Vision Technique for Smart Vehicle Using Ant Colony Algorithm

Sarika Sharma, Preeti Gupta

Abstract—This study presents a new image processing vehicle detection algorithm for smart vehicle vision system. All the edges there in the camera window are detected using multi-thresholding concept to overcome the problem of over-segmentation; so that no vehicle is left behind even if its intensity is very much similar with the background or of low intensity. Ant Colony Optimization technique considering the intensity and area of sub-region, is used in order to merge internal edges with in the area of interest (AOI) and get the segmented vehicle image in the current frame. The non-area of interest (NAOI) region from the image frame is removed and the vehicles are counted using block wise counting analysis. The average accuracy rate comes out to be 98.73%.

Index Terms— Ant Colony Optimization (ACO), Advanced Driver Assistance System (ADAS), Principal Component Analysis (PCA) and Independent Component Analysis (ICA)

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1 INTRODUCTION

Nowadays driving a car involves a huge risk. Although modern technology cannot remove this risk but at least can reduce it to a certain extent. Since 1990, many researchers all over the world have been developing vehicle detection techniques to make on road driving safer. Algorithms developed so far tended to reach two main goals. The first goal is that the algorithm must be potential to run at least the frame rates of 10Hz or more on low-cost automotive grade embedded computing hardware and the second goal is to minimize error rates that are False positives (i.e. it falsely reports a vehicle where no vehicle is present) and False negatives (i.e.it missed the vehicle actually present in the frame. A vehicle detection technique using Ant Colony Optimization is presented in this paper. Ant colony optimization motivated by the foraging behavior of few ant species. These ants deposit pheromone on the ground in order to mark some optimized path (shortest path) that should be followed by other members of its colony. Ant colony optimization algorithms exploit the similar approach in solving optimization problems to find the shortest path.

In this paper, several important issues in image processing and vision systems are discussed. Earlier detection techniques of vehicle were mostly radar-based or laser-based. The range of radar-based systems is approximately 10 times more than that of any other vision based systems, but they potentially suffer from interferences among sensors of the same type and working in same frequency. Laser-based systems are considered more accurate than radar-based systems but their performance is poor in rain, fog and snow. Main advantage of these active sensors is that they don't require large computational cost.

Recent works in the area of image alignment techniques [1][2] have addressed to the needs of computing globally consistent alignment to remove "ghosts" due to parallax problem and object movement, and to deal with varying exposures. These techniques used pixel-based alignment, rather than directly minimizing pixel-to-pixel dissimilarities as done in earlier research works. Some of the algorithms extract a sparse set of features like Haar-like features and match them to each other [3] [4]. The feature-based approaches to image stitching have the advantage of being more immune to scene movement and are potentially faster. In [3] [5] images were captured using multiple cameras. Two cameras fixed with specific angels are used in [5] for capturing images. In this algorithm, a 3D rotational method [1] is applied as an initial warping and feature-based method is used for precise image stitching, in which both direct pixel-based alignment and feature-based methods are combined. To make a color consistent output image for the driver a modified alpha blending method is also developed for blending the aligned images. Vehicle detection has become an integral part of Advanced Driver Assistance Systems (ADAS). Almost all vehicle detection systems employ two step methods. In the first step, every object is considered as potential vehicle. In the second step, these objects are further classified as true or false.

Symmetry is used by many researchers for vehicle detection. The front and rear view of vehicle are similar so it became potential feature to be used for vehicle detection. Author of [6] used this fact that front and rear views of vehicles are symmetrical. But main problem with this approach is that symmetry computations fail when homogenous intensity areas are detected. To cope with this problem, edge information is used to match symmetry of the

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homogenous intensity areas in [7].

The dynamic visual model (DVM), in [8] is used in detection of critical motions of nearby vehicles while driving.The episodic memory is incorporated into such systems through which helps in realizing many features of the system like hierarchical processing, configurability, adaptive response, and selective attention. The DVM is motivated by the human visual intelligence, consists of three analyzers; sensory analyzers, perceptual analyzers and conceptual analyzers.

Besides edges, colors and texture some authors have explored the detection problems in a higher level. R.Wang et al. [9] used standard Principal Component Analysis (PCA) together with independent component analysis (ICA) for automatic vehicle detection. In [10] a Viola-Jones algorithm is used to develop a complete dictionary of Haar wavelet features for vehicles. Gabor filters are used for vehicle feature extraction in [11].these filters can detect edges, lines and textures at different orientations simultaneously. Combination of Gabor features and Support Vector Machines (SVMs) has noted around 90% detection rate. Research shows that algorithms based totally upon the low level features have less sensitivity towards pose change, illumination change and partial occlusions. But they have the problem of noise in the image .And the high level matching techniques have problems of pose variations and illumination changes. Therefore, to minimize the effects of both, a method of vehicle detection that utilizes both high level and low level is developed [13].To extract the edge information, Difference of Bi-Gaussian edge detection method is used. DOBG method reduces noise simultaneously finds edges in the domain of the image. For reducing noise a gaussian function of Euclidean distance is applied to the image in the spatial domain. For hypothesis generation Horizontal Edge Filtering (HEF) [14] on DOBG is used. To consider the vehicle coming from far or from sides, segmented Region of Interest (ROI) approach is used. Further the initial candidates are verified using Bag-of-features (BOF) [15]. The foreground is obtained by subtracting the segmented background. Noise in the image is smoothened. Canny edge detector is used to extract out time of the vehicle. From the temporal information, the precise background model is obtained and through spatial information, complete edge of the vehicle is obtained. Experiments are conducted on five different real-time videos on the city roads and highways at different times (morning, noon, afternoon). It is observed that on an average 98.51% recognition rate comes by using this method for detection of vehicle.

2 PROPOSED METHOD

A new approach vehicle detection system has been devised using Ant Colony Optimization (ACO). ACO is a population-based metaheuristic that is used to find optimal solutions to difficult optimization problems. It was first proposed by

Marco Dorigo in 1992, to calculate an optimal path in a graph, based on the path searched by the ants between their colony and source of food. Since then this idea is diversified to solve a wider range of numerical problems, and as a result, several problems have been solved. Ant colony optimization (ACO) algorithm takes inspiration from the foraging behavior of some ant species. These ants usually deposit pheromone on the ground so as to mark a favorable path that should be followed by other members of its colony. Ant colony optimization exploits this mechanism for solving optimization problems in wider range of application.

The similarity between the ants used in the algorithm and real ants are that they both form the colony of cooperating ants and take the probabilistic decisions. And the dissimilarity between the ants used in the algorithm and real ants are that the ants used in algorithm work in discrete world, quality of solution depends on amount of deposited pheromone by them and these ants do not carry their own memory. ACO algorithm uses a set of variables generated through software called *artificial ants* to search good solutions for a given optimization problem. Now this optimization problem is finally changed into the problem of finding the best optimized path through a weighed graph. The artificial ants build solutions by moving on the graph simultaneously. Originally ant colony optimization algorithm is known as **Ant System** The process of generating the solution is stochastic and is biased by a *pheromone model*, that consist of set of parameters relating graph components like nodes and edges. The value of these parameters are modified at runtime by the ants..

There are in general three steps in ACO algorithm. The first step is initialization. The pheromone of each side is initialized to a smaller number. There is a taboo table with each ant to record the notes that have been passed during the whole process. This taboo table is then initialized to the length of the taboo table. Initialize the pheromone number released by ant at each side as 0. The second step is to construct the path. Ants determine the next destination of city according to a certain probability. Different methods are used for finding probability and in the last step; operation of the pheromone is conducted. In the ACO model, when all the ants have found a legal path, then updating the pheromone using the different updating formulas given in work done [16] [17]. The detection of vehicle algorithm is implemented broadly in three steps. In the first step, the detection of the edges is accomplished using multi-thresholding concept to overcome over-segmentation problem. Various intensity thresholds are considered in this process. In the second step Ant Colony Optimization (ACO) is used for merging of the edges and giving a clear picture of the vehicle present. Intensity and area are considered as food values while using ACO and further the merging is based on the formulae as:

$$I= \begin{array}{ccc} I_{r1} & I_{g1} & I_{b1} \\ I_{r2} & I_{g2} & I_{b2} \\ - & - & - \\ - & - & - \\ - & - & - \\ I_{rn} & I_{gn} & I_{bn} \end{array}$$

Where n are the number of neighbors of the current object has, I is the matrix whose first row represents mean value for current object.

$$F_i = \sum_{2}^{n} |I_{r_1} - I_{r_i}| + |I_{b_1} - I_{b_i}| + |I_{g_1} - I_{g_i}|$$

where F_i is nutrient function for i^{th} neighbor.

If $F_i <$ intensity threshold $\& a_i <$ area threshold then merging criteria is met, else not meeting merging criteria, so the merging will not take place.

Finally, block wise counting of the vehicle present on the each frame is done.

TABLE 1

SPECIFIC-ATIONS	NO. OF FRAMES	TOTAL NO. OF VEHIC-LE	VEHICLE DETECTED	VEHICLE MISSED	RECOGNIT-ON RATE
V1	120	379	376	3	97.37
V2	100	125	123	2	98.40
V3	225	182	179	3	98.35
V4	93	388	382	6	98.45
V5	65	112	111	1	99.10
T (AVG.)	**603**	**1184**	**1169**	**15**	**98.73**

3   SIMULATIONS AND RESULT

MATLAB version R2011b (7.13.0.564) is used for implementing the algorithm. The algorithm is implemented on different videos captured through a camera mounted on a vehicle. A total of 1184 vehicles are considered in 603 frames.

In table 1, V1 is the video which taken in bright sunny day, V2 and V3 are the videos taken in the cloudy day,V4 video is taken on the city road and V5 video is taken in the cloudy evening time. Vehicle detected shows the number of vehicle detected in all the frames of the videos, vehicles missed shows the number of vehicle which were not detected by the algorithm. The recognition rate is the rate of the vehicles detected in each video. T (avg.) is the average total of the frames, vehicles detected, vehicle missed and recognition rate. The total average recognition rate comes out as 98.73% which is better than the recognition rate comes out by using DoBG filters [13]

Figure 1 shows the grey scale image of frame 20 in V1 and detected vehicle in the same frame .likewise frame 40 of V4, frame7 of V2, frame 78 of V3, frame 50 of V50 are shown in subsequent figures. Red circle shows the missed vehicle and green circle shows the detected vehicle.
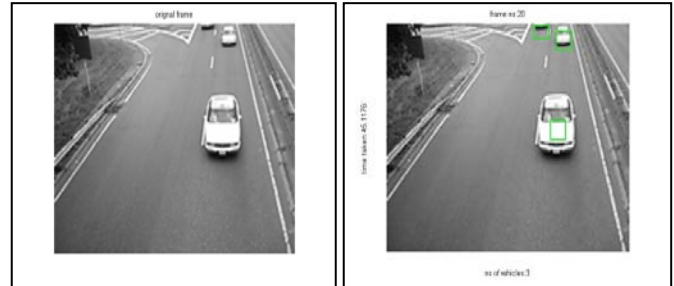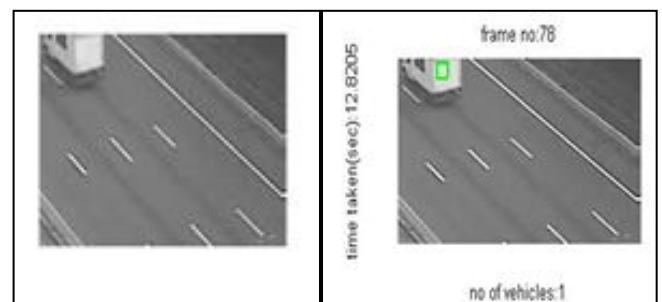

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

4　CONCLUSIONS

In this paper, various vision techniques developed for detection of vehicles have been discussed. Moreover, a new vehicle detection algorithm using Ant Colony Optimization technique is presented. Using this technique, an average accuracy of 98.73% is achieved.

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