TRACKING AND DETECTION OF SUDDEN PEDESTRIAN CROSSING

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Abstract: From last decade, Safety plays a major role in automobile industry, which results in the invention of various safety measures such as air bags, central locking system, automatic breaking system, traffic signal detection etc. In such case pedestrian detection in night vision is one of the vital issues in advanced driving assistance systems. The main aim of the night vision systems is to avoid collision of vehicles with the pedestrians while driving on roads. It is very much important in night time; due to the varying light conditions it is very difficult to detect a pedestrian. FIR (Far Infrared) camera is used in this system to take images of a night scene. In this system we proposed a tree structured classifier which is a combination of Haar like features and OCS-LBP features to detect the pedestrian effectively. And also we used virtual reference lines The SPC detection is determined using the likelihood and spatiotemporal features, like overlapping ratio, magnitude and direction of the pedestrian's movement.

Index Terms: Haar like features, OCS-LBP features, SPC detection, Spatiotemporal features.

I INTRODUCTION

The accidents during night times are increasing day to day due to the poor lighting conditions. Now a day's driving during night time becomes a complex job due to the poor lighting conditions at that time. But the technology has moved more advanced situations where a system can predict the accidents and give the information to the driver there by it can avoid the accident. To decrease number of accidents, earlier automobile producers enhanced their vehicles with the presentation of better brakes and tires. It reduced the occurrences of accidents reliably for an extent, but it did not deal with the things which causes mainly for accidents. For that reason automobile industry put forward their research on other safety measuring elements such as air bags, automatic braking system etc. which is termed as Advanced Driving Assistance Systems (ADAS), with this improvements they moved further for Night vision system. The Night vision systems assists the driver of the vehicle by letting him to know the obstacles especially pedestrians on the road with the help of a Camera and its displaying unit. In this system pedestrian detection plays a major role. Pedestrian detection is significant and most challenging tasks in the image processing field. It has been widely used in Robotics, surveillance and intelligent vehicles. A lot of research works have been done on the detection of pedestrians in recent years, but the task of pedestrian detection is still challenging in the intelligent vehicle systems with cluttered backgrounds and varying light conditions in moving environment. There are two types of sensing technologies present in the night vision systems

1) Far Infrared Imaging systems
2) Near Infrared imaging systems

Both of the systems are having its own advantages and disadvantages in the field of night vision. Both types of systems can be used with high beam headlights but a Near Infrared (NIR) system can have a normal functionality over Far Infrared (FIR) systems. These FIR systems work in darker places where the need of light is necessary. The main aspects in both types of night vision systems are capability of pedestrian detection, effectiveness for avoidance of collision, and the commercial attractiveness.

II EXISTING SYSTEM

The pedestrian detection plays an important role in advanced driving assistance system, Therefore we have to choose the classifiers which gives the better results, So that we can avoid the false detections during night time. In this paper they have used the classifier which is the combination of SVM and HOG. Support Vector Machine (SVM) is works better for only two classes, which means it can be able to train and test only two classes of pixels. SVM classifier is a liner separable classifier. Whereas HOG (Histogram of Oriented Gradient) works based on the pixel magnitude and direction. The computational cost of HOG is very high. This system works with the lane detection to refer the SPC (sudden pedestrian crossing). Lane detection is constant in nature. It just shows path to the vehicle and does not show the left and right sides of the vehicle

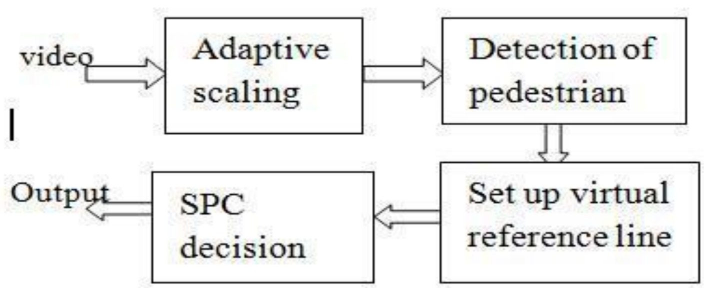
Drawbacks of Existing System

- Inefficient in feature extraction.
- Due to the use of the static reference line it does not give the exact position of the pedestrian.
- It requires more processing time.

III PROPOSED SYSTEM

A) System Description

Fig1: Block diagram of proposed system



B) Adaptive Scaling

Adaptive scaling means to scale the image according to the height of a person. In this process first we need to estimate the region of interest (ROI) for each and every frame of an input video. ROI selects such that it must be four seventh of an image from the bottom. This Criterion is selected according to the average height of a person. In pedestrian detection, different scales of images should be applied to detect the pedestrians of various sizes. Therefore to set up different scales to an image we need to know the knowledge of heights of persons. To reduce the complexity of image scaling we divide the image into six scales according to height of a person. Each scale is selected at an interval of 5m from the camera up to 30m. We then select the bounding box according to the height of the pedestrian at each interval. The size of a bounding box selects according to the size of an image that is 680X480.

TABLE I Bounding box according to the height of a person

Distance(in m)	Size of the bounding box
5	196X83
10	124X54
15	90X83
20	69x29
30	47X20

C) Detection of pedestrian

In the detection of pedestrian feature extraction [10] is very important to extract the object information in the image or frame. Feature extraction is important factor which improves the performance of a classifier. To extract object information in the image we used the classifiers. HOG features are used to extract the human features in an image and also it has a low false positive rate. But the HOG requires more mathematical calculations. Therefore we go for CRF(Cascade Random Forest) classifier, which s a combination of Haar and Ocs-lbp features. They are discussed below.

Haar feature extraction

Haar like features are rectangular patterns which are used to detect the objects in the image. There are 27 patterns are designed to extract the correct object information. By increasing the number of patterns we improve the performance of a classifier.

Ocs-lbp feature extraction

Oriented centre symmetric local binary patterns method is used for extracting features for each pixel in an image. Each pixel creates a binary pattern with the neighboring pixel like this it forms pairs of pixels and calculate the magnitude and gradient of each pixel.

CRF: (Cascade Random Forest classifier)

The cascade random forest classifier [13] is a cascaded version of two feature extraction methods they are Haar feature extraction method and Ocs-lbp feature extraction method. CRF classify the candidate windows into two both human and non-human classes. The CRF works like a filter chain. A random forest is a decision tree ensemble classifier, where each tree is grown using some form of randomization. A random forest has the capacity for processing huge amounts of data with high training speeds based on a decision tree. Each filter is a set of strong classifiers (decision trees) consisting of a number of n weak classifiers (split functions). When the test image is used as input to the trained random forest, the final class distribution is generated by an ensemble (arithmetic averaging) of all tree distributions $L = (1\ l , 2\ l ,\ldots, T\ l)$.

$$f = \arg\max_{i=1\ to\ N} \left\{ \frac{1}{T} \sum_{t=1}^{T} P(c_i \mid l_t) \right\}$$

HMM (Hidden Markov Model)

To overcome the above disadvantages of CRF we extended our work with the HMM (Hidden Marcov Model) as classifier. HMM gives better results compared to CRF. HMM is a straightforward application of the Bayesian classification framework, with the HMM is used as the probabilistic model to describe the data. HMM works based on the flow of states. Advantages of HMM are,

1) Processing starts directly from the raw input data.
2) It can handle variable length of data effectively.

D) Set up of virtual reference lines

Setting up the virtual reference lines [12] is to detect the pedestrian at left and right edges of vehicle. It plays an important role in the detection of sudden pedestrian crossing. There are two types of methods used to make reference lines for the driver. First method is expressing the reference lines as sample points in the lane based on computer vision. However there are several limitations for the lane detection due to occlusions by other vehicles, surface reflections or lack of road lanes. Second method is virtual reference lines have been used for the SPC detection. By this we can detect the SPC at left and right edges of each frame. And these virtual reference lines should be changeable according to the vehicle turning direction. To overcome the limitations of lane detection we set the virtual reference lines in addition, we also proposed a method for changing the direction of lines according to the turning direction of the vehicle.

Algorithm to setup virtual reference line

Here to setup the virtual reference lines we used the curb gradients and vanishing point. Curb gradients of a road are detected by using the sobel-edge detector within the ROI. The reference lines are generated from the vanishipoints.

We determine virtual reference line as the location where the overlapping between the curb gradients and candidate reference lines.

Steps

1) Locate the Cx as the center position in the bottom half of an image.
2) Draw a straight line along the Cx and locate the vanishing points as V1,V2,…
3) Detect the curb gradients B using sobel edge detector.
4) Draw the candidate reference line R(vi) along the selected Vi.
5) The smallest overlapping error between B and R(vi) that is,

$$R(v_i) = \min_{R(v_i)} \left\| B - R(v_i) \right\|_2^2$$

6) Draw the virtual reference lines R(vi).

Changing virtual reference lines

The reference lines should change its direction according to the turning direction of the vehicle. Therefore for that we go for optical flow for the detection of turning degree and direction of the vehicle. Optical flow is estimated from the regular feature points. In this paper, we define three turning classes of a vehicle, i.e., Go-Straight (GS), Turn-Right (TR), and Turn-Left (TL). From the training data, we collect features on the vector of the x-direction (*x d*) and y-direction (*y d*) of the optical flows for these three classes. For optical flow vector **x** consisting of *x* and *y* directional
Magnitudes, i.e., x=[dx ,dy]^T

$$p(\mathbf{x} \mid \omega_i) = \frac{1}{(2\pi)^{d/2} |\Sigma_i|^{1/2}} \exp(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1}(\mathbf{x}-\boldsymbol{\mu}_i))$$

After the turning direction of vehicle it should calculate the turning degree of the vehicle. The vanishing point is moving according to the direction of the vehicle. The vanishing point of time't' is computed by,

$$\begin{bmatrix} v_x^t \\ v_y^t \end{bmatrix} = \begin{bmatrix} v_x^{t-1} \\ v_y^{t-1} \end{bmatrix} + \begin{bmatrix} \bar{d}_x^t & 0 \\ 0 & \bar{d}_y^t \end{bmatrix} \cdot \begin{bmatrix} k_x \\ k_y \end{bmatrix}$$

E) SPC detection

SPC detection is important for safe driving because driver can receive alerts as early as possible to avoid the collision. For the SPC prediction we consider three parameters they are

1) Over lapping ratio
2) Movement direction ratio
3) Movement speed ratio

These three ratios are then applied to the corresponding normal distribution, and the final decision is made using the likelihood estimation.

Overlapping ratio: OR(i)

Here we need to determine the overlapping area between the detected pedestrian and virtual reference line. This is defined as,

$$OR(i) = \frac{area(RL \cap BB(i))}{area(BB(i))}$$

RL-Reference Line
BB(i)-Bounding Box of the pedestrian.
If BB(i) outside the RL then OR(i)=0. If BB(i) is completely inside the RL then OR(i)=1.

Movement direction ratio: MD(i)

As the second feature, we estimate the movement direction of the pedestrian based on the assumption that the direction of the SPC is to the left or right of the driver's view; hence, the motion orientation is estimated using the optical flow. This algorithm estimates the motion orientation using eight discrete directions. The motion code *M* is defined using the orientation (theta) of the optical flow

$$M_{k\in\{0,\ldots,7\}} = \begin{cases} 0 & , if\,(\theta \le 23) \\ \left\lfloor \dfrac{(\theta - 23)}{45} \right\rfloor + 1 & , otherwise \end{cases}$$

After estimating the motion within the bounding box of the pedestrian, the movement direction ratio of pedestrian *i* (*MD(i)*) on *N* optical flows is then computed by

$$MD(i) = \frac{\sum_{k=1}^{N} Score(M_k^i)}{N}$$

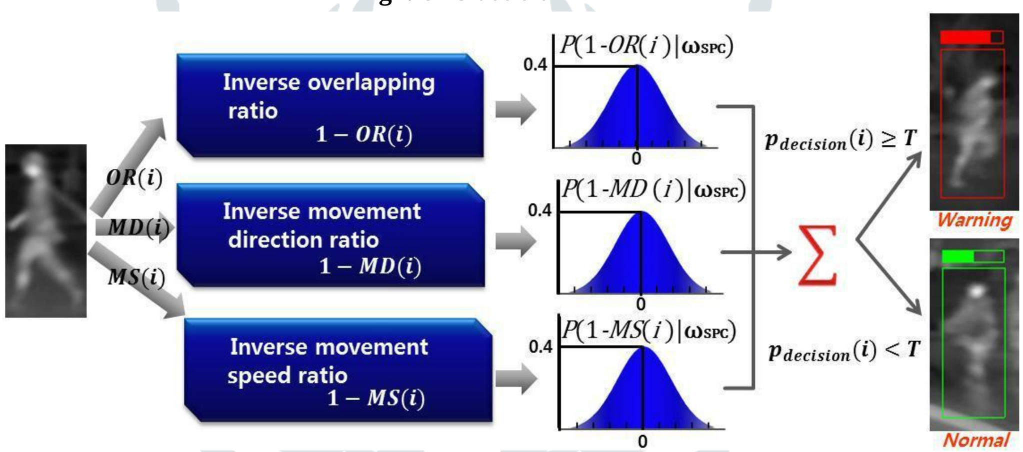
Movement speed ratio: MS(i)

Movement speed ratio estimated by using the speed of the optiacal flow(mag) and the distance of the pedestrain from the camera.Speed of pedestrian 'i' on 'N' optical flows is computed by,

$$MS(i) = \frac{\sum_{k=1}^{N} \left(1 - \dfrac{1}{\exp(dist \cdot mag_k \cdot \gamma)}\right)}{N}$$

F) SPC decision

Fig2: SPC decision



We estimated the 3 ratios of an SPC. We estimate the conditional probability of each ratio based on the assumption that the 3 ratios have normal distribution. For easy calculation we take the inverse form of the ratios and we calculated the means and standard deviations of 3 ratios. For calculating the probability of SPC take all the ratios are conditionally independent. The final SPC decision is given as,

$$\begin{aligned} & p_{decision}(i) \\ & = \log p(1 - OR(i) \mid \omega_{SPC}) + \log p(1 - MD(i) \mid \omega_{SPC}) \\ & \quad + \log p(1 - MS(i) \mid \omega_{SPC}) \end{aligned}$$

IV EXPERIMENTAL RESULTS

The statistical measures of system give the exact idea of any system's performance. To evaluate the system's performance we have to check the system's robust in every season. The performance of the pedestrian detection system can be able to estimate according to the number of frames it detects exactly out of total number of pedestrian frames. For this evaluation we need to form a confusion matrix. Confusion matrix illustrates the correct and non-correct predications made by classifier. Confusion matrix consists of True positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

The confusion matrix is,

$$C = \begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix}$$

TP-Gives the correct number of frames in which pedestrian is there.
TN-Gives the exact number of frames in which the pedestrian is not there.
FP- even though the pedestrian is not there it claims that there is pedestrian.
FN-Even though there is a pedestrian it claims that there is no pedestrian.

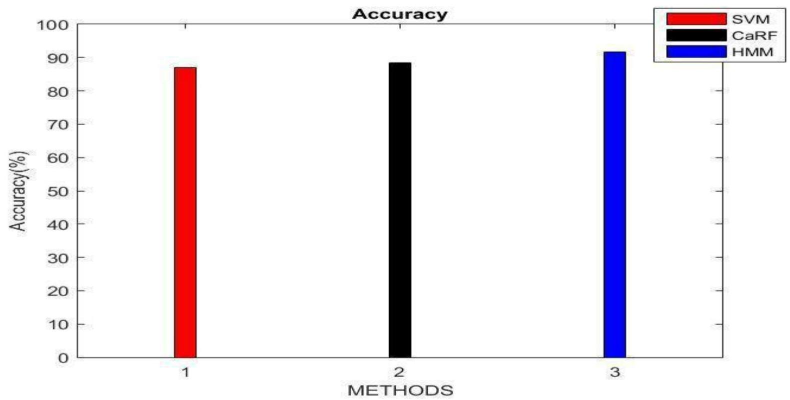
The accuracy, sensitivity and specificity are the three main statistical measures of a pedestrian.

A) Accuracy

Accuracy gives the statistical value of the systems performance thereby we can analyze the robustness of the system. In the pedestrian detection we defined accuracy as the number of frames it detects correctly out of the total number of frames.

Accuracy= (Tp+Tn)/Total frames*100

Fig3: Comparison of accuracy

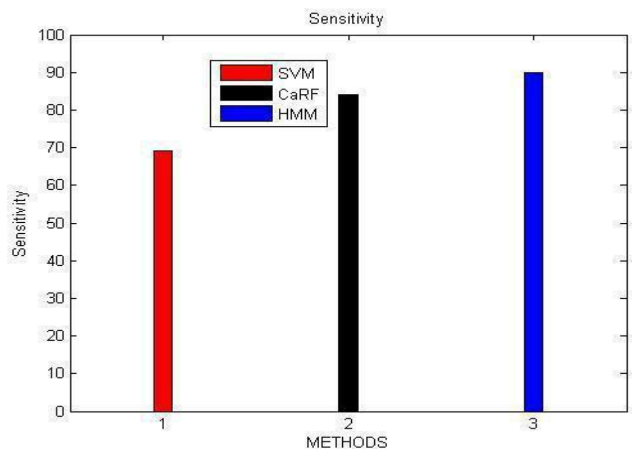


B) Sensitivity

Another important factor to measure the systems performance is Sensitivity. Sensitivity measures the actual positive values which are correctly identified.

Sensitivity: TP/(TP+FN)*100

Fig4: Comparison of sensitivity

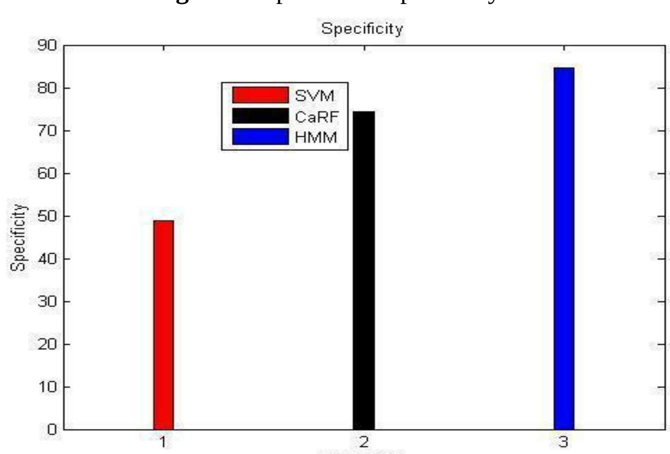


C) Specificity

Specificity measures the percentage of negative values which are correctly identified. Specificity is measured as,

Specificity=TN/ (FP+TN)*100

Fig 5: Comparison of specificity



D) Computational time

Time required detect the pedestrian for each classifier.

Fig 6: comparison of time

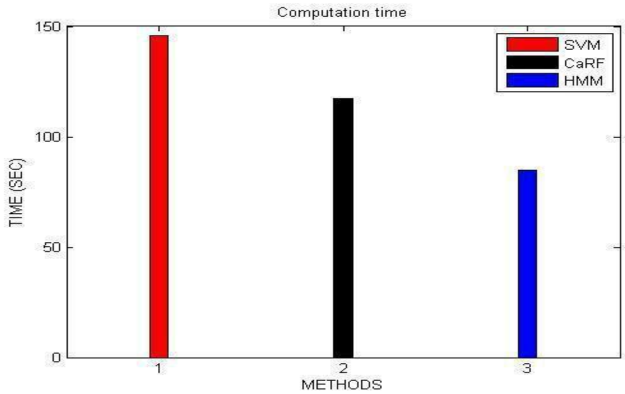


TABLE II Results of different videos

Video	No of frames	Accuracy	Specificity	Time(in sec)
Video1	105	91	84	90
Video2	190	91.6	90	110
Video3	125	87	83	93

V) CONCLUSION

In this paper the proposed system was used the better classifiers and effective techniques to detect and track the Sudden Pedestrian crossing. The classifier used in this system is CRF (Cascaded Random Forest) classifier which detects the pedestrian in less time compare to previous classifiers. For the detection of sudden pedestrian crossing we introduced the virtual reference lines concept which tracks the exact position of the pedestrian. By using the virtual reference lines we also estimate the distance between the pedestrian and the vehicle. The implemented system also added new features to detect the direction and speed of the SPC. The spatiotemporal features which considered for detecting the SPC are Overlapping ratio, Movement direction ratio and movement speed ratio. These features give the exact information of the sudden pedestrian crossing. The system's performance is evaluated by using the statistical measures of accuracy, specificity and computational time. By considering all the comparisons we confirm that the system works well.

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