An Insight into Feature Extraction Algorithms for Vehicle Platoon Management

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***Abstract*—**Vehicle platoon is the current state of the art research area where vehicles travel as road train to reduce aerodynamic drag in lead and follower vehicles. When aerodynamic drag is reduced in road train vehicle, effort required to propel vehicle will reduce this will in turn reduces necessary fuel for vehicle. Vehicle platooning uses multiple cameras to guarantee safe driving and to achieve high fuel efficiency. Research in automotive image processing in vehicle platooning is increasing to achieve safe and fuel efficient vehicles. This work does a comparison study on challenges faced in vehicle platooning with respect to image processing and suitable image processing feature extraction methods to overcome the challenges.

Keywords— Vehicle Platoon, Feature Extraction, Image Processing, Deep Learning

1. INTRODUCTION

In modern days, green mobility in transportation segment are emphasised in majority of countries to support environment protection and fuel economy. Automotive industry is working extensively for new solutions which provides clean and more fuel efficient vehicles. Many approaches have been made towards green mobility like, hybrid vehicles, electric vehicles, bio fuel, weight reduction, aerodynamic improvements etc. This paper emphasis on the vehicle platooning which improves vehicle aerodynamic and potential fuel benefits of 10% to 15 % in each vehicle. However, to meet high fuel efficiencies vehicle platooning has certain challenges, this paper has made an attempt to understand current challenges in vehicle platoon management and how deep learning algorithms can benefit the challenges faced in platoon management.

This paper has been divided as follows, Section II explains what vehicle platoon is and how vehicle platoon managements works and its benefits. Vehicle platoon managements has quite lot of challenges; however in this paper challenges associated with driver interface in platoon management has been explained.

Few of the challenges faced in driver interfaces with platoon management can be addressed using vehicle cameras and deep neural network. Section III of this paper will explain how vehicle cameras and image processing techniques are used. Image segmentation and classification is very important attribute in the vehicle image processing technique. Study has been done on different deep learning algorithms which are used for vehicle classification. Feature extraction methods which can be used to overcome the challenges in vehicle platooning.

The last part of the paper section IV will summarize the potential research area in deep learning based vehicle classification to support the challenges faced in the current vehicle platooning using image processing techniques.

2. VEHICLE PLATOON MANAGEMENT AND ITS CHALLENGES

Green and safe mobility is one of the active research areas in an automotive industry. Industries are working closely with universities for new solutions to achieve green mobility by reducing vehicle fuel consumption and with high priority on the vehicle safety requirement.

Vehicle platooning also called as road train vehicles has become active research in current transportation industry to achieve fuel efficiency, increased safety and to reduce environmental pollution. Vehicle platooning improves vehicle aero dynamics which in turns reduces the fuel consumption.

When vehicle starts moving from 0 km/h to higher speed, the greatest effort from the vehicle must be made to overcome the aerodynamic drag resistance. One method of literature from Society of Automotive Engineers (SAE), the SAE J2263 [1] road load measurement uses Newtons's law as mentioned in Eq1. Where 'F' is required force and 'm' is vehicle mass and 'a' is vehicle acceleration.

$$F = ma \quad (1)$$

$$F_{Mech} + F_{Aero} + F_{Grd} = m\frac{dV}{dt} \quad (2)$$

From equation 2 it can be observed that vehicle has to generate energy to overcome mechanical frictional resistance (F_{Mech}), aerodynamic resistance (F_{Aero}) and road gradient resistance (F_{Grd}). Vehicle platooning focus on reducing aerodynamic resistance (F_{Aero}) and as vehicle speed increases the aerodynamic resistance also increases. Most of the aerodynamic resistance is generated by a pressure difference in the front and rear of the vehicle while moving in the forward direction. According to Arturo et al experimental result [2] aerodynamic resistance is 20% when vehicle is moving at the speed of 10 km/h and resistance will increases to 70% when vehicle speed is 110 km/h.

Gap between vehicles to vehicle shall impact in reducing aerodynamic resistance and this will reduce fuel consumption and in turn reduces emission. Lot of research has been done to estimate fuel efficiency in vehicle platooning [3][4][5].

Vehicle platooning can be defined as a group of vehicles that move co-ordinated in a specific order. In platooning or road train vehicle concept, lead vehicle will set an action and following vehicle shall follow the action as shown in Fig.1.It can be observed that two different road train vehicles are going in two different lanes, in Fig.1. For example in lane-1 there are 3 vehicles in platoon environment, where truck with notation 'Leading V1' is the leading vehicle and 'Follower V2' is a truck which is following 'Leading V1' vehicle and 'Follower V3' is a car following 'Follower V2' vehicle. Here, 'Leading V1' is the leader in the Lane-1 road which shall communicate other following vehicles for efficient and safe platoon management.

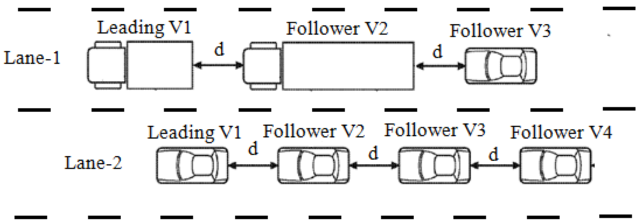

Fig.1. Vehicle platooning example in 2 different lanes (Bird's eyes view)

In 2014, SAE published standard J3016 [6] and in that definition vehicle platooning is a conditional automation vehicle (Level-3 automation) where driver can take rest by sleeping as well.

A. Benefits of vehicle platooning:

The following are the major benefits of vehicle platooning:

- Improved fuel efficiency.
- Reduced CO_2 emission.
- Reduced accidents and fleet owners can rely on unskilled drives in platoon environment.
- Return of investment is more for fleet owner.
- Improved travel time efficiency in defence applications.
- Very good co-operative approach during emergency in defense applications.
- Road capacity optimisation.

B. Platoon Management and its Challenges

Pilot study on Vehicle platooning has been implemented from 2016 in few countries like, US, Sweden, France, Germany, Japan etc. Platoon management shall coordinate by using on board sensors, information from surrounding vehicle, from vehicle to vehicle communication, vehicle to road infrastructure communication and cyber security as shown in Fig.2.

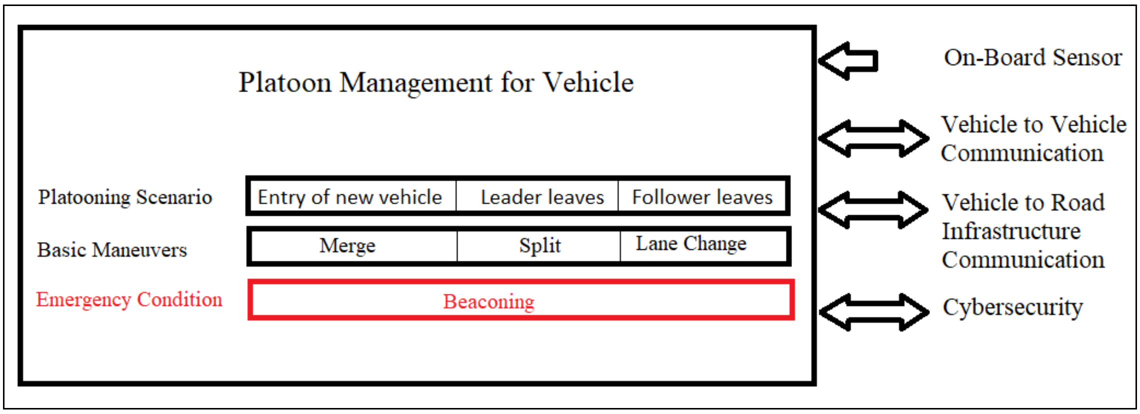

Fig.2. Overview of Platoon Management for a vehicle

The vehicle platoon management shall support three basic manoeuvres, namely merge, split and lane change as shown in Fig.2.In merge, two platoons in two different lanes shall merge to form one large platoon. In split, one large platoon shall split and make larger number of platoons. Lane change, permits to merge one lane platoon to anther lane as shown in Fig.3. Based on these three basic platoon manoeuvres, other scenarios can be executed like if new vehicle wants to join the platoon then split and merge can be executed.
Fig.3 shows example of when one truck wants to merge to existing platoon. The Platoon split can be observed where; a platoon with six vehicles will split in to two small platoon of size three each. Lane change with merging is also shown in Fig.3, where four cars in lane two will get merge with two trucks in lane 1.

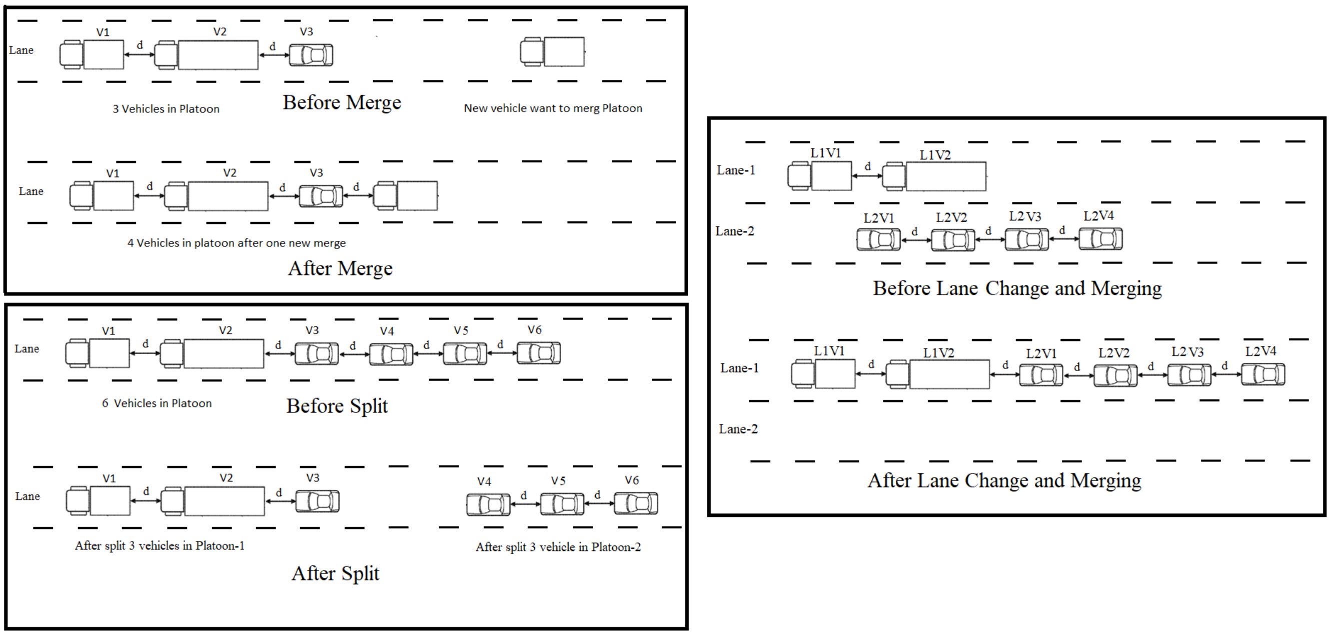

Fig.3. Example of vehicle merging, platoon splitting and platoon lane change with merging (bird's eye view)

One of the main challenge in vehicle platoon management is to provide very good driver interfaces because; drivers in platooning vehicle need to know what necessary intervention has to be made by them. And also, the main challenges in implementing level-3 conditional automated platooning vehicles are as follows:

- Safe vehicle merge, split and lane change.
- Determining driver state and alerting during any emergency .
- Estimate road condition and vehicle surroundings.
- Estimate safe distance between each vehicle depending on the vehicle speed.

Automotive vision sensing technique will play critical role in above mentioned challenges. Because, above mentioned challenges can be effectively implemented using image processing technique considering its ability to monitor wide range of dynamic state changes like road state, driver state, vehicle state, emergency condition, weather condition etc. As per Sunitha Patel et.al [7], level-3 conditional automated vehicles will use 4 to 8 cameras and also by making use of advanced image processing technique above mentioned challenges can be resolved using available cameras in vehicle. In recent years lot of research using deep neural network in automotive image processing has been carried out to provide accurate results [8][9][10]. Next section of the paper makes an attempt to provide insight of deep learning based image processing techniques to support platoon management challenges.

3. DEEP LEARNING BASED FEATURE EXTRACTION ALGORITHM FOR PLATOON MANAGEMENT

In the previous section, we have identified the challenges in the vehicle platoon management. Vision sensor has ability to monitor wide range of varying dynamic states on vehicle driving condition however; image processing technique has its own challenges to implement effective solution in safety critical automotive applications. In this section of the work, we have put an effort to study different feature extraction algorithms used in automotive deep learning image techniques and comparison study on the same to overcome the challenges faced in platoon management.
Deep learning is a part of machine learning which utilizes neural network with many hidden layers to perform the tasks. In recent research, deep learning has shown lot of interest in automotive image processing because of its learning capability and speed of response. In automotive image processing technique, the problem starts from feature extraction because final vehicle identification by deep learning classifier depends on the proper feature extraction hypothesis. The objective of feature extraction is to obtain most relevant information from input data and represent that data in a lower dimensionality space. Feature extraction will transform input data in to set of features for given application. For example, in automotive application typical features can be classified like different vehicles (car, bus, truck etc), different lanes (zebra crossing, left turn, right turn etc), different roads (rough road, smooth road, pot holes etc) so on.

General system flow block diagram for deep learning based automotive image processing has been described in Fig.4. The first part of the block diagram is on video capturing and filtering, where video of vehicle surrounded environment shall be captured. Later, captured video shall be filtered for unwanted oscillations, noise etc and then fed to feature matching where images pyramid is constructed by down sampling and features are matched based on available down sized images. In feature matching the first step is to detect intersect locations in the images and match them accordingly. For example basic vehicle features matching components are like tyres, bumpers, glass shield, mirror, body structure etc. After filtering and feature matching the required image shall be separated which is used for vehicle detection.

To locate vehicles on road, the Region Of Interest (ROI) shall be scanned on the each layer of the image. Image features can be extracted for image by two methods namely global feature and local features. Global features are not sensitive for image tracking application in contrast local feature extraction method is very good in image tracking applications.

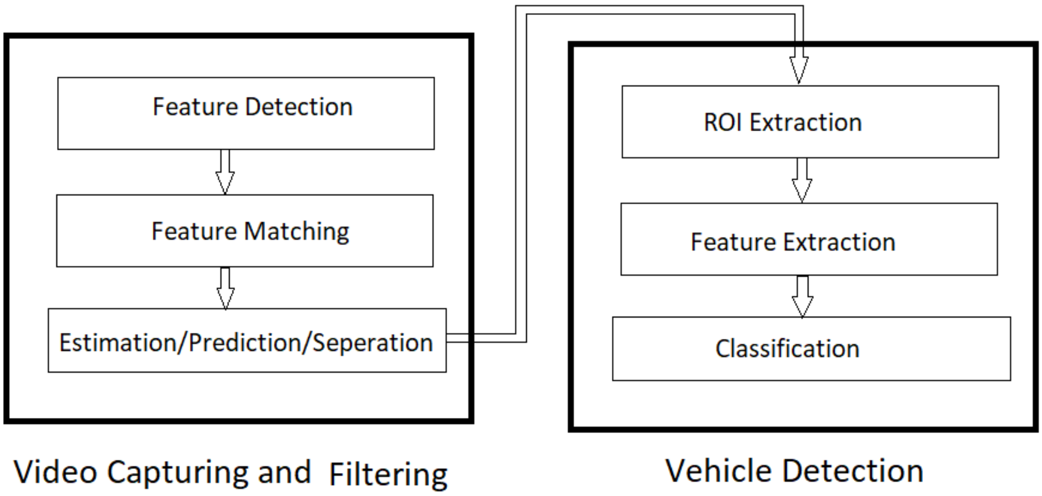

Fig.4. Block diagram for Deep Learning based Automotive Image Processing

For automotive applications, as currently lot of research on feature extraction descriptors are ongoing in this study we have investigated on Histrogram of Oriented Gradient (HOG), Scaled Invariant Feature Transform (SIFT), Speeded-Up Robust Feature (SURF).

A. Histrogram of Oriented Gradient (HOG)

HOG algorithm was proposed by N.Dalal and B Triggs for human detection during 2005. Since then number of studies has been carried out in automotive field for vehicle, pedestrian detection. HOG operates using sliding window technique with width and height that slides across an image. HOG extraction computes the magnitude and orientation of the gradient. Then orientation histogram shall be derived from magnitude and orientation. HOG cell size is usually 4x4, 6x6 and 8x8 pixels when the sliding window size is 32x32, 48x48 and 64x64 pixels respectively. If p(x,y) is a pixel data at (x,y) position of image then HOG feature is to calculate the difference value, dx and dy for x and y direction respectively as mentioned in equation 3 & 4. The gradient magnitude and gradient orientation can be calculated as mentioned in equation 5 & 6

$$dx = p(x+1, y) - p(x-1, y) \quad (3)$$

$$dy = p(x, y+1) - p(x, y-1) \quad (4)$$

$$m(x, y) = \sqrt{(dx^2 + dy^2)} \quad (5)$$

$$\theta(x, y) = \tan^{-1} \frac{dy}{dx} \quad (6)$$

B. Scaled Invariant Feature Transform (SIFT)

SIFT technique is used to extract scale invariant feature from image and this was published during 1999 by David Lowe. Here objects are first extracted from a set of reference images and for given new images an object is recognized individually comparing each feature. Here Gaussian function is applied in the scale space to locate maxima and minima in horizontal and vertical direction.

$$g(x) = \frac{1}{\sqrt{(2\pi\sigma)}} e^{-x^2/2\sigma^2} \quad (7)$$

Where x is the input signal to be filtered, σ is Gaussian bases width as per defined in [9] the number of dimensions in the feature-space will always be 128, that mean every image in SIFT extraction procedure shall result in numeric matrix with 128 multiplied by integer based on previous image characteristics.

To characterize the image at each key location, the smoothed iage A at each level of the pyramid is processd to extract image gradients and orientations. At each pixel, Aij, the image gradient Magnitude, $L_{i,j}$ and orientation $R_{i,j}$ are computed using pixel differences as mentioned in equation 8 & 9 respectively.

$$L_{i,j} = \sqrt{(A_{i,j} - A_{i+1,J}})^2 + \sqrt{(A_{i,j} - A_{i,J+1})^2} \quad (8)$$

$$R_{i,j} = a\tan 2(A_{i,j} - A_{i+1,J}, A_{i,J+1} - A_{i,j}) \quad (9)$$

C. Speed-up Robust Feature (SURF)

The SURF detector descriptor has been proposed by Bay et al on 2008 to improve speed and accuracy compared to scale invariant feature transform (SIFT). SURF uses a scale invariant blob detector based on the determinant of Hessian matrix for both scale section and location. Surf uses an integer approximation of the determinant of Hessian blob detector to detect the intersect points as mentioned in equation 10. Once intersect point is done then local neighborhood description is done using Hessian matrix, given a pixel, the Hessian of the pixel is as shown in equation 11.

$$S(x,y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i,j) \quad (10)$$

$$H(S(x,y)) = \begin{bmatrix} \frac{\delta^2 s}{\delta x^2} & \frac{\delta^2 s}{\delta x \delta y} \\ \frac{\delta^2 s}{\delta x \delta y} & \frac{\delta^2 s}{\delta y^2} \end{bmatrix} \quad (11)$$

Table.1 Literature Survey Summary of Feature Extraction Techniques

Feature Extraction	Classifier	Target Object	Reference	Summary
SIFT	SVM	Car, Bike, and may more	Ashish Kapoor et.al [11],2007	Gaussian Process with Pyramid Match Kernal has been implemented to achieve wide range of target detection.
SURF	Not mentioned by author	Car, Truck, Van	Mounir Amraoui et.al [12], 2019	SURF has been compared with other extractors, the accuracy of SURF is 100% compared to others bio-inspired approach however author has suggested to improve average time of response then bio-inspired approach has been proposed.
HOG	Adaboost & SVM	Any vehicle with emergency indication	Abhisek Nayak et. Al [13], 2019	Here authors have done study on multiple features with multiple classifiers and as an interest of our study on HOG feature, it shows HOG with Adaboost gives 40% more accurate

				and precise result.
HOG	SVM	Human detection	Yanwei Pang et.al [14] 2011	Here authors have presented efficient computing the HOG feature by reuse the features for a detection window.

4. CONCLUSION

Vehicle automation level-3 also called as vehicle platooning is the current state of the art research work in automotive world. Several countries like US, Japan, Sweden, France, and Germany etc are interested to roll out vehicle platoon management system in their countries considering benefits like, fuel saving, improved safety, improved road capacity and reduced CO_2 emission. At the same time vehicle owners or fleet owners are also interested in platoon management considering benefits like fuel saving, improved travel time efficiency, more return of investment. There are many complexities in platoon management; however we have focused on the challenges in achieving efficient driver interfaces during platoon management. The main challenges are safe vehicle merge, split and lane change, determining driver state and alerting during any emergency, estimate road condition and vehicle surroundings and estimate safe distance between each vehicle depending on the vehicle speed. Owing vision sensors ability to monitor wide range of dynamic an attempt has been done here to exploit the benefit and challenges in image processing feature extraction techniques. Wide variety of feature extraction for deep learning algorithms are used in automotive applications, however our current study focused on the SIFT, SURF and HOG feature extraction. Considering the need of high speed and high accuracy in automotive image processing it is always good to analyse different available feature extraction with different classifiers to see speed of response and output accuracy. Next part of our work shall be simulating vehicle data set suitable for "safe vehicle merge, split and lane change" using Python tool. The features considered in data sets are like road lanes, different vehicles and speed of response, output accuracy shall be compared using HOG+ SVM, SURF+ SVM, HOG+ Adaboost, SURF+Adaboost.

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