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Detecting Footpath Trespassers and Preventing Accidents

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Abstract. Vehicles will eventually be fully automated, according to the automotive industry. While the automation of vehicles might lighten the burden on humans, we must also take care to ensure that safety is not compromised. The goal of this project is to identify any pedestrians in front of the host vehicle. The idea of project is to increase the accuracy in detection of pedestrian with minimal reaction time. This approach mainly focuses on developing optimized algorithm to detect pedestrian with accurate distance with host vehicle to generate AEB,ACC warnings. Distance of the pedestrian is estimated with width based distance correction. Further by introducing different classifier models for different distances better system accuracy can be achieved. A tracker module is used to keep track of the detections and make sure there are no wrong detections.
Keywords: Automation, Obstacles, Classification, Adaboost, Support Vector Machine, Pedestrian, Detection.

Introduction

Any intelligent video surveillance system must perform pedestrian identification since it supplies the necessary data for comprehending individual video footage segments [1]. It certainly has an extension to automotive applications due to the potential for enhancing safety systems[2]. The automotive industry is moving towards full vehicle automation[3]. While vehicle automation can decrease human workload, we also need to ensure that security is not compromised in the process[4]. The detection of several barriers is one of the essential parts of vehicle automation. Obstacles may include traffic lights, pedestrians, livestock, cars, etc. This project includes detecting pedestrians in front of the host car [5].Training and Support from Adaboost [6]. The categorization is carried out using vector machine training in two stages [7]. A learning algorithm called Adaboost (adaptive boosting) can be applied to classification or regression problems [8]. The Support Vector Machine (SVM) technique works by locating the hyper plane that provides the maximum minimum distance between the training instances [9]. The SVM is a discriminative classifier that is officially characterised by a separating hyper plane [10]. As a result, this Adaboost classification is completed first, and only the good results are passed to the Support Vector Machine classifier [11]. This will guarantee that the classification process using the support vector machine won't take any longer.

Related Work

Benenson et al., [1], desktop computer enabled by CPU+GPU, this paper approaches novel pedestrian detector operating at 135 fps. The approach's key novelties are reversing Dollar FPDW (fast pedestrian detection approach) detector. To prevent multi-scale resizing of the input picture and using a latest technique to rapidly access geometric stereo data. Because of solution's elevated parallelism, it will benefit directly from future hardware improvements. This paper enhances the quality of the training for classifiers and extends the present scheme to detect vehicles, bicycles and other mobile items in multi-class / multi-view.

Andriluka et al., [2]: Strong self-similarity traits, when added to colour channels, significantly improve pedestrian recognition both in single-frame environments and with additional motion data. The state-of-the-art reported state of the art is outperformed by a combination of precisely implemented HOG characteristics, a HOF version for encoding picture movement, and the new CSS function, along with HIKSVM as a classifier, by 5%–20% over a wide range of accuracy.

Lakshmi et al., [3], she includes detecting pedestrians using edge detection algorithms at night time are created in this article. Usually this sort of method is developed to lower execution costs. This approach can be expanded to address problems with object detection because it focuses largely on edge detection. In this pedestrian detection algorithm dark background is a very significant necessity; it provides batter precision for road types of situations.

Javier Mar´ın et al.,[4] studied how realistic virtual worlds in the ADAS region can contribute to the teaching of appearance-based models for pedestrian detection. This uses HOG / linear-SVM method to use only samples from virtual worlds to know a pedestrian classifier. In such a classifier, we have plugged into a conventional technique of pedestrian detection and assessed how this detector operates when applied to true pictures, i.e. when the pedestrian classifier is used outside its environment.

Tanmay Bhadra1 et al.,[5] Detecting pedestrians using vision is still an open problem. Some people are moving, some are immobile, and some are unpredictable in their changes of direction, making them easy to spot in different backgrounds. To try to overcome the issues listed above and others like them, various ways have been created. Automobile makers are working hard to ensure the safety of the car and pedestrian by using pedestrian detection systems that inform drivers when any pedestrian is identified in front of the car, even though pedestrian traffic fatalities remain a worry.

Hailong Li et al., [6] he uses pedestrian detection based on convolutionary neural networks. It tested the scheme on INRIA pedestrian datasets to demonstrate the excellent efficiency of our technique and use the selective search algorithm and edge boxes algorithm to get regional proposals. Results of the experiment show that the suggested scheme exceeds traditional algorithms based on characteristics both handcrafted and learned.

Yonglong Tian1 et al., [7] He shows superiority over hand-crafted characteristics and characteristics acquired from existing sophisticated models by using the innovative Task-Assistant TA-CNN to learn properties from various datasets and assignments (pedestrian and scene features). This is because high-level representation can be acquired via sematic activities and a range of data sources. Numerous studies support its effectiveness.

Amnon Shashua et alwork.'s [8] offers functional parameters and the design of a pedestrian detection system for on-board driving assistance apps. The method for the single-frame classification phase is based on a novel system that continuously trains a number of very basic classifiers on the clusters of the training set in order to reduce class variability.

Proposed methodology

The Fig.1 gives the detailed of the description of the entire algorithm that is used for the pedestrian detection process. The pedestrian films that already exist are used to record frames. This method alone must produce the photos needed for the dataset. The pictures are cut out of their corresponding frames. The positives and negatives from these photographs must be separated. Adaboost or SVM models are trained using both positive and negative pictures. Since there are more pixels required for the same screen size when the distance is greater, the far region must be in HD. While the middle region only requires VGA photos because it is closer than the far region and the IHOG classification may be done with fewer pixels.

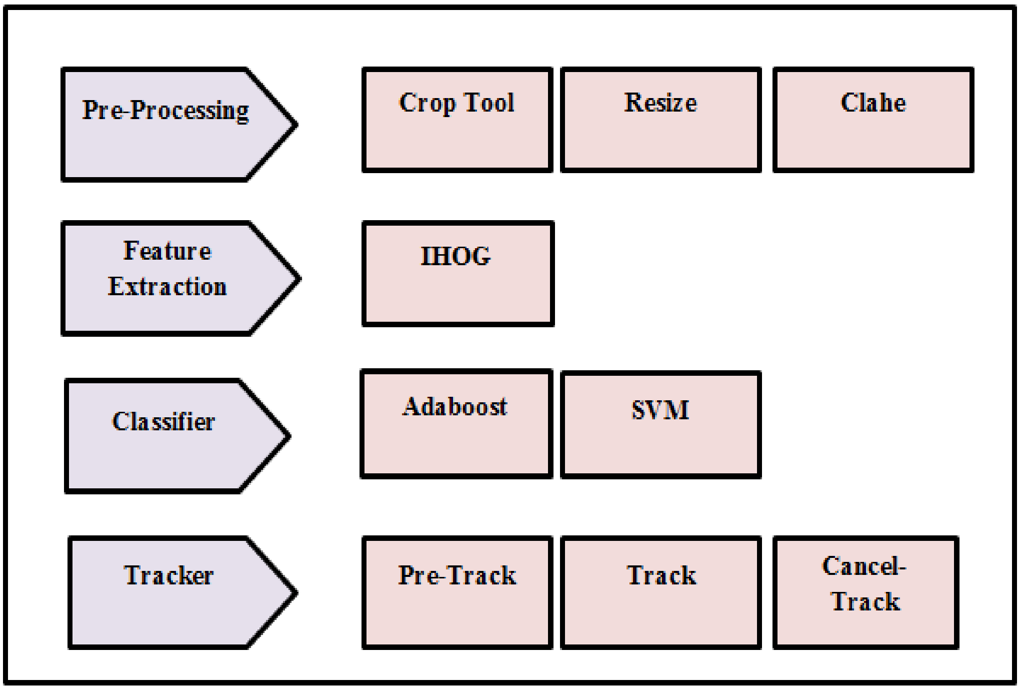

Fig.1: Proposed Methodology

Firstly the initialization is done, in the algorithm there are certain computations such has taking the captured frames from videos and later cropping those images resize them and applying clahe that are required to be done only once. Once the initialization is complete the Scanning Window selection process has to start. In this Scanning Window Selection the Region of Interest is computed.

The Scanning is done in three scales (far region, mid region and near region). Image resolutions of HD (1280*960), VGA (640*480) and QVGA (320*240) are used. For each region the scanning happens separately. A feature description streamlines the image by removing unnecessary information and extracting useful information.. The scanning window is represented by respective feature vectors. In this approach Histogram of Oriented Gradients is used as a feature descriptor in which scanning windows with different size will be represented. Integral HOG is used to reduce the repetitive HOG calculation for overlapping windows.

Fig. 2 Feature extraction using HOG

Figure.2 explains how each feature is extracted in detail. Image is taken in consideration and is divided into blocks of 8*8 pixel cells. These blocks are the feature vector dimension.

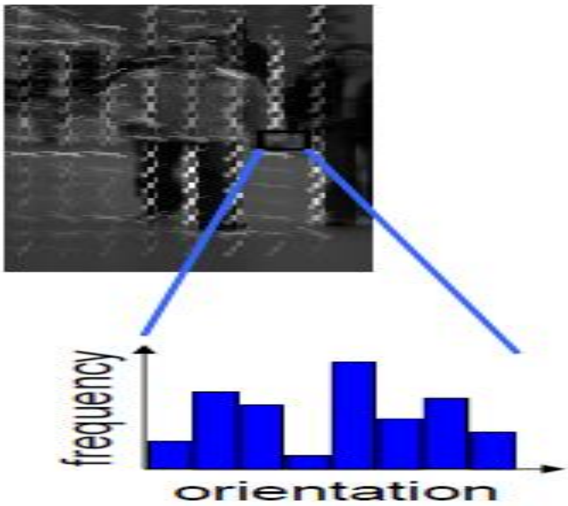

Fig 3: HOG Calculation

Figure 3 explains the HOG calculation. As shown in the figure each block is taken in consideration from which frequency and orientation is done.

The next step is the object classification that is done in two stages. IHOG feature from each scanning window is fed in to the Ada-boost classifier. Ada-boost classifier has few weak classifiers and it will pass almost all the pedestrian and few non pedestrian. Windows classified as positive from Ada-boost classifier is fed in to the SVM. As the images are passing through the Ada-boost classifier prior to the SVM, it reduces the load to the SVM. Figure 3.4 shows how objects are classified as pedestrian and no pedestrian.

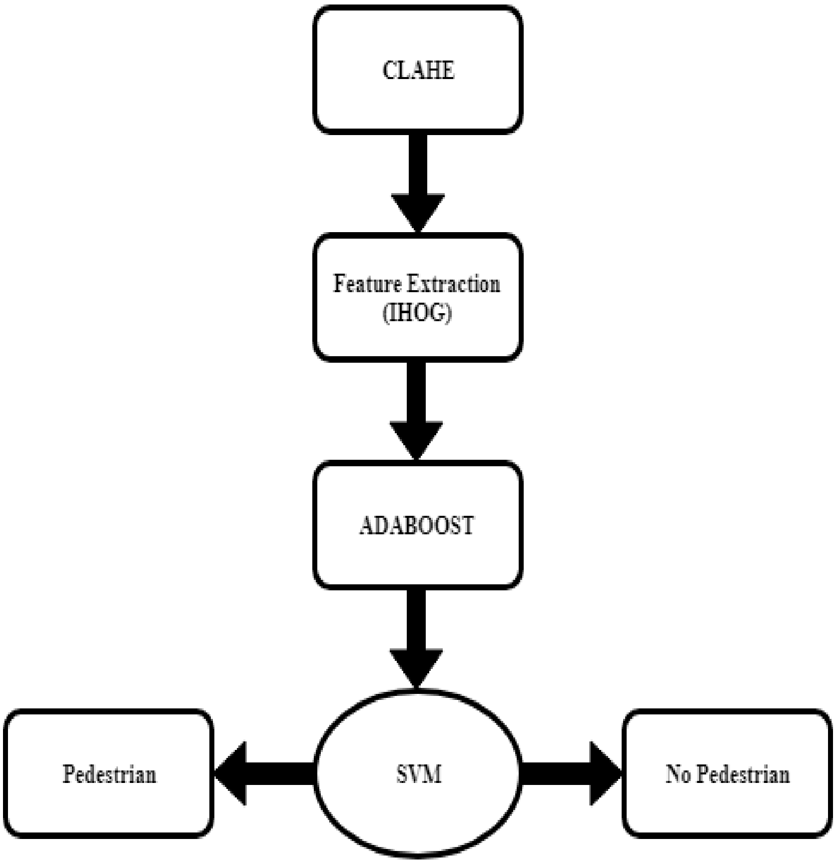

Fig 4: Feature Object Classification

Classifier turns on the windows consisting of pedestrian. As windows are tightly overlapped, there can be multiple windows around one pedestrian. Non Maximal Suppression (NMS) module will suppress these multiple boxes and give single detection box around the pedestrian based on SVM classifier and centroid location.A tracker is used to keep track of any missed detections while continuously detecting and at the same time take care of any false detections. In the pre-tracking stage the successive frames are taken and count the occurrences and the missed count are taken into account. The respective value of occurrence and missed count are incremented based on detection in each successive frame. Whenever the occurrence count reaches the threshold value the tracker moves to the tracking stage and whenever the missed count reaches the threshold value the tracker moves to the cancel track stage.

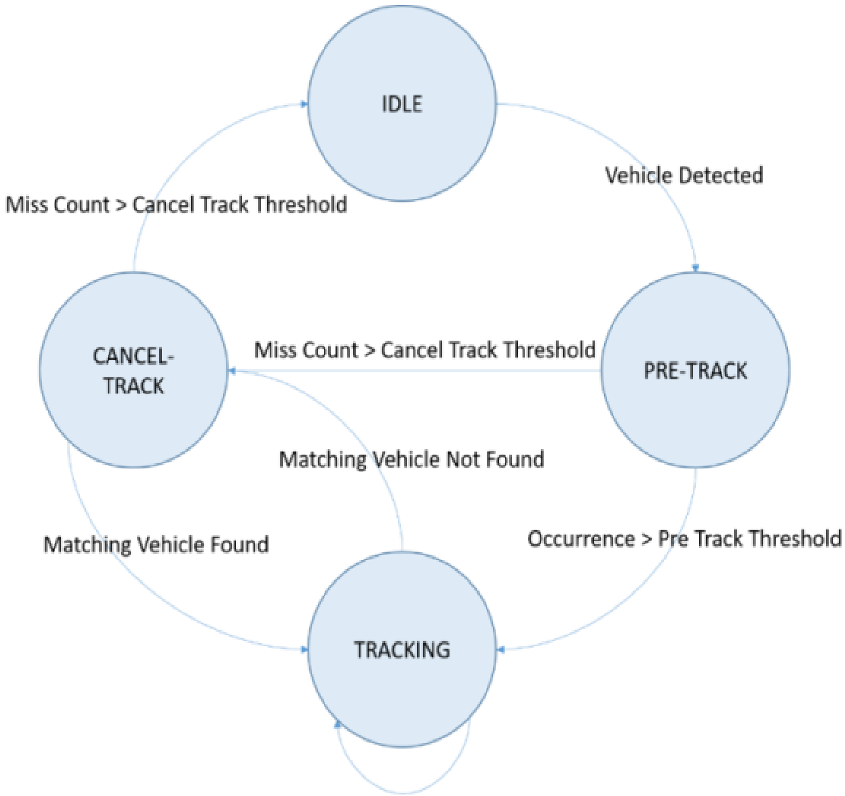

Fig 5: Tracker Process

Adaboost classifier

The goal of AdaBoost is to combine various the objective of AdaBoost is to integrate weak learners or classifiers to improve classification performance; each weak learner is trained using a small set of training samples. Each sample has a weight, and all sample weights are repeatedly adjusted. AdaBoost develops a weight for each poor learner after training them; this weight reflects the learner's resiliency.

Figure 7 displays a detailed flowchart of the procedure. The following are the main steps of the AdaBoost algorithm: Methods for sampling In this stage, some samples (Dt) from the training set are chosen to represent the set of samples from iteration t. The error rates (et) for each classifier are computed after each classifier has been trained using Dt in the training phaseand Each classifier's error rates (et) are computed. All trained models are integrated in the combination stage.

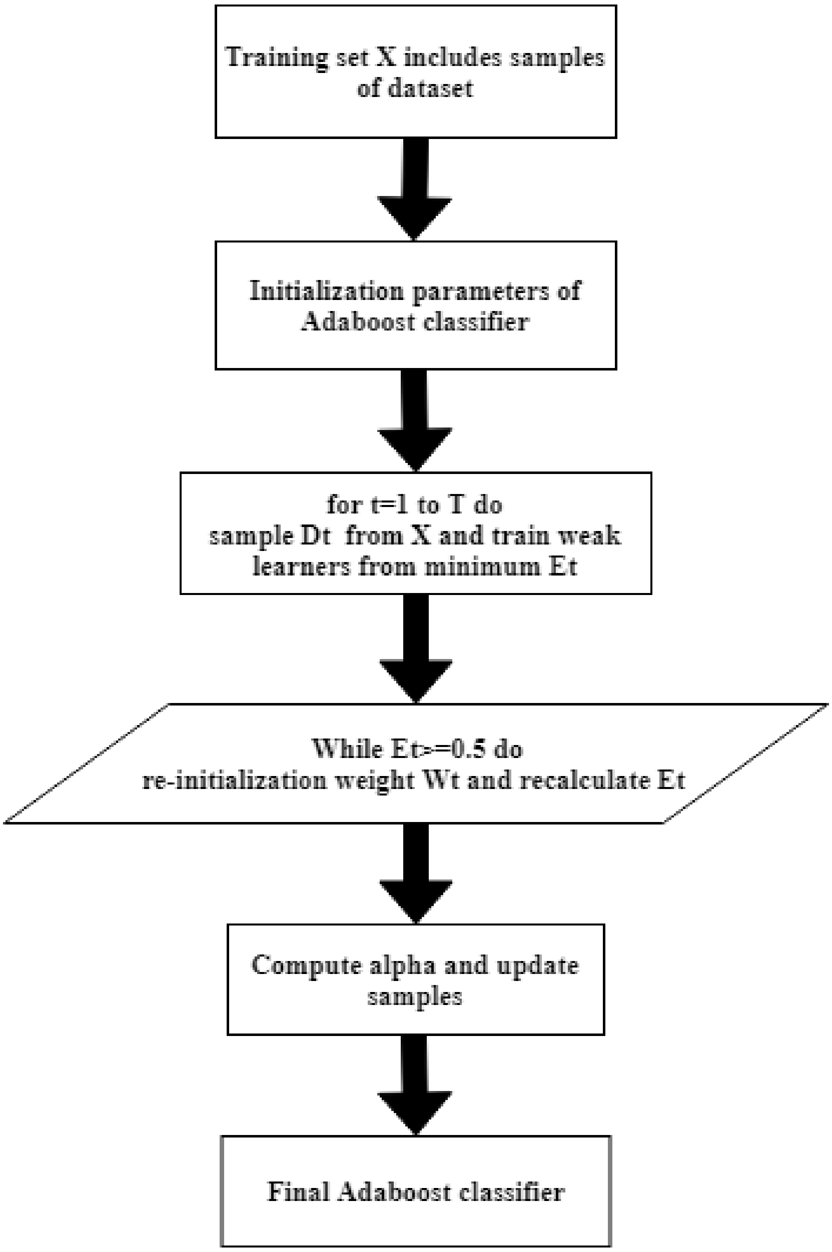

Fig7: Flow diagram for Adaboost Classifier

Error rate is calculated using the below mentioned formulae,

error = (correct – N) / N

where N is the total number of training instances, correct are the number of training cases correctly predicted by the model, and error is the misclassification rate. For instance, if 68 out of 100 training cases were properly predicted by the model, the error or misclassification rate would be (68-100)/100, or 0.32.This is modified to use the weighting of the training instances:

error = sum(w(i) * terror(i)) / sum(w)

Results and Analysis

Contract limited adaptive histogram equalization is an optimization technique used to improve the efficiency of the classification system. This system will increase the contrast and at the same time keep it within a particular frame and equalization is done. Figure 9 explains the input image that is given to CLAHE.

Fig 9: Example of Clahe Input Image

Fig 10: Clahe output Image

The CLAHE output image and how it boosts the image's contrast are described in Figure 10. The segmentation process aims to make an image representation more understandable and straightforward to analyse. Image segmentation is frequently used to recognise objects and borders in images (lines, curves, etc.).

Conclusion

The detection overall has improved. After the balance between the positive and negative pictures, the false positives have decreased and are achieved without altering the 1:2 ratio between them. This will assist to improve the efficiency of the entire system and thus increase the system's accuracy and precision. Positive and negative are varied according to the corresponding areas resulting in increased precision. The accuracy is measured by the impact of the true positives effects, while the accuracy is affected by the impact of the false positives. The true positive detection in all areas has enhanced. The system's accuracy and consistency has increased and is above 90%. The false positives have decreased and the detection's reaction time in all areas has also improved significantly.

Author Details

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