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A Novel Approach for Image Localization Using SVM Classifier and PSO Algorithm for Vehicle Tracking

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Abstract— In this paper, we propose a novel methodology for vehicular image localization, by incorporating the surveillance image object identification, using a local gradient model, and vehicle localization using the time of action. The aerial images of different traffic densities are obtained using the Histograms of Oriented Gradients (HOG) Descriptor. These features are acquired simply based on locations, angles, positions, and height of cameras set on the junction board. The localization of vehicular image is obtained based on the different times of action of the vehicles under consideration. Support Vector Machines (SVM) classifier, as well as Particle Swarm Optimization (PSO), is also proposed in this work. Different experimental analyses are also performed to calculate the efficiency of optimization methods in the new proposed system. Outcomes from experimentations reveal the effectiveness of the classification precision, recall, and F measure.

Keywords- Support Vector Machine (SVM), Image localization, K nearest neighbour (KNN), Object Recognition, Histograms of Oriented Gradients (HOG) Descriptor.

I. INTRODUCTION

The development in wireless communication and information technology had a drastic impact on a human's daily life. In addition to making life easier and providing convenient access to services, the development of advanced vehicle technology is one of the most beneficial aspects of this combination. Thus, with the availability of wireless technology, ICT may be incorporated into vehicles, enhancing security, traffic control efficacy, driver support, and information[1-4]. With the aid of these ultramodern technologies, vehicles can connect one to another and with the RSU's (Road Side Unit) situated near the road, thus contributing to the emergence of the innovative communication era and the development of self-structured networks. This network model is well-known as a road network, and it is connected to roadside units (RSU). Both units are endpoints and routers in a scenario like this. It is a commercial implementation of ad-hoc mobile networks (MANETs), a network that is ad hoc by nature and supports context awareness[5].

Figure 1 Schematic Representation of a VANETs V2V (Vehicle to Vehicle) communication, communication between vehicle to the base station, and communication between base station to the vehicle. Vehicles can now benefit from the variety of topographies of distinctive apps like disaster advice systems, traffic info controller and inhibition systems, and systems to observe the environment and climatic change. The vehicle besides appreciates online performance, advertising, and advancements. Each vehicle typically operates in a continuous mode that allows it to connect to multiple geographically dispersed locations and enhances the bandwidth resources. Research agencies may additionally observe those communication strategies to increase the system intelligence, safety, and effectiveness of transportation machines. These Adhoc networks can also assist automobile-to-automobile conversation after the automobile shifted at a fast speed and automobile to substructure communication whenever the velocity of the car is gradual or stationery. This enhanced many secure and non-secure applications[6, 7]. There are three types of road network communication. They are namely:

1. Vehicle to Vehicle (V2V) or automobile to automobile signaling.
2. Automobile to Road Side Unit (RSU) signaling.
3. Road Side Unit (RSU) and the base station signaling.

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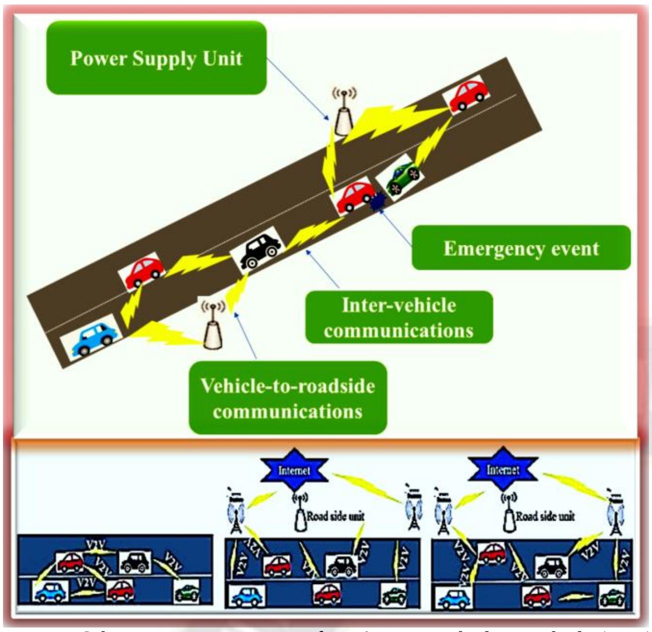

Figure 1 Schematic Representation of a VANETs. Vehicle to Vehicle (V2V) or automobile to automobile signaling, Automobile to Road Side Unit (RSU) signaling, Road Side Unit (RSU), and the base station signaling

Automobile or Vehicular signaling includes many packages including small changes in-car information data as well as complicated records like infrastructure incorporation. However, confirmation is the important thing in every section of verbal exchange. Several functions associated with VANETs are in the starting stage and until now it is subtle and consistent. But, a well-known review of the structure provides the mirrored image of the standard procedure, constituents, and limits concerned in the system[8].Whilst discussing road traffic networks, it is imperative to word that several awesome functions want to be considered when protection is to be integrated.

Those functions consist of;

(a) The communication method: VANET performs operations depending on the node to node conversation, in which every single node is accountable to launch a link with another node for statistics distribution.

(b) Dynamic nature and system mobility/ flexibility: The vehicular road traffic network, given above in Figure 1 is a part of MANETs, and therefore, the flexibility function is congenital. Though in the VANET, the position of all nodes changes their position continuously with varying speed and path except RSU due to the fact its miles are mounted along the street. Sooner or later, the network turns very dynamic.

(c) Recurrent change of statistics: We know that nodes are changing position or movable in VANETs, consequently, they constantly sent signals to other neighboring nodes' internal street community.

(d) Time handling& self-establishment: As mentioned in the above section, VANET calls for the instantaneous working of vital statistics in a short period to alternate data efficaciously.

(e) Infrastructure-much less nature: All the nodes in VANET are interconnected via a network devoid of any bodily channel; for this reason, they are established on 'infrastructure much less' environment.

(f) Less volatile: Basically, in all VANETs, the period for the nodes signaling is quite short.

(g) Information price v/s distance: VANETs signaling area is always limited to 5–10 km. VANETs signaling can be split as follows. Primarily, OBU permits signaling between Vehicle to Vehicle and Vehicle to infrastructure. Then, they possess a block of sensors intended to calculate their unique homes i.e. gasoline intake and their surrounding atmosphere possess a greasy avenue, protection distance. Consequently, this vital information is informed to other vehicular networks cars to enhance attention as well as network security. Ultimate, however, a TPM (relied on Platform Module) is frequently hooked up on motors. But, those gadgets are specifically intended to be used for safety purposes because they possess consistent storage and calculation. There is a consistent internal clock that is always purported to be damage-resistant [9], Hence, this allows crucial records like consumer credentials or facts to store efficiently.

This paper defines a method of image localization and recognition with required results using the SVM- classifier and KNN algorithm. This proposed method can enhance the e efficiency of image localization. Support Vector Machine (SVM) classifier is a binary classifier; which is appropriate for the organization/recognition in greater dimension and thereby fit for image localization and recognition.

II. LITERATURE REVIEW

Here, numerous examine applied Convolutional Neural network an identifier in automobile categorized through the shade[10-14]. Hossein et al. [15] advised a vehicle function like region on the location angle by way of a method to categorize to the special versions or kind of the car. Then accurate the category or identity with their worried records from dataset incorporates 12,605 pics from the vehicle dataset with the aid of diverse periods coloration of the automobile, gain 90.52% accurateness in the classify on the car, in [16-18] observe on Convolutional Neural community with numerous companies of the dataset [15, 19-24]. Also, the consequences displayed 92.273% and 92.508% rate of precision, corresponding to the results. Zhou et al. [17, 25, 26] recommended a singular Convolutional Neural community model named Color net which attained the uppermost of their vehicle color class on accurateness experimentation of 94.24%. The introduction crushed Alex net[27] and Google Net[28-31].

Labeled on the vehicle like automobile using photograph snapshots got from an RGB digital camera or grey-level photo [30] throughout both day-time or night time-time, however, vehicles can't be labeled by way of vision-based photos discovered on the night if right here is good enough lighting fixtures. Consequently, an extra type of information is desired as entering to a detector utilized by a car-like vehicle at night time. YOLO[31]deep mastering runs algorithm utilized, anchor container clustering is achieved founded on the ground fact of the schooling set, which recovers its act at the particular dataset. The truncated type accuracy hard afterward template-primarily based feature extraction is disentangled utilizing the most excellent characteristic depiction extracted concluded CNN studying, Spatial Pyramid Pooling (SPP) is used, vehicle classification network which resolves the difficulty of truncated accuracy because of image falsification produced via picture resizing. By using merging CNN with SVM and normalizing capabilities in SVM, Fig. 1 shows the car's viewpoint precise module on the category. There are classifications discussed in kinds, i.e. unique types of automobiles and variations of the shade have been mentioned [32-37]. In class, categorized four classes are used, i.e. minsize, midsize, max size, and unidentified. Eight instructions are categorized on shade, i.e. black, white, blue, inexperienced, yellow, magenta, pink, and additionally unidentified colors. Classifications on kind and coloration involve unidentified variations. The variant of the magnificence consists of ambiguous characteristics at the automobile and unrelated color variations at the vehicle [31, 38-41], overlay automobiles on color versions like brown shade, etc. fashionable potential intention at the exceptional training used by kind and coloration classify on the vehicle. Assist Vector gadget is utilized by a classifier to train the Histogram oriented Gradient to extract the function vector [30, 31, 38, 42, 43] of training models on automobile type. The HOG function vector of samples on test is located into a classifier to locate the category result of test samples utilized by SVM, consenting to the movement class on car, the automobile types of the automobile are divided into major kinds: i.e. mini automobile, small car, compact vehicle, medium vehicle, medium and huge automobile, luxury automobile, Audi, SUV, Sedan, Benz, and so forth.

III. Proposed Methodology

Automobile localization is a very virtuous platform to use the VANET model (in Figure 1). The dimensions of the car or any automobile resemble a polyhedron and certain previous expertise of site visitor's sections may be followed. The localization is found out from the pose refinement result data and at the same time as the acknowledgment is done through comparison techniques or tables evaluation scores of health the usage of exclusive models. However, this technique has some vulnerabilities. The success of these systems relies intensely on how appropriately the version seizures the geometries of actual motors. Because there isa lot of same class type vehicles and a countless quantity of constant prototypes or vehicle models are available. It is not possible to form such a lot of models for experimentation and the processing interval is directly related to the sum of fashions. There are many algorithms used to study these Vehicular network Models.

1. Shape Variables of Deformable Vehicular network Model

A deformable vehicular network (VANET) model can triumph over the negative aspects stated in the above section. On one side, it can employ blessings of vehicular network model primarily established techniques, on the other side, it may adjust themselves to treat with almost all car types, model proposed by Koller[44] that's implemented in-car monitoring. Ferryman, etc. [45]developed a new version with 29 parameters and used different PCA quantities as recognition parameters. One of the major disadvantages are they require a very big pattern including three-D fashions of snapshots and can't get better precise shape constraints.

2. Generic 3D vehicular model

The generic 3D vehicular model has numerous benefits. Initially, their straightforward nature is to arrange themselves in shape with specific motors. In reality, there are distinct models of automobiles or vehicles, together with sedan models, lorries, trucks, containers, buses, mini and large vans, hatchbacks, etc. Even if the vehicular model is limited o one type, they may be different from one another in each element. If we use a constant and consistent vehicular model, there must install a big wide variety of prototypes and match one with other pics if you want to seize the geometry accurately. It's far a powerful painting, misguided and time-eating. When we use these types of conventional deformable vehicular network models, there must install any one vehicular network model and make it acceptable with extraordinary motors. As compared to constant version primarily based techniques, this technique is highly precise, handy, simple and 12 parameters are sufficient to refer to the well-known version. Since motors are by hook or by crook loss of nature, this 3D vehicular network road model is the wired-frame type and possesses the simplest 26 3D line fragments. They are mild and additionally handy for picture processes. We forget about a few volatile systems like wheels that rolled on the road, the four side windows, and fancy as well as emergency lights which are now not considered for an image of vehicular model localization and reputation. Also, these model versions are highly widespread and may very much be adaptive to compact with the motors [46-51].

3. Histograms of Oriented Gradients (HOG)

The Histogram of oriented gradient (HOG) explains one of the best characteristic descriptor methods that help to find an item in PC and image/photograph processing technique. This process reconstructs structures through measurement and statistics using a histogram of nearby vicinity pictures. In a picture, the directional density distribution of the gradient or area can properly describe the characteristics of the nearby target region [52, 53]. HOG uses this concept to make information on the gradient statistics and generate the very last characteristic description. Inside the system, a photo is divided as follows: image -> detection window (win) -> pictureBlock (block) -> mobile unit (mobile).Descriptor.

4. Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO acquired vast interest within the scheduling area[54-56]. Research results illustrate that genetic algorithms and simulated annealing algorithms are afflicted by many demerits or limitations whilst carried out with complicated optimization difficulties. Consequently, a set of rules upgrades focussed on different fusion thoughts have been suggested with the aid of domestic scholars[57, 58].

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Particle Swarm Optimization (PSO) has many featured benefits, along with speedy conjunction, fewer implementation parameters, and easy and smooth operation. As a result, they are widely employed o find the solution to different nonlinear, non-differentiable, as well as multi-peak optimization issues, especially in science, technology as well as in engineering fields[59-61]. But, these generic algorithm agonizes from foremost demerits[62, 63].The inadequate conjunction velocity and inadequate precision of the PSO algorithm avoid the most consistent usages. Further, their international search capacity is very weak, and it falls into the nearby limits[64]. These disadvantages cause destruction unavoidable within the progression and facilitate the catastrophe of locating the worldwide top-quality effects. These features revealed via messy mind display that messy sequence chains perform to be unsystematic, the pathways of messy variables are ordinary, and the search space is continuously searched without replication; consequently, messy or chaotic sequences are grander to blind random search and remove the downside of the algorithm[65-68].The PSO algorithm includes a set of rules, which is intended for the multi-objective purpose of optimization layout [72,73]. When we compared the results of the PSO algorithm with the traditional PSO algorithm, the effects display that the latest one is more advanced than the traditional particle swarm optimization, which contains a different set of rules in phrases for optimization impact and velocity.

5.Support Vector Machines (SVM) Classifiers

To examine and realize the automatic identity of car models, since the road traffic video surveillance system is based totally on the restricted sample of real-time processing of a big variety of information, this paper uses the SVM principle to construct the classifier[69]. Help Vector gadget (SVM) is to start with labeled for 2 types and is carried out in two instances: linear separable and linear indivisible. Nonlinear problems can be transformed into linear problems in a high-dimensional area consistent with non-linear transformation. Of course, SVM can be extended to multi-classification issues, and can skilfully remedy many practical problems such as small pattern length, excessive size, non-linearity, nearby minimization, and so on[70, 71].

METHOD FLOW OF PROPOSED SYSTEM

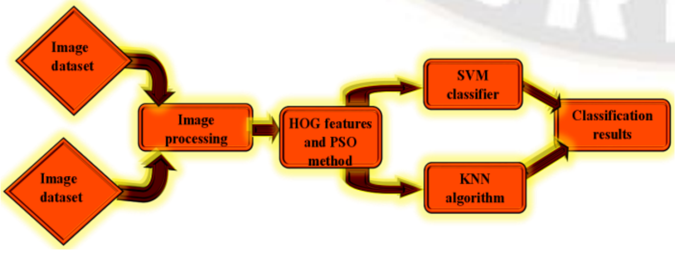

Figure 2. Proposed system workflow

The different stages of applying the SVM classifier, HOG descriptor, and PSO algorithm are given the Figure 2. At first, the training set or image data set of vehicles for localization are collected, undergo image processing. Then the suitable image algorithm and optimization method for arrangement is selected,
the SVM classifier and KNN algorithm are trained to get the organization, and at last, the test results are analyzed.

IV. RESULTS AND DISCUSSION

Here, 85 ambulance vans and 275 other vehicles are used for image localization and optimization. The precision,recall, *F* measures for the ambulance and other vehicles are shown in TableI.F-score or F-measure is a measure of a test's accuracy. From Table I, It is clear that optimized values of precision, recall, and F measure is higher than the non-optimized values and among that, the results of SVM-with optimization showed better results.

The classification accuracy, translation, and rotation for the ambulance and other vehicles are also analyzed for comparing the results. Figure 3 shows the percentage of accuracy for different techniques of the SVM classifier and KNN with and without optimization. Table II also shows that the SVM-with optimization method increased precision for an ambulance by 3.53%, 2.45%, and 1.96% when compared with KNN-without optimization, SVM-without optimization, and KNN-with optimization methods. The SVM with optimization method increased precision for other vehicles by 13.65%, 8.55%, and 5.98% when compared with KNN without optimization, SVM-without optimization, and KNN with optimization methods. The SVM-with optimization method increased recall for the ambulance by 4.83%, 2.87%, and 1.90 % when compared with KNN-without optimization, SVM-without optimization, and KNN-with optimization methods.

	KNN-without optimization	SVM-without optimization	KNN-with optimization	SVM-with optimization
Precision for ambulance	**0.93**	**0.94**	**0.95**	**0.96**
Precision for other vehicles	**0.60**	**0.63**	**0.65**	**0.69**
Recall for ambulance	**0.83**	**0.84**	**0.85**	**0.87**
Recall for other vehicles	**0.81**	**0.84**	**0.85**	**0.90**
F measure for ambulance	**0.69**	**0.72**	**0.73**	**0.78**
F meaure for ambulance	**0.88**	**0.89**	**0.90**	**0.91**

Table I. Precision for the ambulance and other vehicles, recall for the ambulance and other vehicles, *F* measures of for ambulance and other vehicles

The SVM-with optimization method increased recall for other vehicles by 10.70%, 7.55%, and 5.98% when compared with KNN-without optimization, SVM-without optimization, and KNN-with optimization methods. The SVM-with optimization method increased *F* measure for the ambulance by 12.41%, 8.09%, and 5.98% when compared with KNN-without optimization, SVM-without optimization, and KNN-with optimization methods. And the SVM-with optimization method increased the *F* measure for other vehicles by 4.17%, 2.65%, and 1.93% when compared with KNN without optimization,

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SVM-without optimization, and KNN-with optimization methods.

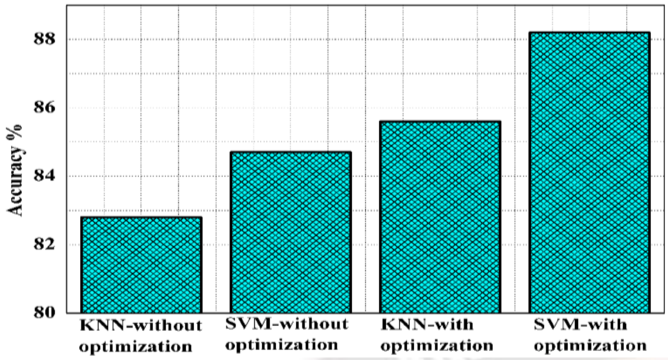

Figure 3. Accuracy % of different techniques.

Figure 3 shows that the SVM-with optimization method increased classification accuracy by 6.25% for KNN-without optimization, 3.99% for SVM without optimization, and 2.89% for KNN-with optimization methods .From Table 1 and Figure 3, it is clear that the results of SVM with optimization experimentation showed better accuracy percentage results than KNN without optimization, KNN with optimization and SVM with optimization. Thus it is sure that, optimized SVM classifier is an efficient tool for image localization in vehicular networks.

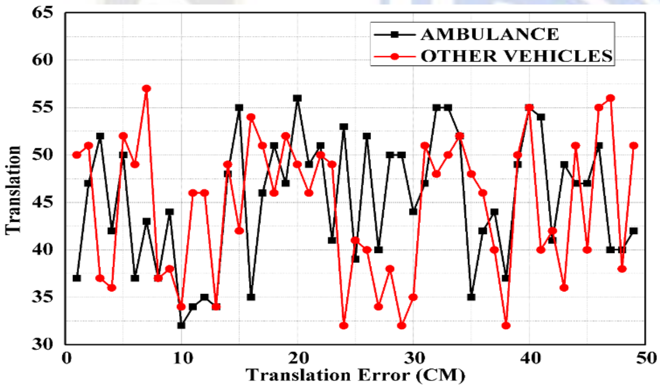

Figure 4. Translation and Translational error during image localization

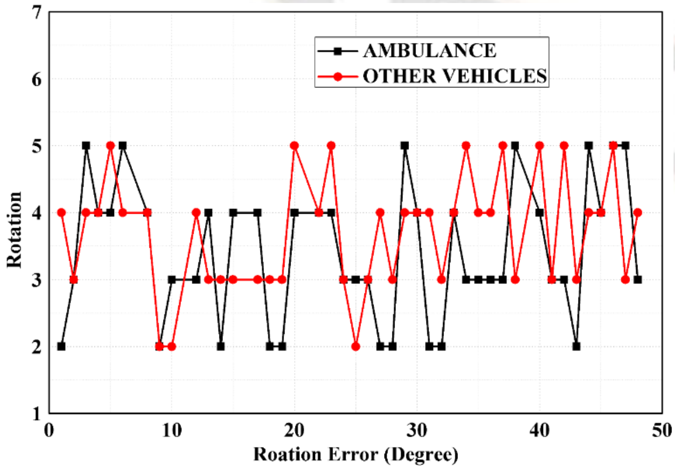

Figure 5. Rotation and Rotation error during image localization

Figure 4, revealed that the other vehicles improved average translation by 1.28% when compared with the ambulance. From Figure 5, it can be observed that the other vehicles improved average rotation by 10.44% when compared with the ambulance, and the other vehicles improved average rotation by 10.36% when compared with the ambulance.

V. CONCLUSION

In the current work, an approach for object identification and localization for surveillance images is extracted from monocular images by fixing the camera in a precise setting. Conventional vehicle tracking has two major limitations that heavily affect the tracking accuracy and time taken to extract the vehicle objects. First, conventional vehicle tracking used the position and orientation of vehicle objects for vehicle identification and localization. Second, the changes in the orientation model further increase the time taken to compute the tracking of the vehicle. The proposed model overcomes these limitations by obtaining a deformable model camera that is fixed utilizing a ray-traced template, while an effective approach based on HOG descriptor-based image gradient is suggested to judge fitness among protrusion of the vehicular models as well as image information. The PSO by utilizing enhanced local gradient models can not only infer vehicle localization as well as identification but also retrieve the actual shape of various types of vehicles. Further, vehicle localization is performed using a continual localization approach based on the time of action to increase the localization accuracy. The behavior of the proposed approach has been evaluated on various test images using an improvised gradient model and a continual localization approach. The results of the vehicle tracking approach show the potential of the model concerning recognition and localization, computational time, and vehicle recovery. Outcomes from experiments reveal the effectiveness of the classification precision, recall, and *F* measure. Further investigation related to the traffic control mechanism can be carried out. Thus, it is revealed that optimized SVM classifier is an efficient tool for image localization in vehicular networks.

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