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Active Pedestrian Safety Systems

Rudrappa B. Gujanatti[1], Arun S. Tigadi[2], Anil Varghese Koshy[3]

[1] Assistant Professor ,Electronics and Communication Department, KLE Dr M.S Sheshgiri College of Engineering, rudraguj@gmail.com

[2]Assistant Professor, Electronics and Communication Department, KLE Dr M.S Sheshgiri College of Engineering, arun.tigadi@gmail.com

[3] Electronics and Communication Department, KLE Dr M.S Sheshgiri College of Engineering, varghesekoshyanil24@gmail.com

Abstract

We study the question of feature sets for robust visual object recognition; adopting linear Support Vector Machine (SVM) based human detection as a test case. After reviewing existing edge and gradient based descriptors, we show experimentally that grids of Histograms of Oriented Gradient (HOG) descriptors significantly outperform existing feature sets for human detection. We study the influence of each stage of the computation on performance, concluding that fine-scale gradients, fine orientation binning, relatively coarse spatial binning, and high-quality local contrast normalization in overlapping descriptor blocks are all important for good results. The new approach gives near-perfect separation on the original. Massachusetts Institute of Technology (MIT) pedestrian database, so we introduce a more challenging dataset containing over 1800 annotated human images with a large range of pose variations and backgrounds.

Keywords*-Histograms of Oriented Gradients (HOG); Support Vector Machine (SVM); Region of Interest (ROI); Stereo Vision; Optical Flow.*

I. INTRODUCTION

When people originally thought about intelligence and machine, they probably had an idea of something like a robot. Some people had a very different view of future machine intelligence. Its the first large scale deployment of embodied machine intelligence and it comes to us in a form that is very familiar, it's our modern car.

Modern car has sensors to sense the surroundings. They obtain the information, they reason upon this information and they act upon their environment. Machine intelligence comes to us in bits and pieces that we call driver assistance. They help us to operate the vehicle more safely, comfortably and energy efficient fashion.

We see here in figure 1 driver assistance currently available in the market. We consider driver assistance as a stepping stone for fully autonomous driving. By focusing on this intermediate step, where the driver is still involved and by focusing on cheap and reliable hardware we can make an impact on traffic safety now and with every new vehicle generation that we introduce to the market.

Figure 1: Driver Assistance

II. WHY IS IT DIFFICULT?

Now let us assume, that we are travelling down town and our kids are making fuss backside or you are setting the radio or typing the destination in the navigation module and you are not paying attention, suddenly a traveller runs on to the street just infront of the vehicle.

This is a typical dangerous situation that can occur when the driver is not paying attention or the visibility conditions are poor perhaps at the night. Such situations have had much emotional appeal, but it's not just emotions, it's hard figures. Figure 2.1 shows worldwide traffic fatalities.

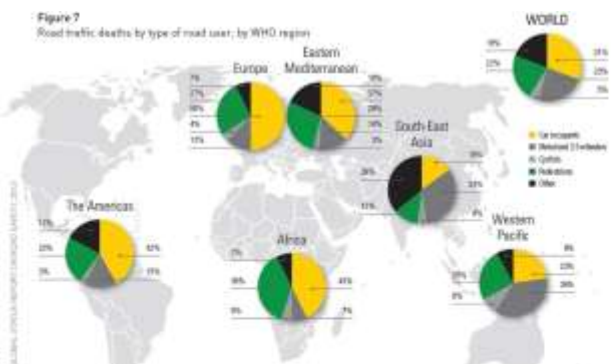

Figure 2.1: Worldwide fatalities

We can see that about 22% of fatalities are due to collision of the car with the pedestrian worldwide. Triggered by this accident number, there have been large numbers of steps taken from legislative on pedestrian safety. So basically, we aim at designing a system that uses sensors to detect such dangerous situations involving pedestrians, bicycles and take safety measures, like either warn the driver or take control over vehicle control system.

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Now let us consider why this technology is difficult to implement and so why is not implemented in the earlier days. Following are the points which contribute.

1. Large variation in pedestrian appearance induced by viewpoint, pose, clothes.
2. Dynamic and cluttered background.
3. Pedestrians can exhibit a highly irregular motion which makes it difficult for path prediction module and situation assessment module to figure out what is going on.
4. Real time processing is required.
5. Stringent performance requirements, especially for emergency maneuvers.

III. PEDESTRIAN RECOGNITION

3.1. Pedestrian recognition today

Figure 3.1: Modes of operation of current pedestrian detection equipments

Now the field is quite mature. We have a large number of universities working on Pedestrian Detection equipments and we can see many products coming into the market. Each of these products basically distinguish three main application systems

- Scenario for far range for secondary roads typically at night time
- Intermediate range for the urban area, typically pre-crash scenario
- Surround View setting for the immediate neighborhood of the vehicle helps the man while taking turns, parking when the driver would like to see if pedestrians are around you.

All the above settings have adverse setup requirements in terms of sensor range, sensor speed, vehicle speed involved, field in view and also in terms of performance i.e a response in terms of warning the driver is different from that of emergency braking. Here we focus on the pre-crash setting as it contributes to the accident number largely.

3.2. Pedestrian recognition performance (last decade)

Figure 3.2: Performance since the last decade

From Figure 3.2 we see that in the year 2003, the efficiency was about 40% i.e. there were 600 false pedestrian detections per hour, when the vehicle moved at a speed of 30 Kmph. In the year 2005, with few developments the experiments were repeated and we obtained an efficiency of 65% with a number of false detections reduced to 100, with vehicle speed 40 Kmph. In the year 2008, the number of false detection was 10 resulting into an efficiency of 85% when the vehicle moved at a speed of 50 Kmph. But now we have 100% performance with no false detections when the vehicle moves with a speed of 50 - 65 Kmph.

IV. HOW WAS A BETTER PERFORMANCE MADE POSSIBLE

4.1. Better algorithms

Figure 4.1: Logical Architecture for Pedestrian detection systems

We have a set of modules like ROI generation module which could use a stereo or optical flow if we are using monocular vision or we can use geometric views where we assume that pedestrians walk on a ground plane. From the ROI generation module, we get a bunch of windows, which are then tested against the classification module and for those that pass we temporarily integrate and we perform tracking. We also at this stage fuse it with any other sensors, e.g. RADAR and then pass it to the path prediction and risk assessment module and then to driver warning and vehicle control.

Now let us brief up with the technologies which emerged for pedestrian detection.

1. HAAR wavelets as features+AdaBoost: It basically sums up pixel intensities in the white region and that of the black region and finds the difference to get a scalar value over an image feature. It was then combined with SVM.This was working very well for face detection, but didn't work well with articulated objects like people or motorbikes. The system improvement then just went on in designing a robust system for generic object detectors.
2. Edge Templates: Here edge templates for people were determined from images for pedestrian detection in smart cars like Mercedes Benz. This worked very well for pedestrians on the road, but when the same concept for generic objects detection, it didn't work very well.
3. Key detectors: [1] Here we determine the most characteristic points for example in figure we can see that all corners are detected as characteristic points. But when we apply those for object detection incase of finding people we observe that

from one frame to next frame the key points don't remain the same.

Figure 4.2: Key features for consecutive frames of a video

[3]So what really worked was a simple system. The system working starts like this we have an image. We mark big bounding box which forms the last layer of the pyramid (figure 4.3). We put a detection window on this image. This detection window is of fixed size. We now scan all possible locations of the image. We then reduce the image size and then scan the location again; Each time we scan we extract certain features. These features are given to a learning algorithm (like SVM, Boosting board framework). We now get multiple search outputs of these detections. Final System just combines such systems outputs and then gives you a final output. This was proposed by Viola and Jones in 2001 for face detection. and only when people got to know how to best detect features from an image they obtained a method to design a robust system for object detection.

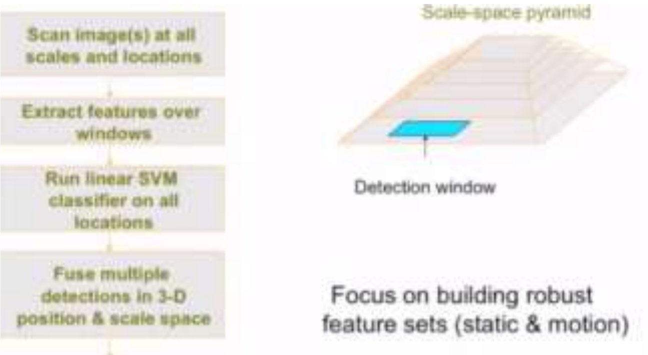

Figure 4.3: Simple detection system.

V. HOG Feature

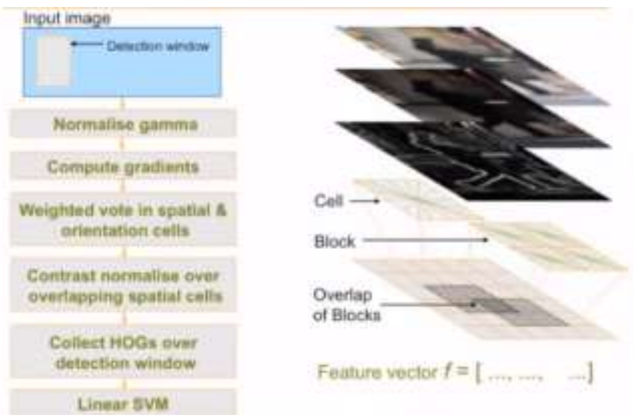

Figure 5.1: Basic Algorithm for HOG Features

[2]Here we have a detection window of size 128X64. We take about 3000 images and mark bounding boxes around the pictures. Then we normalize the image by taking the square root of the pixel intensities or take its log, depending upon what kind of image it is. Next we compute image gradients. We calculate magnitude and orientations of the gradients. We then split the window into a dense grid. In each grid we have cells. In each cell we take a pixel gradient, We figure out its orientation and magnitude, we create a Histogram of Orientation in this cell and weigh that histogram by the magnitude of the gradient. So we create histogram of oriented gradients and hence this technology gets its name. Now if we consider 8 bins from 0-180 degrees then we consider a pixel orientation and then based on it we add its magnitude to a particular bin. Next we combine several of these cells to create a block. A block allows us to normalize the image. Normalization allows us to get rid of the effects in change in light. Now these blocks are partially overlapped. We put them one after the other in a feature vector. Now we use learning algorithm. Basically here linear SVM. We give it these features vector; We also tell it that in this window we are expecting a person so we give it a label +1. Similarly we follow the same steps for all positive images. Now we repeat this process for negative images with -1 label and give it to linear SVM. Now when both of these images are given at a shot to L-SVM it compares each time it gets a similar feature vector, it checks "Hey did i see a person??". So it's basically a data driven algorithm in which you have a bunch of data, fixed way of computing and give it to L-SVM and it learns over them.

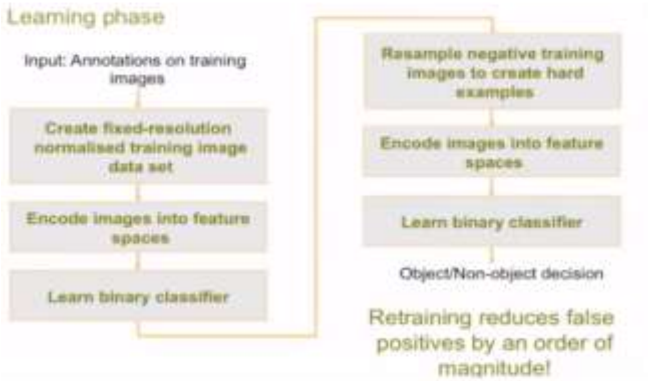

Figure 5.2: Final System outlook

So this is how the overall system looks like figure first we create fixed resolution normalized training image data set. Then we encode images into Feature spaces(i.e. the computation of feature vector). Next we give it for learning to a binary classifier. So now at this stage we have a system but its not robust. Now we go back to the original training images, but now we are looking at negative images. We resample all the locations and then do a dense scan at every location and every scale. Then we encode all the scanned images into feature spaces and now you learn the same binary classifier and check it's output whether positive or negative. If positive, a person is detected and then the image becomes the part of data set. Now this boosting or bootstrapping significantly reduces the false detection rate.

5.2. More Data

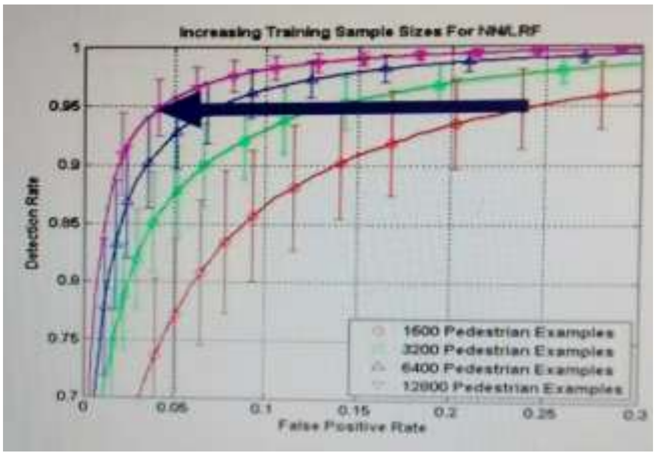

Figure 5.4: Performance of increasing data sets.

As we all know when we train on more data the more better we all are going to be. Here figure we have some experiments where we are doubling the samples or the data set. We have on the X-axis Detection Rate and on the Y-axis False Positive rate. Here we can see the performance graph is steeper.

Earlier data set was prepared from actual pedestrian then pedestrians' data samples were created using synthesized examples. Now there are even larger data sets. So labeling all these pedestrians sets is a tedious job. Also a lot of effort goes into devising intelligent tools to acquire and enrich the data that we collect. So we basically manipulate the existing data sets like late mirror images, enlarge/compress the images change their appearance, texture and hence multiply the data set.

.VI. ADVANTAGES AND DISADVANTAGES

6.1. Advantages

- The algorithms are such as Histograms of Oriented Gradient (HOG) descriptors significantly outperform existing feature sets for human detection.
- The each stage of the computation on performance, such as that of fine-scale gradients, fine orientation binning, relatively coarse spatial binning, and high-quality local contrast normalization in overlapping descriptor blocks are all important for good results.
- The pedestrian detection safety system prevents accidents to a greater extent.

6.2. Disadvantages

- May lead to hijacking of the car.
- A lot of development is yet required and the concept is still progressing.

VII. CONCLUSION

We have successfully analyzed the difficulties behind pedestrian detection and learnt the different algorithms used for pedestrian detection and safety systems such as the early HAAR wavelet like features+Adaboost, Edge Template, Key features characterization and the recent, currently being used HOG feature for human detection technology. There are yet a lot of research that is being done in this field and more efficient algorithms with no false detection even at high speed of mobility are likely to emerge in the near future.

We have also gone through the aspect of a system response. Analyzed the role of transfer function in determining the stability of a system and the different types of stability and their characteristics.

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