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Traffic sign and Obstacle detection in Vehicular Ad-Hoc Network (VANET) using HOG and Haar Classifier Techniques

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Abstract: ***Wireless technology is progressing faster with time. People are doing research these days generally in the field of Wireless communication. VANET is the most developing exploration territory in remote correspondence. With the headway and development of the VANET, there will be an incredible upheaval in the field of telecommunication regarding quick handovers, arrange accessibility, security, wellbeing with the utilization of cutting edge applications and so on. VANET innovation is progressing with the progression of time however there are numerous issues that must be routed to make the system more overwhelming. In this paper we have proposed an effective mechanism for object detection in highways using Neural Networking and proving driver assistance to enhance the existing system to the next level as Intelligent Transportation System.***

Keywords: Vehicular Ad-hoc Network (VANET), Intelligent Transportation System(ITS), Convolution Neural Networks(CNN), Object detection, HOG and Haar Classifier.

I. INTRODUCTION

VANET: VANET has turned out to be the most essential research area in the field of remote telecommunication. Before going deep into the details of VANET it is important to talk about its background. WANET is the base field of all the temporary networking (Ad-hoc) systems. The most widely recognized use of MANET is in defense services for its effective and fundamental correspondence strategy like information sharing between different devices and so on. VANET is like MANET alongside a few adjustments. VANET includes the Portable (mobile) unit called Nodes, Road side units (RSU). Portable units are the sensors devices inserted in the vehicles that are called as onboard units (OBU) for the processing of signals (information sharing) to and from RSUs. RSUs are fixed units that act as a portal for the communication between vehicle's OBU and the servers or to the outside world (Internet).

In general there are two kinds of communications are possible in VANET that is Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I). In the case of V2V communication the vehicles which possess Onboard Unit can communicate with other OBU enabled vehicles; such communication may include sharing of information about the current or near future traffic condition, road conditions and so on. On the other hand, the Vehicle to Infrastructure kind of communication is the communication between the vehicles's OBU and the Road Side Units, which are fixed along the road side electrical or lamp posts or in the dedicated posts. The type of information that is shared among these units may include the current traffic information forecasting to the centralized server or to the internet via RSU, which helps to broadcast the traffic information to the preceding vehicles. On the other side the information from centralized traffic servers can be received by OBU through RSU, the information such as take diversion messages, Accident alerts, road condition alerts and so on.

Statistics:

As indicated by the Government of India(GoI) statistics* discharged about the street accidentss by our administration of India, amid the schedule year 2016-2017, the all out number of street accidentss is accounted for at 4,80,652 making wounds 4,94,624 people and asserting 1,50,785 lives in the nation. This would decipher, on a normal, into 1317 accidentss and 413 accidents passings occurring on Indian streets consistently; or 55 accidentss and 17 passings consistently. Among the vehicle classes autos, jeeps and cabs (23.6 percent), trucks, beats, tractors and other explained vehicles (21.0 percent), Busses (7.8 percent). The National Highways comprise around 2 percent of the all out street system of India, however they represented 29.6 percent of all out street accidentss and 34.5 percent of all out number of people executed. The State Highways represented 25.3 percent of all out accidentss and 27.9 percent of the all out number of people executed in street accidents in 2016-2017. From this factual report it has been gathered that the quantity of accidents taken places in Highways are radically expanding over years. By virtue of this, we are proposing a most recent yet compelling method to diminish the accidentss in thruways by consolidating Artificial Intelligence, Computer vision alongside Intelligent Transportation System.

** Source- Release from the Government of India, Department of Road Transports & Highways, Transport Research Wing, New Delhi (www.morth.nic.in)*

II. PROPOSED WORK:

Vehicle Detection is one of the major research areas in the field of VANET, which includes various Artificial Intelligence techniques to detect as well as improve the probability of detection of the objects.

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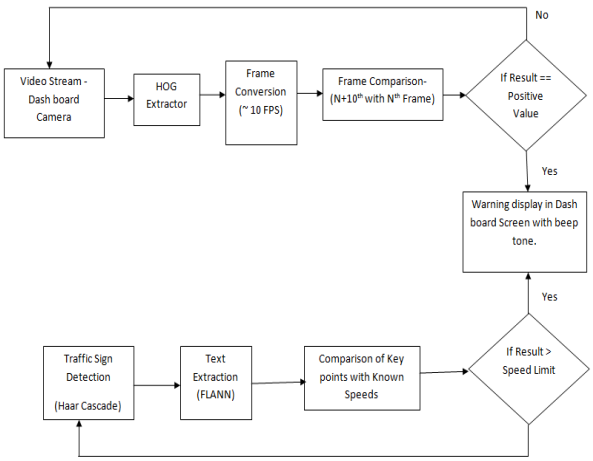

Fig.2: Overall Flow diagram of Proposed Work

The proposed work includes the following things to be done in the serial passion to accomplish the obstacle detection, traffic sign detection and recognition.

III. OBJECT DETECTION:

In the vehicle, the front cam installed near the wind shield is turned on automatically when the vehicle is ignited. It continuously captures the video and converts the captured videos in to frames, approximately 10 frames per second. The frames are compared to find the distance of the object, if anything identified in the frame. This work in the following manner, i.e. the first frame of the obtained video is compared with the 10th frame. It is obvious that if any object found in the frame 1 is increased by its dimension in the 10th frame when it is comes closer. This dimension variation is taken as a parameter to confirm that the object is getting closer to our vehicle. This comparison is done using Open Computer Vision (OpenCV) technology.

The OpenCV technology has the features of detecting objects from the real time videos, but for our work it is not necessary to have such real time detection. Since we are about to compare the 1st and 10th frames.

Fig.2: Vehicle detection with OpenCV

The OpenCV library HOG (Histogram of Oriented Gradients) extractor is used to identify the vehicles or obstacles with identification marks (Colored Square boxes). These square boxes and its dimensions are taken in to account to compare the object distances. The square box found in the 1st frame and its dimensions are calculated and store it as $OD_{N^{th}\ Frame}$ (Obtained Distance) and the same has been calculated for 10th frames and store it as $D_{N+10th\ Frame}$. Then by subtracting N+10th frame with Nth frame, we can obtain a result which is stored in OD_{Result}. If the OD_{Result} is a positive value, it is confirmed that the object is moving closer to our vehicle, then we are about to take any pre-safety measures by any means. If the result is a negative value then, we can say the objects are moving away from our vehicle so, it is not necessary to take any active safety measures.

$$OD_{Result} = OD_{N+10th\ Frame} - OD_{Nth\ Frame}$$

If,

$OD_{Result} < 0$, then the object is moving outwards.

$OD_{Result} = 0$, then the object is moving with the same speed of our vehicle.

$OD_{Result} > 0$, then the object is getting closer to our vehicle.

IV. TRAFFIC SIGN DETECTION:

It is obvious that, sometimes we may unintentionally forgot to notice the traffic sign boards which may causes slight damages to even heavy accidental losses. One such thing we commonly do in our day to day life is, forget to notice the speed breaker sign, speed limit signs, men at work signs and so on, this may or may not cause that huge loss/damages, but still it is a common mistake that every one experienced at least one in their life time. So, in order to avoid such mistakes out work concentrates on analyzing the traffic signs and intimate the same over voice and even display to sign in the vehicle's dash board screen.

The traffic sign detection is done using Local Binary Patterns (LBP) or Haar Cascade classification algorithms. Unlike Convolutional Neural Networking (CNN), these algorithms don't learn by itself. i.e., these are supervised algorithms, that are need to be labeled manually and it does not support self learning. This type of algorithms have their own advantages and disadvantages i.e., it won't take time much time for self learning, since everything is labeled by the developer itself. But the results are not getting improvised every time since; self learning is not supported by these types of algorithms.

Our work has time critical constraints, so it is mandatory to convey the sign details as and when a sign board is found. In this case we should least bother about increasing accuracy of the sign detection by using unsupervised CNN algorithms. In our work, LBP and Haar cascade algorithms were trained with around 2000 positive images (Images with sign boards) and 1000 negative images (images without sign boards). When compare with LBP it is preferable to go with Haar cascade algorithm, which detects the signs as quicker when compared with LBP algorithm and also support slow computational mechanisms i.e., it doesn't require high configuration systems for its computation.

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Text Extraction and Warning System:

The second phase of our work concentrates on detecting texts present in the identified speed limit sign boards. This is done using Fast Library for Approximate Nearest Neighbor (FLANN) search Library feature matching algorithm. FLANN has a collection of library for performing fast approximate nearest neighbor searches in the high dimensional spaces. It contains set of different algorithms that found to work best for the nearest neighbor search and a system for automatically choosing the best algorithm and idle parameters depending on the given dataset.

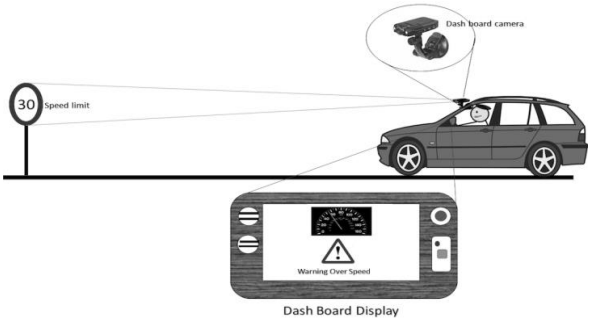

Fig.3: Speed Detection and Warning system

FLANN can contain binding for python language which we are already using it for OpenCV implementation on object detection in the first phase. After detection of texts presents in sign board is stored as a "Key points" and compare them with all known speed limits. The key point obtained is compared with the current speed limit. If it exceeds the limit, a warning signal is triggered. Warning can be a beep sound or it can be a visual signal in the vehicle's dash board screen. This will be acted as a active safety system, which alerts the driver to take necessary action towards the warning signs. Speed Assistance is done in the following manner. When a new speed limit is detected, it is added as current speed limit. After every frame, script compares current speed to current speed limit. Script runs specified command when over speeding is encountered (e.g. beep and dash board display).

V. CONCLUSION

In this paper, we proposed the newer application area for Haar cascading classification algorithm, so far which is implemented in facial recognition purposes but in our work we incorporated Haar algorithm for detecting traffic signs. Therefore we come to a conclusion that it works better for sign detection when compared with existing CNN based unsupervised algorithms. Here we also used FLANN algorithm which is capable of choosing the appropriate text detection algorithms among the variety of algorithms present in its library and this algorithm selection is purely based on the type of dataset which we are feeding as the input for FLANN. The result shows that our supervised learning algorithm takes nearly 20% lesser time then the traditional supervised algorithms, and it also supports lesser configuration machines for its computation. In future various unsupervised algorithms can also be added to the FLANN library to improve the timing efficiency.

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