Delta y_a^2} + \sqrt{\Delta x_a^2 + \Delta y_a^2}}\right] \end{array}\right\} \quad (2)$$

$$\left.\begin{array}{l} where, \\ \Delta x_a = |x_a^* - x_a| \\ \Delta x_b = |x_b^* - x_b| \\ \Delta y_a = |y_a^* - y_a| \\ \Delta y_b = |y_b^* - y_b| \end{array}\right\} \quad (3)$$

Here, $(x_a^*, y_a^*) and\ (x_b^*, y_b^*)$ represents the new position vectors of the vehicles a and b respectively. This angle of deviation measurement is correlated with the ω in perpendicular and l in parallel angles respectively. The change of (x_a, y_a) to (x_a^*, y_a^*) and (x_b, y_b) to (x_b^*, y_b^*) is represented and observed at a time t that is estimated as the sum of update intervals (t_u). The update is performed for any change in physical attributes of the vehicle. The maximum update time before a new neighbor communication/handoff is computed as

$$t_u = \frac{n \times Range\ (a)}{\Delta v \times (n+1)} \quad (4)$$

Where, n is the density of vehicles within the range of the tracking vehicle.

Let m represent the count of update message from a vehicle, then the t_u is segregated unevenly (based on $\Delta v$and θ) for the tracking vehicle. The observed features are processed using fuzzy decision-making in the TMC. In this decision-making, the inputs and possible constraints are distinguished from the first level to the x^{th} level of the process. The resultant output is notified to the user as a warning/alert message. If an abnormal event probability is observed, through sophisticated controllers, the operations of the vehicles can be paused. The fuzzy decision making functions is progressed as a linear normalization addressing multiple constraints. Withrespect to Δv, the normalization of distance $(\aleph_D)$

$$\left.\begin{array}{c} \aleph_D = 1 - \frac{Range\ (a)}{D} \\ for\ all \\ f(t_u) = \int_0^{v_a or\ v_b} \Delta v.(\Delta v.t_u, v_a)dv \\ \int_0^{v_a or\ v_b}\left[|t_u|.\frac{2}{\sqrt{4 \times v_a^2 - \Delta v}}.\frac{1}{\pi}\right]\frac{d(\Delta v)}{dt_u} \end{array}\right\} (5)$$

Eq. (5) determines the normalization from of the distance metric for all the velocities of a vehicle. The initial members of a fuzzy set $S = (\aleph_D, \theta, \Delta v)$ for which the above equation holds. The optimal values of the above set are determined in any normal event as updated int_u. Let r_θ represent the relaxation values for the observation with respect to distance. The maximum variation in the distance irrespective of safe distance is considered as error. The error (e) is estimated as

$$e = 1 - \left(\frac{D - r_\theta}{D}\right) \quad (6)$$

This error indicates that an abnormal event has occurred irrespective of the relaxation distance, post the error estimation process the fuzzy constraints are analyzed for validating the optimal event detection. Therefore, the significance of the physical attribute (τ) is estimated for the vehicles as

$$\tau = \sum_{i=1}^{t_u} (\aleph_D \times e)_i \forall\ \aleph_D > e \quad (7)$$

The significance factor (τ) is used to form the initial solution set of the fuzzy processing. The significance factor is estimated during the varying t_u in the communication period. The member of S during the t_u are validated for their errors based on the maximum deviation of either of the independent values. Such that optimal output= $\{\tau | max\aleph_D \cap \min e\}, \forall\ v_a\ and\ \theta$. This optimal output is verified

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using the constraints illustrated in Figure 2(a) to 2(d). Therefore, to retain a normalized fuzzy output, a normalization matrix for $\aleph_D$ and e constricted using weight as

$$\left.\begin{array}{l}[\aleph_D].\tau = \frac{1}{e}\omega \\ where\ \omega = \left(\frac{D-r_\theta}{D}\right)_i \forall\ i = 1\ to\ t_u\end{array}\right\} \quad (8)$$

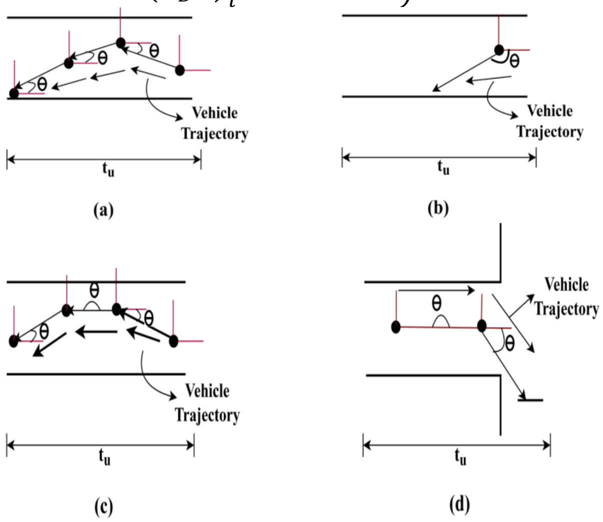

Fig. 2. Constraints in Vehicle Attribute Deviation

The constraints in Figure 2(a) to 2 (d) are discussed as follows. The process of achieving optimal solution for the constraints through fuzzy normalization is discussed independently.

Constraint 1: The trajectory of the vehicle displaces and does not regain the original position (despiter_θ) [Refer Figure 2(a)].

Analysis 1: The position of the vehicle is different with respect to θ provided Δv need not be the same. In the last t_u, $\aleph_D < e$ and hence, $\frac{d(\Delta v)}{dt_u}$ tends to 0 such that $v_a$or$v_b = 0$. The variation of θ with respect to $(w \times l)$ generates two results such that $D > \frac{1}{2}w$ which means the vehicle moves in the opposite direction. Instead if $D \leq \frac{1}{2}w$, then $\Delta v = v_a$ or v_b in the previoust_u. The relaxation value and D becomes equal for a maximum error case. This condition is verified using Eq. (8) as a linear fuzzy derivative such that

$$\begin{bmatrix} \aleph_{D(1,1)} & \cdots & \aleph_{D(1,t_u)} \\ & \vdots & \\ \aleph_{D(r_\theta,1)} & & \aleph_{D(r_\theta,t_u)} \end{bmatrix}.\tau = 1 \times \omega \quad (9)$$

If $D = r_\theta$then the above matrix consist of at least one zero row/column, such that $\omega = 0$. This validation indicates that there is a change is S where S represents $(0, \theta, \Delta v)$.

Constraint 2: In this constraints an immediate change in θ results in two t_u updates.

Analysis 2: The first t_u is received during the change and the second t_u is received if $(l - D)$or$(l - \omega) = 0$. This means the mobility of the vehicle is retarded [Refer Figure 2(b)]. In this case, $\aleph_D < e$ and θ in the last t_u is a constant. Therefore, $\omega = e$,$\aleph_D = \tau$ in all $i = 1\ to\ t_u$. In particular, $\omega = e$ in $i = t_{u-2}\ to\ t_u$. Therefore, the vehicle is observed in an abnormal event and from equation (8), $\aleph_{D(r_\theta,t_u)} = \frac{1}{\tau}$ such that $\omega = e$ in the last two t_u of the vehicle.

The above two solutions for the constraints represent the abnormal event correlating the physical features of the vehicle. The further two considerations represent the varying S in a normal event of vehicle mobility.

Constraint 3: The angle of deviation is different at various t_u but the position of the vehicle (x_a^*, y_a^*) is similar to its old position (x_a, y_a).

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Analysis 3: This means the vehicle has temporarily changed its position without a halted t_u. In this constraint, the (x_a, y_a) or (x_a^*, y_a^*)lies within$\frac{1}{2}w$. Also, the similar position is deviated/ separated by a distance D. The normalization in this case follows non-zero rows and columns of the fuzzy matrix represented in Eq. (9). Here, e is too small (i.e.) $e \ll \aleph_D \; \forall$ all D and therefore,

$$\omega = \aleph_D . \tau = \frac{D - r_\theta}{D} \qquad (10)$$

is the optimal solution represented and here, $\tau = \aleph_D$ for atmost t_u update other than θ variation and therefore, $\aleph_D^2 = \frac{D-r_\theta}{D}$ is the better observation for the weight. This indicates that w relies on $\aleph_D^2$ for the change in position temporarily of the vehicle. In this constraint, the angle of deviation forms the decision factor other than Δv and $\aleph_D$of S.

Constraint 4: The angle of deviation changes between $90°$ and $180°$.

Analysis 4: The complete change of angle of deviation indicates that the vehicle direction is changed. The vehicle parallel to l or w is shifted to the same condition with different θ. The chances of θ deviation occurs in one condition (i.e.) intersection. The possible of θ shift in an intersection region is ½ and therefore, θ is the deciding factor of S. Here, r_θ need not be considered and therefore, $\omega = 1$. The error is then estimated as

$$\left.\begin{array}{c} e = \sqrt{\frac{1}{[\aleph_D].\tau}}, \aleph_D > e \\ else\ e = \frac{1}{\aleph_D}, if\ solving\ equation\ (7) and\ (8) \forall\ \aleph_D < e \end{array}\right\} \qquad (11)$$

Hence the first case (i.e.) $\aleph_D > e$ generates optimal results and the second case (i.e.) $e = \frac{1}{\aleph_D}$ results in abnormal event.

The above constraints are estimated on the basis of D and Δv validation emphasizing the individual members of S for identifying the change in vehicle attributes. The validation is continuous for allt_u update in tracking the positions and location of the vehicle with respect to the varying distance and velocity of the vehicles. The processing of these observations is done in the traffic monitoring center to estimate the changes in moving vehicle. This classification helps to improve the accuracy of event through physical observations.

IV. Results and Discussion

The performance of the proposed STLS is assessed using simulation with a maximum vehicle density of 100. The 100 vehicles are placed in a region of $2500m * 1000m$ consisting of intersecting and non-intersecting road segments. In Table 1, a detailed experimental parameter and its values are presented.

Table 1
Experimental Parameters and Values

Parameters	**Values**
Traffic Region	$2500m * 1000m$
Vehicles	20-100
Maximum Communication Time	40min
t_u	0.25s
Transport Protocol	UDP

For a better analysis, the proposed STLS is compared with the existing CTP [13] and CLM [6] using the metrics processing time, average accuracy, distance error and error factor.

4.1 Processing Time Analysis

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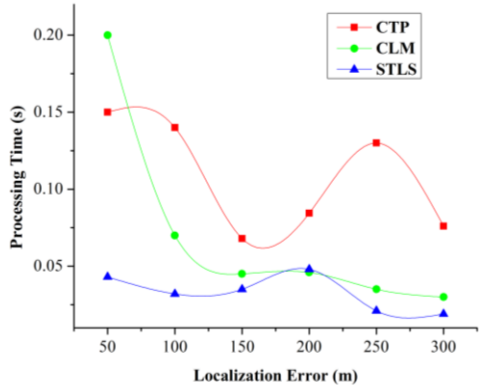

Fig. 3. Processing Time Analysis

In Figure 3, the processing time of the existing methods and the proposed scheme is compared. With respect to the localization error, the processing time varies. The variations in$\aleph_D$ due to $\omega = 0$ and $\omega = e$increases the errors in detecting the location of the vehicle. The location of the vehicle varies by an error e at the time of estimation. This is due to the limited and paused update int_u due to which the processing time in evading the error varies. In the proposed STLS, the variations are pre-estimated with the probable constraints in determining the location errors, reducing the processing time.

4.2 Accuracy Analysis

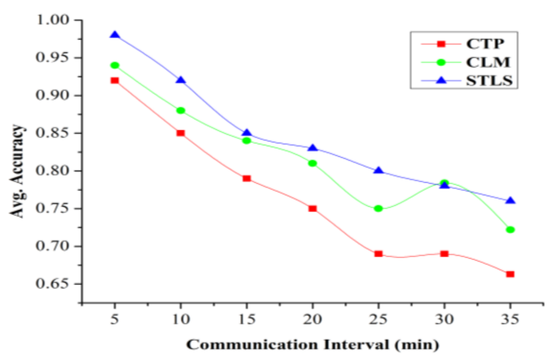

Fig. 4. Accuracy Analysis

As the error in localization and vehicle position determination in the proposed STLS is less due to various constraint analyses, the accuracy of the scheme is retained at a high level. With respect to the increase in communication interval, the update is prolonged due to which the precise estimation of values is lessened. However, this validation is processed along the$[\aleph_D].\tau$ or$\frac{D-r_\theta}{D}$ representation, that helps to suppress or approximate errors. This factor helps to retain the accuracy of the proposed scheme (Figure 4).

4.3 Distance Error Analysis

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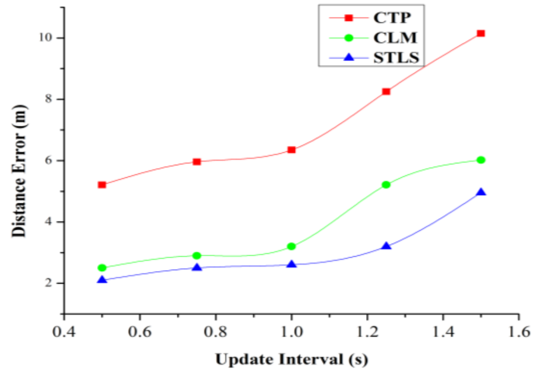

Fig. 5. Distance Error Analysis

With respect to the update interval, distance error is compared between the existing methods and the proposed STLS in Figure 5. As the update interval varies, the reception of positions and sequence of the vehicle is not continuous. Therefore, a constant accuracy of the vehicles and position determination cannot be maintained. This factor increases the error is distance estimation. In STLS, the possible constraints are separately analyzed using the independent metrics associated with the road and vehicle. The normalization of the distance at any update interval oft_u produces an optimal result of accuracy that suppresses error. However, this error is augmented with the observed value due to which a non-precise distance is discovered. The constraint based validations reduces the errors in the proposed scheme.

4.3 Localization Error Analysis

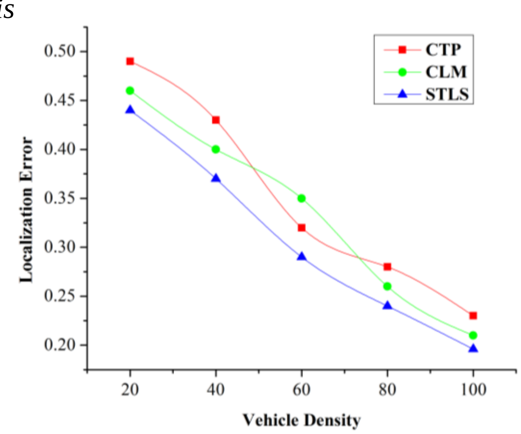

Fig. 6. Localization Error Analysis

The cumulative error in estimating the vehicle position is presented in Figure 6. This error is augmented as the localization and distance errors in the proposed scheme. Distance normalization; update time based constraint classification using fuzzy decision making helps to elevate the error concerned issues in the proposed scheme. The constraints are scrutinized using the members of S, emphasizing the individual features at anyt_u. This helps to organize fuzzy functions that results in identifying less error bound localization and positioning.

The comparative analysis results are tabulated in Table 2.

Table 2
Comparative Analysis Results

Metrics	CTP	CLM	STLS
Processing Time (s)	0.076	0.03	0.019
Avg. Accuracy	0.663	0.722	0.76
Distance Error (m)	10.15	6.02	4.96
Localization Error	0.23	0.21	0.196

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Conclusion

This article discusses selective vehicle tracking and localization scheme for monitoring vehicle features and identifying abnormal events in road side. The analysis of the observed features is performed in the traffic monitoring center at each update interval to track the vehicle physical position and location. The processing is preceded using fuzzy decision making where the constraints are classified based on the independent attributes of the vehicle. This decision making and constraint classification helps to improve accuracy and reduce errors in tracking and localization.The event detecting level is improved with better location accuracy through precise distance and localization error estimations. This helps toimprove the choice of STLS in real-time ITS.

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