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An Approach of Gray Level Co-Occurrence Matrix to Vehicle Detection

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Abstract: Now these days' automotive manufacturers have equipped vehicles with Advanced Driver Assistance Systems (ADAS) for safe driving, like collisions with other road users. Our research work gives the ideas for monocular vision which based on the vehicle detection. A system which may robustly detect and also track the various vehicles in an image. It consist three major modules: shape analysis is based on HOG is used as the main feature descriptor. It is a machine learning part which is based on support vector machine for vehicle verification and recent days these techniques is applied for feature extraction by using the concept of gray level co-occurrence matrix (GLCM). we are also explore detection of cars from different viewpoints of camera and diverse lightning conditions like night, sunlight, normal day light and further handling occlusion. Experiments have been processed on large numbers of car images with various angles. Results and future work would be discussed.

Keywords: Texture analysis, Shape analysis, Vision based systems, GLCM, SVM.

I. INTRODUCTION

Advanced driver assistance systems is technology which provide a driver to essential information, automate difficult and lead to an overall increase in car safety for everyone. Some of these technologies has been used for a long time and already prove result in changed driving experience and overall road safety. Now these days there has been an increase in number of embedded electronic processors in automobiles from 3% in 1985 to over 22% in 2006 [1]. From various embedded system driver assistance systems (ADAS) are becoming more and more popular in now these days because of availability of cheap cost, high-resolution and pervasive cameras [2]. Due to increasing demand in the vision-based ADAS manufacturers like as Texas Instruments etc. are also releasing latest embedded platforms which are specifically catered for the implemented vision algorithms in automobiles [3]. Navigation systems is used in a huge range of applications like as: Global Positioning System, Automotive Navigations System, Marine Navigation System, Robotic mapping, Surgical Navigation System, Inertial Guidance system and Surgical Navigation System in addition to navigation systems for advance driver assistance system for maintain safe speed, , collision avoidance driving within lane, at last reducing the accident. There are a wide range of issues and difficult issue in domain of navigation systems like weather conditions ,complex backgrounds, weather conditions, cast shadows, low-visibility, strong headlights, direct sunlight during dusk and uneven street illumination ,dawn and the problem of occlusions on which this paper is concentrating. In modest term there are 4 levels which would like to accomplished to make a robust navigation system like as recognition, localization detection, and understanding. In this research work we performed a number of experiments which were carried out at different real world data sets for analysis of the formula applied to obtain the good results for detection of vehicles. In the field of surveillance autonomous navigation scene understanding the occlusion is one of most common problem and also due to this lots of vision based algorithms are not robustness. The problem of occlusion is commonly defined under object tracking and object detection. Results are calculated by using the shape features with HOG and calculating the features such as: energy, entropy, correlation, homogeneity and contrast. For result we used statistica on different dataset. The dataset that we used in experiment is collected by online with images of size 64*64 pixels. The feature vector window with the cell size of 3*3 is also used for HOG on the images with output of the feature vector with 1*14400, after that minimize the feature vector rather by using principal component analysis and any other methods we implemented window size of 32 * 32 to find feature vector of the length 1*144. We all know that Texture is one of the important part in the biological vision system, concept of gray level co-occurrence matrix and further concatenating on the feature vector which is basis of homogeneity , contrast, correlation, entropy and energy with three different colour channels red, green and blue and concatenation of the feature vector finally, gives us the feature vector which is further classified and it tested on basis of svm using Statistica. The dataset has been tested and using support vector machines with two different kernel types: RBF and linear. The overall results have accuracy with 91% of rate in overall system. The dataset is collected online with various samples of car and non-car for testing purpose. In this paper we performed the experiments on dataset which involves on images under different six categories.

II. LITERATURE REVIEW

In vision higher level of the understanding with camera as a sensor which involves the tasks like as: place recognition, object categorization, scene understanding, object detection and action recognition. other existing vision based systems are not only able of giving complete information on the individual vehicles but they are also limited to measure the traffic flow only. Traffic control must be performed in different kind of environment, light conditions and weather, which has capability of handling the occlusions and illusions. Furthermore urban scenes are particularly complex because of background condition is variable. The human perception is intelligent as compare to machine system so the various researches is going to design the real world applications with that help it may be possible and easy to designs a vision to machines. huge range of applications are in the field of vision like as: Unmanned Ground Vehicles (UGV's), Unmanned Aerial Vehicles (UAV's), Automated visual Traffic Surveillance (AVTS), Unmanned underwater vehicles (UUv's), Advanced driver assistance systems (ADAS), Scene Understanding, Pedestrian Classification, Autonomous Navigation. In vision the sensor we use camera which is used for vision to machines the researchers work on commonly two platforms: monocular [4] or binocular (stereo) [5] vision. Now, what is difference between the one image of a scene and two image of same scene which is taken from the different viewpoints. Object detection and tracking is a research area in the huge field of the computer vision from the decades. many kinds of applications are the dependent on area of the object detection, like as the advance driving system and autonomous navigation, traffic surveillance, scene understanding etc. Due to increase in traffic on the roads the intelligent traffic surveillance systems are also updated in many countries for the highway monitoring and road management system. Traditionally, the shadow detection method has been used for the removing shadows from background and foreground, but the Sadeghi & Fathy used it as a feature for the vehicles detection and the occlusion handling.

2.1. Slam – Simultaneous Localization and Mapping

It can be implemented in various way. First reason it has big amount of different kind of hardware used. Secondly reason SLAM is like a concept than the single algorithm. Slam has many steps and different steps could be implemented with the help of number of different algorithms. SLAM has multiple parts; data association, Landmark extraction, landmark update, state update and state estimation. It has various way to solve every tin part. The SLAM is basically used for robot navigation systems in the unknown environment. Slam has first basic step is process to obtain the data about surroundings of robot system and the Extended Kalman filter, which is a traditional approach is and quite often used for estimation in the robotics system. It is mainly concerned with the problem of building a map with an unknown environment by the help of mobile robot system. while at same time period navigating environment with the help of the map. SLAM contain of multiple various parts; state estimation, Landmark extraction, data association, landmark update and state update. The SLAM is basically based on the Extended Kalman filter by which utilize priori map of locations. The main objective of SLAM problem is also estimate the orientation and position of robot system together with locations of all features. SLAM is used in Autonomous underwater vehicles and unmanned aerial vehicles [9].

2.2 Surf – Speeded Up Robust Features

Speeded up robust features (SURF), is based on Scale Invariant feature transform (SIFT).this is the local feature descriptor and detector which can be used for object recognition or 3D reconstruction. But basic version of SURF is various times faster than the SIFT and is also much more robust. The algorithm is works on the interest point like detection, matching and local neighborhood description. It is uses wavelet responses in the vertical direction and horizontal for the neighborhood pixels. surf algorithm is mainly based on the two basic steps for the feature detection and description. The detection of the features in the SURF relies on the scale-space representation and combined with the first and second order the differential operators. The SURF algorithm (Speeded up Robust Features) is operations which speeded up with use of box filters techniques [10].

2.3 Dpm – Deformable Part Based Model

Deformable part is based on the object category which represents presence of parts and how can they relate to each other and Any element of the object or scene which may be reliably detected with using local image evidence. In the part based model each part is represents local visual properties. The main idea behind the deformable parts is to explain the object model with the help of lower resolution of root template and also set a flexible the high resolution part templates and the Deformable part is based model on the next revolutionary idea after Histogram of orientation gradient in the object detection method. Threshold is employed in deformable part which is based on the model in non-maximum suppression filter and is key root of that algorithm. Lower the threshold value and higher number of the detection [11].

III. SHAPE ANALYSIS

The shape could be thought of the silhouette of an object There are various applications where the image analysis may be reduced to analysis of the shapes like machine parts, organs, characters, cells etc. Shape analysis methods is important for object recognition, matching, registration, and analysis. The aim of shape analysis is to give a simple presentation of original shape so that vital characteristics of shape are also preserved. The general definition explain that analysis can be either numeric or non-numeric. The input to the shape analysis algorithms is the shapes (example binary images). Research in the shape analysis is motivated. Methods for the shape analysis are mainly divided into various groups. But the classification is according to use of the shape boundary or interior and also according to type of the result. For result we combine global scalar, boundary space domain, boundary scalar and global space-domain methods.

There are various work done from past to till on shape analysis. The low level features like as shape, colour, corner, texture etc are used to define approximate the perceptual representation of image with similarity and dissimilarity of an images are computed. But it is explain that perceptual representation of the image in the terms of low level of the features fails to capture the semantic information of image and it is more difficult to the model accurately. In our work we use

Histogram of oriented gradient [12] approach to utilize the first to figure out best features. It s operates on the dense grid of the uniformly spaced cells and also used in the local contrast normalization on the overlapping blocks for the improved correctness. main idea behind the HOG is the appearance and the shapes of local objects within the image could be well described with the help of distribution of intensity gradients as votes for the dominant edge directions. These descriptor could be obtained by the first dividing an image into tiny contiguous regions of an equal size which is called cells, after that collecting the HOG directions for pixels with the each cell and at end combining all of these histograms. To improve the detection correctness against the varied illumination the local contrast normalization might be applied by the computing a measure of intensity around larger region of image called the block and by using the resultant value to normalize all the cells within the block and there are two main variants of the HOG descriptors manly used: Circular HOG and Rectangular.
It has complex masks ,as like canny , prewitt, and sobel or diagonal mask.But these mask has poor result performance. So magnitude and the orientation at each pixel I(x, y) is calculated by the following method:

Gradient of an image:

$$\nabla f = \frac{\partial f}{\partial x}\hat{x} + \frac{\partial f}{\partial y}\hat{y} \qquad (3.1)$$

Gradient direction

$$\Theta = \mathrm{a\ tan\ 2}\left(\frac{\partial f}{\partial y}, \frac{\partial f}{\partial x}\right) \qquad (3.2)$$

$$G_{mag}(x,y) = \sqrt{G_x{}^2\,(x,y) + G_y{}^2\,(x,y)} \qquad (3.3)$$

$$\Theta\,(x, y) = \mathrm{arc\ tan}\,\frac{G_y\,(x,y)}{G_x\,(x,y)} + \frac{\pi}{2} \qquad (3.4)$$

$G_x(x, y)$ and $G_y(x, y)$ are the gradient values of each pixel in the direction horizontal and vertical both and for colour images, channel with largest magnitude that gives the pixels has orientation and magnitude.
So here we have basically five main steps.
Step 1: Input image In the first step images are pre-processed on basis of size to find out optimum and the best features in feature vector queue. It was performed on image size of 64*64 pixels.
Step 2: Gradient calculation the orientation and Magnitude at each pixel is analysed, with gradient values at the each pixel in both x and y directions.For the samples we used largest magnitude which gives pixel dominant direction and magnitude.
Step 3: Orientation binning and normalization the Histograms of the each cell are created. So every histogram bin has the spread of 20° and every pixel in cell casts the weighted voting up into one of nine histogram bins so that the orientation is belongs to (0° - 180° = 90°). After that the block normalization feature vector is also calculated that contains elements of normalized cell the histograms from all of block regions. So that slope is checked called as the orientation gradient and put in a bin. So the region is also sampled until the entire image has been sampled. Finally by the help of the slopes edges are also determined.
Step 4: Block normalization and descriptors the Histograms are normalized which is based on their energy across the blocks and the basic testing blocks we has a step size of one cell and a cell would be part of four blocks. This is discover four different normalized versions of cell's histogram. There are four histograms concatenated to find the descriptor for cell. After the block normalization feature vector is also calculated that contains elements of normalized cell the histograms from all of block regions.
Step 5: Feature vector At the end we minimize feature vector rather than using the principal component analysis or any of other technique we improved window size of 32 * 32 to analyse the feature vector of the length 1*144.

IV. TEXTURE ANALYSIS

Texture is vital for the biological vision systems to calculate boundaries of the objects. Texture gradient is also use to implement orientation of the surfaces. Let us discuss in example on the perfect lawn grass texture is same everywhere. So that we look, finer texture becomes this change is also called the texture gradient and for same reasons, the texture is a useful feature for the computer vision. GLCM is computed, so firstly we also separated intensity in an image into small number of the various levels. After normalization of matrix is done by the determining sum across all the entries and dividing each and every entry with this sum. This is co-occurrence matrix hat contains important information about texture in examined area of an image. GLCM is calculated from a gray-scale image. We calculated and also examined three parameters for Red, Green and Blue colour channels.

$$\text{Energy} = \sum_{a,b} P^2(a,b)$$

$$\text{Entropy} = \sum_{a,b} P(a,b)\log_2 P(a,b)$$

$$\text{Contrast} = \sum_{a,b} |a-b|^{\kappa}\, P^{\lambda}(a,b), \text{ usually } \kappa = 2, \lambda = 1$$

$$\text{Correlation} = \frac{\sum_{a,b}\left[(ab)P(a,b)\right] - \mu_x \mu_y}{\sigma_x \sigma_y}$$

$$\text{Homogeneity} = \frac{P(a,b)}{1+|a-b|}$$

V. SUPPORT VECTOR MACHINE

A support vector machine is a classifier which defined separating the hyper plane. SVM is belong to family of the linear classifiers.Support Vector Machines (SVM) has been developed by Vapnik and it gained popularity due to interesting features like as good empirical performance. SVMs are mainly use to solve classification problem. SVM is very useful technique for the data classification. A classification task is usually involves with the training and testing purpose data that consist of some the data instances [14]. SVM is mainly based on statistical learning theory that was introduced in 1992. But SVM becomes popular due to its success in the handwritten of the digit recognition. It is an important example of “kernel methods”. In this paper we are using 1 D feature vector and also for the classification of problem of the cars and non – car. The aim of SVM is to design the model that predicts the target value of the data instances in testing set that are only give the attributes value [15]. The main step in SVM classification is involves in identification that intimately connected to known classes, called feature extraction.Support vector machines is used to classify the two classes, as in this paper we used car and non-car.Consider a two classes like car and non- car,that is a linearly different classification problem.

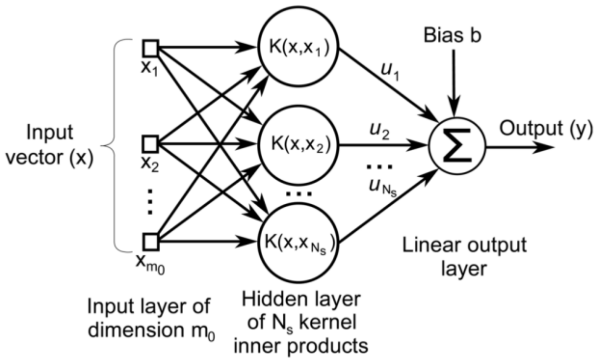

Figure 5.1 Support Vector Machine Classifier

VI. RESULTS

Our method was firstly tested on the number of sequences .for testig purpose we use image of size 64 × 64 pixels and algorithm has been developed by using Matlab and for result purpose Statistica is used. The algorithm is performed on an Intel Core I5, 3.00 GHz.The first one, which is based on method suggested by [17] the builds appearance model that is based on shape feature vector and also normalizing histograms which is based on gradient. The feature vector of GLCM is based on three different colour channels, Red, Green and Blue. The Energy , Contrast, Correlation, Entropy and Homogeneity are calculate for all images to get best results using the texture and shape features. The HOG is implemented with 20 * 20 cell size, to collect best feature vector. The classification is also performed by using Statistica and also implementing by Support vector Machines (SVM). But Handling occlusion was one of most critical parts in this experiment. Vehicle tend to on roads and also in different the traffic conditions so that chances of the occluding one car with the another that is further depending on the self-occlusion, as the camera viewpoint to the angle are different So that to solve this problem, there are some methods try to position camera in ceiling or at the vertical angle in hopes of the decreasing chances of the occlusion in the surveillance systems. The vertical angle of the camera may solve the occlusion problems, but it is not applicable in all the potential uses of the vehicle tracking. The feature extraction gave us optimum the results for handling the occlusion and with both of the shape and texture features, but we were able to get correctness of more than 91% in both conditions of real world scenarios.

Table 6.1

Total Number of samples	Cars	Non - Car
1390	645	645

Case – 1 LOW LIGHT CONDITION

Kernel Type – RBF

Table 6. 2 Case – 1 Classification Summary – Support Vector Machine

Class Name	Total	Correct	Incorrect	Correct (%)	Incorrect (%)
Car	645	602	43	92.34255	6.666667
Non - Car	645	620	25	95.12403	4.875969

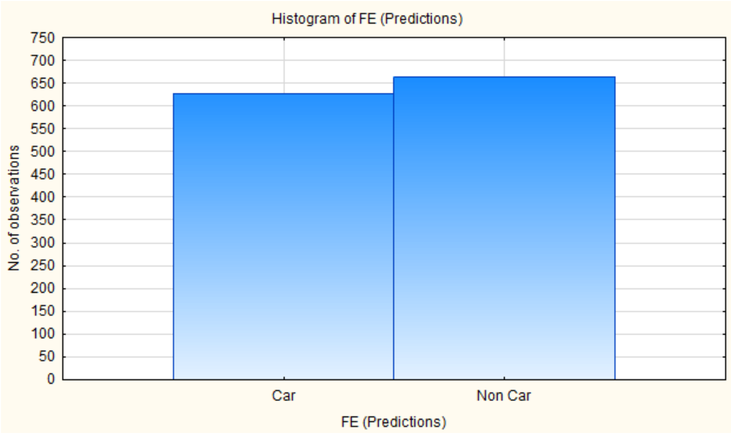

Figure 6.1 Case-1 Histogram of observed dataset

```
Dataset Book1 final features to svm:
  Dependent: FE
  Independents: B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S.
  Sample size = 1104 (Train), 1290 (Test), 2394 (Overall)

Support Vector machine results:
  SVM type: Classification type 1 (capacity=10.000)
  Kernel type: Radial Basis Function (gamma=0.006)
  Number of support vectors = 306 (264 bounded)
  Support vectors per class: 150 (Car), 156 (Non Car),

  Class. accuracy (%) = 95.924(Train), 94.729(Test), 95.280(Overall)
```

Figure 6.2 Case-1 Overall performance of detector

Case – 2 NIGHT CONDITIONS

Kernel Type – RBF

Table 6.3 Case - 2 Classification Summary – Support Vector Machine

Class Name	Total	Correct	Incorrect	Correct (%)	Incorrect (%)
Car	70	70	0	100.00	0.00
Non - Car	70	70	0	100.00	0.00

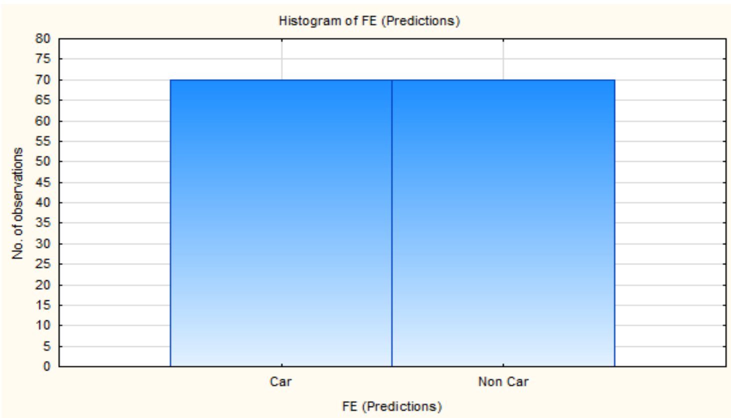

Figure 6.3 Case - 2 Histogram of observed dataset

```
Dataset Sheet1 in Book2 features to svm:
  Dependent: FE
  Independents: B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S.
  Sample size = 120 (Train), 140 (Test), 260 (Overall)

Support Vector machine results:
  SVM type: Classification type 1 (capacity=10.000)
  Kernel type: Radial Basis Function (gamma=0.006)
  Number of support vectors = 27 (10 bounded)
  Support vectors per class: 14 (Car), 13 (Non Car),

  Class. accuracy (%) = 100.000(Train), 100.000(Test), 100.000(Overal
```

Figure 6.4 Case - 2 Overall performance of detector

Case – 2.1 NIGHT CONDITIONS

Kernel Type – Linear

Table 6.4 Case - 2.1 Classification Summary – Support Vector Machine

Class Name	Total	Correct	Incorrect	Correct (%)	Incorrect (%)
Car	70	70	0	100.00	0.00
Non - Car	70	70	0	100.00	0.00

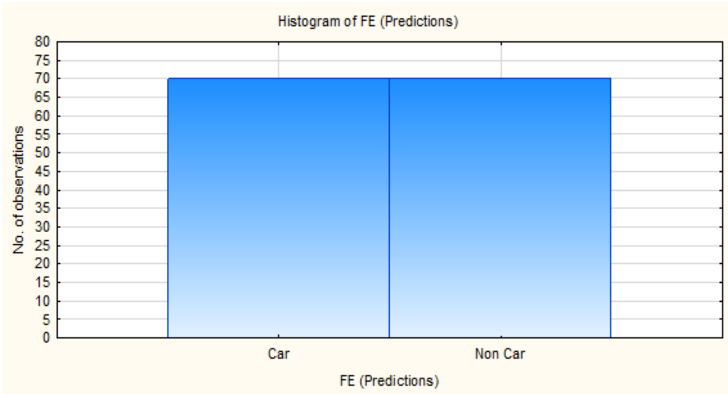

Figure 6.5 Case - 2.1 Histogram of observed dataset

```
Dataset Sheet1 in Book2 features to svm:
  Dependent: FE
  Independents: B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S.
  Sample size = 120 (Train), 140 (Test), 260 (Overall)

Support Vector machine results:
  SVM type: Classification type 1 (capacity=10.000)
  Kernel type: Linear
  Number of support vectors = 18 (0 bounded)
  Support vectors per class: 10 (Car), 8 (Non Car),

  Class. accuracy (%) = 100.000(Train), 100.000(Test), 100.000(Overal
```

Figure 6.6 Case - 2.1 Overall performance of detector

Case – 3 BRIGHT SUNNY DAY

Kernel Type – RBF

Table 6.5 Case – 3 Classification Summary – Support Vector Machine

Class Name	Total	Correct	Incorrect	Correct (%)	Incorrect (%)
Car	310	301	9	97.09677	2.903226
Non - Car	308	297	11	96.42857	3.571429

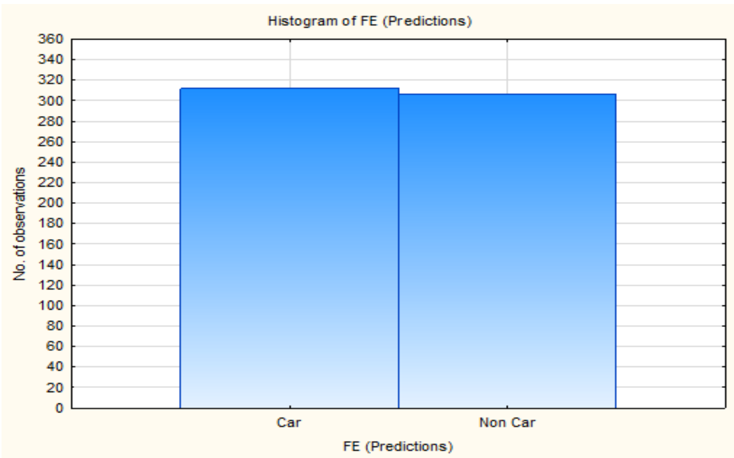

Figure 6.7 Case – 3 Histogram of observed dataset

```
Dataset Sheet1 in Book3 to SVM:
  Dependent: FE
  Independents: B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S.
  Sample size = 531 (Train), 618 (Test), 1149 (Overall)

Support Vector machine results:
  SVM type: Classification type 1 (capacity=10.000)
  Kernel type: Radial Basis Function (gamma=0.006)
  Number of support vectors = 140 (106 bounded)
  Support vectors per class: 66 (Car), 74 (Non Car),

  Class. accuracy (%) = 97.928(Train), 96.764(Test), 97.302(Overall)
```

Figure 6.8 Case – 3 Overall performance of detector

Case – 3.1 BRIGHT SUNNY DAY

Kernel Type – Linear

Table 6.6 Case – 3.1 Classification Summary – Support Vector Machine

Class Name	Total	Correct	Incorrect	Correct (%)	Incorrect (%)
Car	310	298	12	96.12803	3.870968
Non - Car	308	298	10	96.74325	3.246753

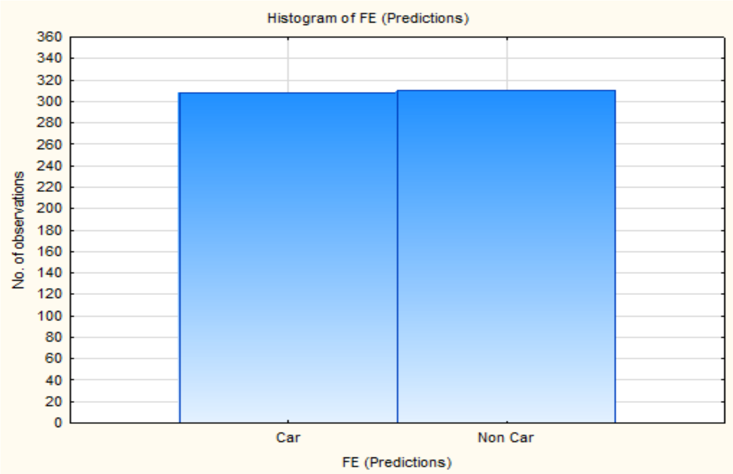

Figure 6.9 Case – 3.1 Histogram of observed dataset

```
Dataset Sheet1 in Book3 to SVM:
  Dependent: FE
  Independents: B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S.
  Sample size = 531 (Train), 618 (Test), 1149 (Overall)

Support Vector machine results:
  SVM type: Classification type 1 (capacity=10.000)
  Kernel type: Linear
  Number of support vectors = 70 (1 bounded)
  Support vectors per class: 35 (Car), 35 (Non Car),

  Class. accuracy (%) = 100.000(Train), 96.440(Test), 98.085(Overall)
```

Figure 6.10 Case – 3.1 Overall performance of detector

Case – 4 NORMAL DAY LIGHT CONDITIONS

Kernel Type – RBF

Table 6.7 Case – 4 Classification Summary – Support Vector Machine

Class Name	Total	Correct	Incorrect	Correct (%)	Incorrect (%)
Car	892	878	14	98.43149	1.569507
Non - Car	900	864	36	95.00000	5.000000

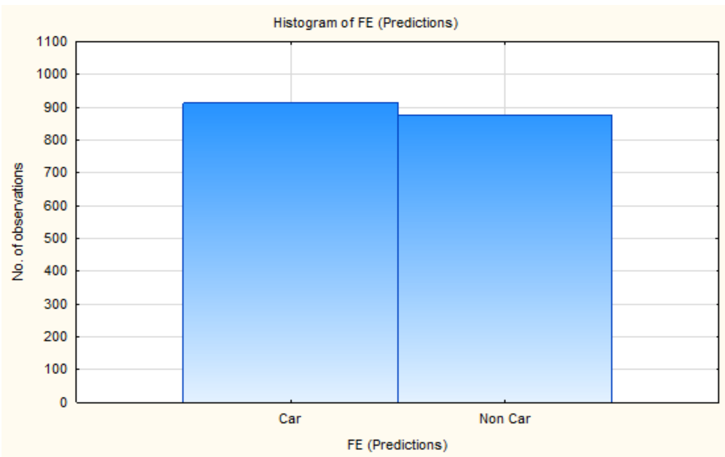

Figure 6.11 Case – 4 Histogram of observed dataset

```
Dataset Sheet1 in Book4 to SVM:
  Dependent: FE
  Independents: B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S.
  Sample size = 1533 (Train), 1792 (Test), 3325 (Overall)

Support Vector machine results:
  SVM type: Classification type 1 (capacity=10.000)
  Kernel type: Radial Basis Function (gamma=0.006)
  Number of support vectors = 252 (208 bounded)
  Support vectors per class: 128 (Car), 124 (Non Car),

  Class. accuracy (%) = 97.847(Train), 97.210(Test), 97.504(Overall)
```

Figure 6.12 Case – 4 Overall performance of detector

Case – 4.1 NORMAL DAY LIGHT CONDITIONS

Kernel Type – Linear

Table 6.8 Case – 4.1 Classification Summary – Support Vector Machine

Class Name	Total	Correct	Incorrect	Correct (%)	Incorrect (%)
Car	892	858	34	96.18734	3.812659
Non - Car	900	870	30	96.65667	3.332333

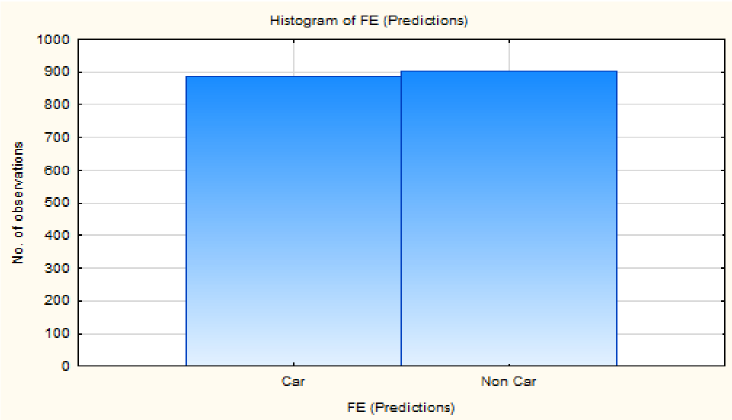

Figure 6.13 Case – 4.1 Histogram of observed dataset

```
Dataset Sheet1 in Book4 to SVM:
  Dependent: FE
  Independents: B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S.
  Sample size = 1533 (Train), 1792 (Test), 3325 (Overall)

Support Vector machine results:
  SVM type: Classification type 1 (capacity=10.000)
  Kernel type: Linear
  Number of support vectors = 167 (7 bounded)
  Support vectors per class: 93 (Car), 74 (Non Car),

  Class. accuracy (%) = 99.543(Train), 96.429(Test), 97.865(Overall)
```

Figure 6.14 Case – 4.1 Overall performance of detector

Case – 6 OVERALL PERFORMANCE ON WHOLE DATASET

```
Dataset Sheet1 in Final feature set:
  Dependent: FE
  Independents: B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S.
  Sample size = 3676 (Train), 4301 (Test), 7977 (Overall)

Support Vector machine results:
  SVM type: Classification type 1 (capacity=10.000)
  Kernel type: Radial Basis Function (gamma=0.006)
  Number of support vectors = 708 (648 bounded)
  Support vectors per class: 352 (Car), 356 (Non Car),

  Class. accuracy (%) = 95.947(Train), 95.536(Test), 95.725(Overall)
```

Figure 6.15 Case – 6 Overall performance of detector

	Model summary (Support Vector Machines), FE (Sheet1 in Final feature set)
Model specifications	Value
Number of independents	159
SVM type	Classification type 1
Kernel type	Radial Basis Function
Number of SVs	708 (648 bounded)
Number of SVs (Car)	352
Number of SVs (Non Car)	356

Figure 6.16 Case – 6 Model summary - Support Vector Machines

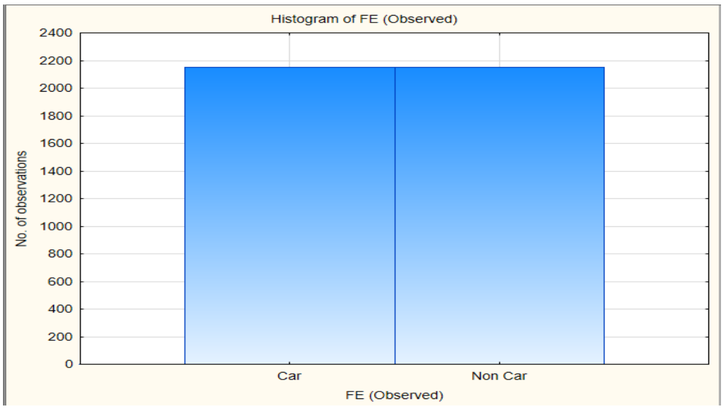

Figure 6.17 Case – 6 Histogram of observed dataset

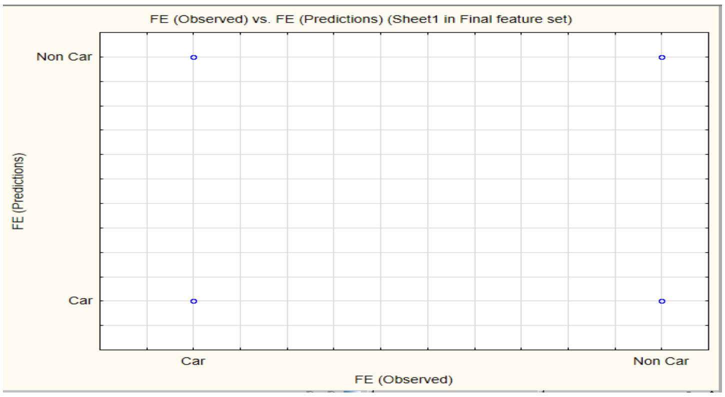

Figure 6.18 Case – 6 Observed V/S Predicted

Classification summary (Support Vector Machines), FE, Test sample (Sheet1 in Final feature set)
SVM: Classification type 1 (C=10.000), Kernel: Radial Basis Function (gamma=0.006)
Number of support vectors= 708 (648 bounded)

Class Name	Total	Correct	Incorrect	Correct(%)	Incorrect(%)
Car	2152	2051	101	95.30669	4.693309
Non Car	2149	2058	91	95.76547	4.234528

Figure 6.19 Case – 6 Classification Summary – Support Vector Machine

Confusion matrix (Support Vector Machines), FE, Test sample (Sheet1 in Final feature set)
SVM: Classification type 1 (C=10.000), Kernel: Radial Basis Function (gamma=0.006), Number of support vectors= 708 (648 bounded)
Observed (rows) x Predicted (columns)

Class Observed	Car	Non Car
Car	2051	101
Non Car	91	2058

Figure 6.20 Case – 6 Confusion matrix – Support Vector Machine

VII. CONCLUSION

In this paper work, a vehicle detection algorithm is based on gradient and the concentrated on the shape analysis is used. For the shape feature vector with the texture analysis we used Gray level Co-Occurrence matrix. At the end results show that by using gray level co – occurrence matrix feature vector gives a better result when handling the occlusion and different weather and the light conditions.The occlusion is also still challenging in the terms of dataset. In this work, two efficient image features are based on the texture and the shape analysis that were implemented and also popular classifiers– the SVM was studied and performances for the vehicle classification systematically evaluated under same setups. So for shape and texture features, the SVM classifier is achieved the better performance. It was found out that the employing these method helps in reduce false detections and also improves detection system’s performance. Further it must be done on the video with the stereo camera. So one of possible for future directions concerning use of our suggested the detection framework that would be improved by the using of concepts of the Pictorial structures and also some of occlusion patterns for the specifically in the car detection. In future the deformable part is based on model that can be tested for better result and performance.

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