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Pedestrian Detection by Using Random Decision Algorithm with Support Vector Machine

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Abstract: *Achieving pedestrian detection by means of computer vision is not a new topic in the field of computer vision research; however it is still being pursued with renewed interest because of the huge scope for performance improvement in the existing systems. Generally, the task of pedestrian detection (PD) involves stages such as pre-processing, ROI selection, feature extraction, classification, verification/refinement and tracking. Of all the steps involved in the PD framework, the paper presents the work done towards implementing the feature extraction and classification stages in particular. It is of paramount importance that the extracted features from the image should be robust and distinct enough to help the classifier distinguish between a pedestrian and a non-pedestrian, while a good classification algorithm would go a long way in precisely identifying a pedestrian as well as in simplifying the verification stage of the PD framework. The presented work focuses on the implementation of the Histogram of Oriented Gradients (HOG) features with modified parameters that can represent accurate intrinsic information of the image. Classification is achieved using Support Vector Machine (SVM). However instead of employing a readily available SVM library, the linear SVM implemented uses the Sequential Minimal Optimization (SMO) algorithm. The results observed by this HOG-SVM combination show promise to be the best feature extraction cum classification module for a full-fledged PD system.*

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I. Introduction

In view of the fact that 22 % of the world's road traffic deaths occur among pedestrians [1], measures intended to minimize pedestrian fatalities due to negligence on part of the driver or other such unfavorable circumstances, are becoming important. Pedestrian Detection Warning System (PDWS) in automobiles detects pedestrians in front of the vehicle and warns the drivers to take appropriate decision. Such an advanced warning system achieves pedestrian safety by employing cameras along with computer vision and image processing algorithms. Generally, the task of pedestrian detection (PD) involves stages such as pre-processing, Region of Interest (ROI) selection, feature extraction, classification and tracking [2]. Figure 1 shows the flow diagram of a general pedestrian detection framework. Pre-processing (e.g. image smoothing, contrast enhancement etc.) is done on the input image/video in order to aid the performance of the subsequent stages. The enhanced image is then subjected to segmentation to obtain a set of ROIs, which in this case are the regions in the image which are more likely to contain a pedestrian. Feature extraction stage aims at acquiring certain image characteristics, which will most meaningfully represent the „pedestrian‟ information in the image. In a PDWS, the features so extracted help in classifying the input image samples as those containing „pedestrian‟ or not. Lastly, tracking is carried out to maintain the pedestrian estimates — obtained after classification — over the subsequent frames of a video, under real-time scenario.

Input
(image/video)
⇩
Pre Processing
⇩
ROI Selection
⇩
Feature Extraction
⇩
Classification
⇩
Tracking
⇩
Output
(image/video)

Figure 1: Flow diagram of major modules in vision based pedestrian detection system

II. Literature Survey

This section derives help from the work done in [5] to provide a brief overview of the feature extraction and the classification methodologies adopted by various researchers towards achieving PDWS. Amongst all the features employed across the literature, the most discriminative stand-alone feature is the HOG feature [3]. Much of its advantage comes from its ability to reliably capture the local edge/gradient information; along with a built-in invariance to local illumination condition. Almost all modern detectors employ HOG as a stand-alone detector or in combination with some other features. For instance, HOG in combination with Local Binary Patterns (LBP) and Local Ternary Patterns (LTP) has been used in [6], with improved gains in detection results. Enhancements to HOG also include the works described in [4],[7], [8], [9], [10] amongst others. Some other shape-based features have also been successfully employed. Most noticeable works amongst them, being based on shape context [11], edge let [12] and shape let [13] features. Edge lets, which are short line segments/curves, act as efficient local shape descriptors (e.g. useful for describing the head shoulder curve) and hence provide robustness against occlusion [2]. Shape let features are based on the principle of extracting gradients from the salient regions of an image, which are more likely to contain a pedestrian [11]. Both, shape let and edge let features are learned using a boosting based approach. Shape Context, similar to HOG descriptors are based on location and orientation of edges, however are represented using a log-polar histogram [11]. Covariance descriptors [7] are another popular approach for pedestrian detection. They employ a covariance matrix sensitive to parameters such as positions, gradients, gray-level of pixels, etc. Features can also be extracted from optical flow images. Dalal et al. [14] obtained the Histogram of Oriented Flow (HOF) features (describing motion) using optical flow images. However, the results obtained using motion features showed only little improvement over its counterparts. Upon obtaining the feature space representation of the ROIs, a classifier is employed to divide this feature space into the class „pedestrian" and „non-pedestrian". One of the popular classifiers is Support Vector Machine (SVM). It solves a binary classification problem by defining a decision boundary between two distinct classes, so as to have maximum margin between the classes. In case of non-linear data, kernels can be applied to linearize the data in some higher dimension, thus enabling their linear classification. Linear SVM gives good performance when used in conjunction with some discriminative feature like HOG or its variants [3], [14]. Employing a kernel-based non-linear SVM [15] yields slightly better results but at the cost of increased computation time and memory requirement. A general form of SVM, called as latent SVM, has also been used in part-based pedestrian detection scheme in [16]. Latency here refers to the initially unknown part locations in a particular detection. Boost-based classifiers are another popular classification approach. They combine various weak learners, over a number of iterations to build a robust classifier [17], [18]. Though the boosting framework requires more time to train, it is capable of making real-time detections. Cascade classifiers or a fusion of classifiers can also be used to improve detection speed and accuracy by using the output of a fast yet weak classifier, to drive a strong but slow classifier [19]. ANN (Artificial Neural networks), with their ability to store experiential data, can also be employed for the classification task. Multiple layers of neurons allow for non-linear decision boundaries between classes. The scheme used in [20] employs ANN to model parts and occlusions. Another classification approach in use currently is that of Decision forests [21]. Decision trees calculate the membership to a particular class by repeatedly partitioning a dataset into uniform subsets. Decision forests are obtained by combining the predictions of multiple independent Decision Tree Models to obtain a single prediction. Output of ANN and decision forest strategy has been found to be at par with each other [22]. However greater complexity incurred in these approaches, advocates the usage of SVM, which gives comparable performance with a much smaller implementation complexity.

III. Implementation Of Hog:

From the literature survey performed, HOG emerged as the most successful stand-alone descriptor for supervised classification. This section describes feature extraction as proposed in [23] and its implementation. Figure 2 shows the block diagram of the HOG extraction process. The following sub-sections detail each of the constituent blocks.

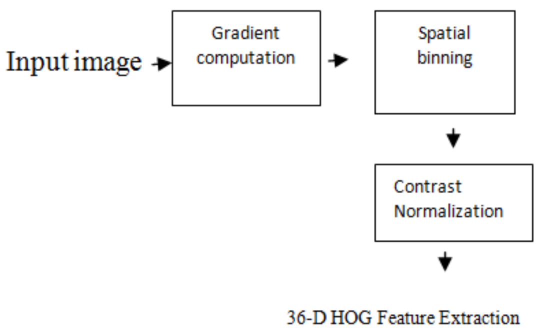

Figure 2: Block Diagram for extracting HOG from an input image

IV. Implementation Of SVM:

Support Vector Machine is a classification method and is widely used in supervised classification in machine learning applications. Using of this is Simple and accuracy, the SVM classifier is popular because of the ease and it is convert the low dimensional data to high dimensional data. It performs binary classification by defining a hyper-plane that classifies the input data into two classes. As shown in Figure 3, SVM has two variants - Hard margin SVM and Soft-margin SVM. Hard margin SVM requires all data points to be classified correctly into their respective classes. However, the more popular soft-margin approach allows controlled misclassification of difficult or noisy examples — using a parameter „C" — to achieve a maximum margin linear classifier by avoiding over-fitting and hence, the usage of kernels.

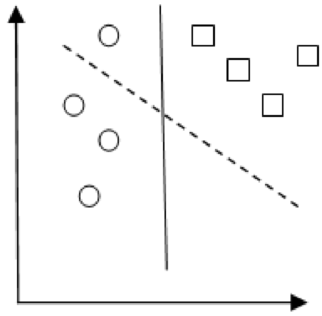

Figure 3: Hard-margin (solid line) and soft margin (dotted line) SVM Classifier

V. Implementation Of Random Decision Algorithm

A conventional RDF learning procedure is based on feature vectors of the whole object - in our case, of a person. Following the classifier's internal structure, introduced in the above Section, a randomly selected element from HOG is not a discriminative representation of the sample. Thus, we propose to apply the forest to deduct discriminative information from image patches, i.e. from parts of the human body. Instead of mixing randomly selected local patches from The tree-training procedure focuses on the appearance of the body parts.

Using such localized regions, simple split functions yield better performance compared to an application of the whole bounding box for tree training random locations, we use the same location and size of a patch in each training sample as a tree training set. In this way, the location of body parts is kind of "encoded" for training.

VI. Conclusion and Future Work:

In this paper, feature extraction and classification are presented in the implementation of two key blocks in the pedestrian detection frame work. We use the HOG features for implementation of feature extraction, with a cell size of 16X16 (for computational speed up) and an efficient normalization strategy. Implementation of the classification module we use a soft margin linear svm based on the simple yet efficient SMO algorithm. Here classifier uses a subset of the pedestrian Dataset CVC-02, which is specifically aimed at the training and testing of the classification stage. It shows high pedestrian classification accuracy (TP) of 95% and overall classification accuracy (TP+TN) of 92% of results, the implemented feature-classifier ensemble can act as a fast and robust building block for a complete PDWS. However, to further improvise the results of the presented work, measures such as increasing the amount of training data of the classifier and using a suitable verification strategy — to reduce the number of false positives incurred — can be undertaken. Future work can also be aimed at the implementation of an equally efficient segmentation approach, which would complement the presented feature-classifier modules.

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