PEDESTRIAN DETECTION ALGORITHM BASED ON LOCAL COLOR PARALLEL SIMILARITY FEATURES

Xianxian Tian, Hong Bao*, Cheng Xu, Bobo Wang

Beijing Key Laboratory of Information Service Engineering

Beijing Union University, Beijing, China

Emails: tianxianxian@buu.edu.cn, baohong@buu.edu.cn,

xucheng@buu.edu.cn, hbcxwtb@163.com

Abstract: HOG Feature is the mainstream feature applied in the field of pedestrian detection .HOG combined with CSS has good effects on pedestrian detection. Because of the large amount calculation of HOG and CSS, HOG and CSS has poor real-time performance, we propose LCSSF (Local Color Self Similarity Feature) avoiding calculating the global color similarity distribution of CSS. The tested results of the Inria and the street pedestrian database show that the accuracy of the HOG with LCSSF has better detection performance and better real-time performance than HOG and CSS.

Index Terms: Pedestrian detection, Local Color Self-Similarity Feature, SVM, HOG

I.   INTRODUCTION

With the rapid development of information technology, Pedestrian detection has been a focus of recent researches due to its importance to practical applications，such as driver assistant[1], visual surveillance[2][3] and Argument Reality[4][5]and so on. In recent years, human beings are the main body of social activities. The crowd analysis is the important content of the intelligence crowd surveillance [6]. With the increasing of people's social activities, the large population density might cause for numerous casualties. In our daily life, people often   come in and out of the subways, railway stations, supermarkets and other places, visual surveillance for human detection is very necessary and is widely used, so pedestrian detection has a broad application prospect and research value. There are many research institutions developing intelligent vehicles [7] all over the world, they are scientific community and industries, the technology of intelligent driving has become a hot topic in recent years. In the field of intelligent driving, human detection is the most challenging task in realization of vehicle automatic driving. To make sure the safety of people in front of the vehicles is the most important part of ADAS which is short of Automated Driving Assistant System. With the development of argument reality [4] [5], pedestrian detection technologies have been used to locate the people in the real world coordinates by computing the 3D position of the virtual world, and the technologies of argument reality has also worked with the visual surveillance system, the managers can easily get sufficient information about the people in the situation and do with the results of the alarming system.

In intelligent monitoring system [2] [3], by detecting pedestrians in the camera view, we can analyze the behavior of the pedestrian [6][8][9], estimate the crowd flow[5][6][10] and so on. Through video processing technologies and image processing technologies, the workers can regulate and control the safety of the public places. By combining the pedestrian detection technology and target tracking technology, the workers can get the information of suspicious person in the public places at anytime without consuming large amount of time and costing lots of workers, the intelligent monitoring system can automatically recognize the interested

persons and track, then give an alarm of anomalies, avoid the losses of the public property. The people in front of the vehicles is usually upright, but the pedestrian captured on the image plane changes from position to position and from person to person .This is due to the various of pedestrians in the world and the pedestrian's perspective projection phenomenon, in other words, the image formation captured from on-board camera varied is due to the different distances from the on-board camera to the pedestrian.

There are many difficulties for pedestrian detection. For example，pedestrians wear colorful clothes from person to person, pedestrians stay in different environment, pedestrians' postures change from time to time and from person to person, so it becomes a very challenging task to achieve the pedestrian detection in the intelligent driving system. In intelligent driving system, the application of the pedestrian detection technology is necessary for the drivers driving a long time or driving in the night, fatigue driving [11] is a major source causing the car accident, therefore, building intelligent control system in hardware and designing warning system on board is very important. These systems can avoid unnecessary accidents both for the safety of drivers and the people walking in front of the car. These systems can provide a win-win situation.

Target detection is the basis of target recognition [12], pedestrian detection is the premise of pedestrian analysis which include target recognition, target tracking, pedestrian behavior analysis etc. Pedestrian detection has two important parts: feature extracting and detector designing. Pedestrian detection has three steps. Firstly, extract characteristics of pedestrian, such as the contour characteristics of the pedestrian, color characteristics of the pedestrian or texture characteristics of the pedestrian etc, then train a classifier, finally get the pedestrian detector, the detector can be used for pedestrian detection in images and videos. The pedestrian detection in videos will provide the location information of pedestrian and the identification of the pedestrian, in the future's processing step, we will use these information to track and analyze the behavior of pedestrian etc.

Pedestrian detection has an important role in the application and scientific research field. For example, the Chinese academy of sciences, Tsinghua university, Xi 'an Jiaotong university and other academic units do lots of relative works like gait analysis of pedestrian, pedestrian's

posture estimation etc. Some abroad researchers ， such as Carnegie Mellon university, Massachusetts technology institute etc., they established the relevant standard library for the pedestrian detection and proposed some standards for evaluating the characteristics of the detector. The pedestrian detection system based on infrared camera [12] has been used in the Honda vehicle system; the University of Parma in Italy developed a pedestrian detection module in the intelligent vehicle system. Many experts and scholars are inspired to study the pedestrian characteristics and detector.

Due to the diversity of the human clothes, non-rigid of the pedestrian body, the light transformation of the environment, it makes extracting strong applicability characters of pedestrian harder and harder, the pedestrian characters within the class has a big discrete degree, the pedestrian detection algorithm with the high detection rate and high speed is still a difficulty in academic research field and is still a hot spot in the field of application.

Dalai [14] proposed HOG (Histogram of Gradient) first in 2005,and HOG is now still the mainstream character of the pedestrian detection, its detection performance is very good, but with higher consuming of the computation time , so it cannot get widely be used. Later, a lot of researchers try to improve HOG, such as the literature [15] put forward using the GPU/FPGA to accelerate, literature [16] used the method of integral vector diagram to speed up the calculation and improve the detection performance, literature [17] proposed HOG with LBP texture information ,the algorithm on the Inria pedestrian database got very good classification effect, but the literature [18] pointed out that LBP features with poor performance on the other standard database ; Literature [18] proposed the CSS(color self symmetry information), the CSS feature combined with HOG got good performance on different kinds of database for example TUD-Brussels[19], Caltech-pedestrians[20], Inria[21]. The paper [18] points out that HOG and CSS combined with the optical flow method making the detection rate higher and can be used in the video to do pedestrian detection. However, to achieve good real-time applications, such design is not satisfied with the moving cameras and it also cannot detect the still pedestrian in the scene with still cameras, it doesn't solve the fact of time-consuming of feature extraction, literature [18] as the first one proposed the application of the color information of pedestrians in pedestrian detection and got a good

performance, it is a innovation character of pedestrian detection , before that the color information of objects has been widely used in image retrieval and other fields, it's mainly due to the diversity clothes of pedestrians. To try to apply the pure color information to describe the pedestrian is not workable, because the pedestrians' clothing is colorful. Though the color of the clothes is different, the body's color has characters of symmetry distribution and similarity distribution, therefore to quantify the color distribution structure of pedestrians, and to get the color similarity and symmetry distribution features of pedestrians can be another more effective feature except for the contour features of HOG .The literature [18] is the pioneer of using color distribution analysis of pedestrians, but the literature [18] caused a large amount of redundant information and redundant computation in the way of extracting the color information of pedestrians, it has a bad impact on the detection accuracy and real time performance of pedestrian detection . This paper puts forward a new feature based on color distribution characters of pedestrian named LCSSF (Local Color Self Similarity Feature), including selecting color symmetry and similarity areas of pedestrians, extracting statistical characteristics of color, measuring the similarity of the color histograms. In our method, we set a limitation area of similarity measure, the experimental results showed that the LCSSF has better detection performance than paper [14] and paper [18] and has better performance in extracting feature time, the training detector time, predicting time on the same datasets in the experiment section, we introduce concrete results compared with paper [14] and literature [18] in the experiment section.

II.   RESEAERCH METHOD

The paper[18] used HOG with CSS features and tested it on different pedestrian database[19][20][21], it got a better classification effect, but due to HOG and CSS features' time-consuming shortcomings, the method of literature [18] cannot be widely used. By analysis the feature structure and the time consuming reason of CSS feature in ref. [18], this paper puts forward the LCSSF (local color self Similarity Feature) which is quite different from the global color similarity with the literature [18].

In this paper, we divide the people's color similarity regions and symmetric regions into three parts, they are head-should part, upper body part, leg part as Fig. 1 showed. Through Fig. 1, we can see the color in each part has similarity and symmetric distribution features. In this paper, we propose a method to describe those color features. Finally, we propose the LCSSF (Local color self similarity feature). The proposed LCSSF feature is composed as following.

Step1: Divide pedestrians image into blocks, as shown in the Fig. 1, this is an average image of multiple samples of pedestrian, the size is 64×128 . We divide the average image into 8×16 blocks, each block is 8×8 pixels, each block with no overlap .We use the average pixel values as the pixel values of the block, the first rectangle region shows the head-shoulder of a person ,we can see in the same row ,the blocks in the same row has similarity and symmetric. In the second rectangle region, there is a larger region with similarity and symmetric blocks .In the third rectangle region, there are blocks with similarity and symmetric distribution in the same row. In the second and third rectangle part, we can also see in the same column, the blocks also have similar distributions, but it can only provide similar characters only without symmetric information, so in this paper, we only use in the horizontal row to calculate the similarity of the color blocks. Above all, we can get this conclusion, the symmetry distribution of pedestrians have characters, these symmetry regions are mainly distributing in the head and shoulder part, upper body part, leg part. Each part has the obvious local color similar distribution and symmetric distribution. Based on those characters, it is necessary to measure the local color's similarity and symmetry of the human in horizontal direction.
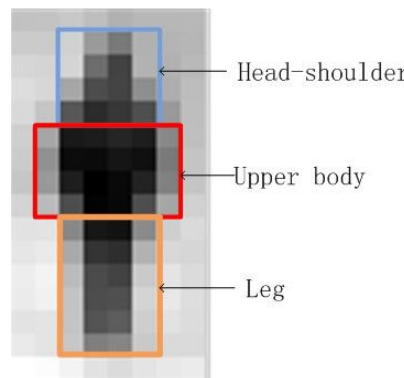

Figure 1.   The Local color similarity and symmetry distribution diagram of pedestrian
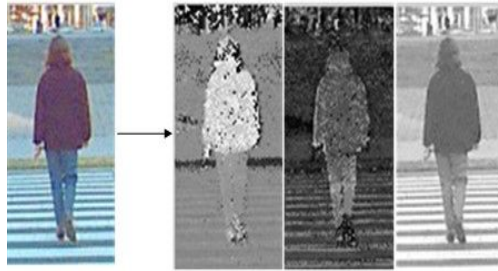
Figure 2.　Original image and each channel image in HSV space

Step2: Convert Color space. The input image, namely row image, will be convert into a color space, such as convert into HSV color space, as shown in Fig 2, the row image is in RGB color space and it is converted into HSV color space, the three pictures on the right side are the images which are split into H channel and S channel and V channel from the row image. In the following part we will extract color information through those images.
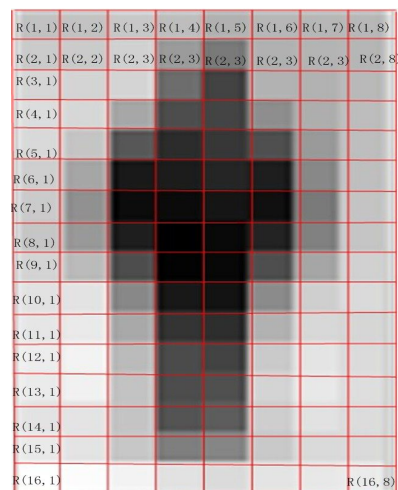

Figure 3.　Block Serial Number Schematic diagram

Step 3: Calculate the Color Histogram of each block. As shown in Fig. 3, we describe the color histogram of each block using number ranked by its row and column number. For example, we give the color histogram expression of the first block using R(1,1), the second block expression use R(1,2)…,the last block use R(16,8). It is ordered for the following steps to do the calculation of the feature. After step1 and step 2, we know each block has three color channels, for each color channel of the block, we calculate the color histograms with three bins, and finally each block will get $3 \times 3 \times 3$ histograms. To calculate the histogram, we use trilinear interpolation, Fig. 4 shows a 8×8 block, the block with a center(x1,y1), the color value of a pixel we use expression with c , the c will be distribute in the region between c1

and c2 by function (1). To make the difference expression of color value in different channels , we use channl1(x,y),$\cdots$,channel3(x,y) instead of c. The block center (x1,y1) can get different color histogram chnl1h(x1,y1,c1), chnl1h(x1,y1,c2),$\cdots$ chnl2h(x1,y1,c2), chnl3h(x1,y1,c1), chnl3h(x1,y1,c2) , the function (1)shows the trilinear interpolation of the each pixel in each color space, x,y express the position of the pixel in the image, dx and dy express the block's width and height, dc expresses the interval of the histogram. The rest of the blocks can also be calculated as above.

$$chnl1h(x_1,y_1,c_1) \leftarrow chnl1h(x_1,y_1,c_1) + channel1(x,y)(1-\frac{x-x_1}{d_x})(1-\frac{y-y_1}{d_y})(1-\frac{chnnel1(x,y)-c_1}{dc})$$

$$chnl1h(x_1,y_1,c_2) \leftarrow chnl1h(x_1,y_1,c_2) + channel1(x,y)(1-\frac{x-x_1}{d_x})(1-\frac{y-y_1}{d_y})(\frac{chnnel1(x,y)-c_1}{dc})$$

$$chnl2h(x_1,y_1,c_1) \leftarrow chnl2h(x_1,y_1,c_1) + channel2(x,y)(1-\frac{x-x_1}{d_x})(1-\frac{y-y_1}{d_y})(1-\frac{chnnel2(x,y)-c_1}{dc})$$

$$chnl2h(x_1,y_1,c_2) \leftarrow chnl2h(x_1,y_1,c_2) + channel2(x,y)(1-\frac{x-x_1}{d_x})(1-\frac{y-y_1}{d_y})(\frac{chnnel2(x,y)-c_1}{dc})$$

$$chnl3h(x_1,y_1,c_1) \leftarrow chnl3h(x_1,y_1,c_1) + channel3(x,y)(1-\frac{x-x_1}{d_x})(1-\frac{y-y_1}{d_y})(1-\frac{chnnel3(x,y)-c_1}{dc})$$

$$chnl3h(x_1,y_1,c_2) \leftarrow chnl3h(x_1,y_1,c_2) + channel3(x,y)(1-\frac{x-x_1}{d_x})(1-\frac{y-y_1}{d_y})(\frac{chnnel3(x,y)-c_1}{dc})$$

(1)

Eq. (1) and Fig. 4 express the trilinear interpolation schemes of each block , the distances from the position of the center of the block to the pixel is used to weight the color values of each pixel to calculate the color histogram.
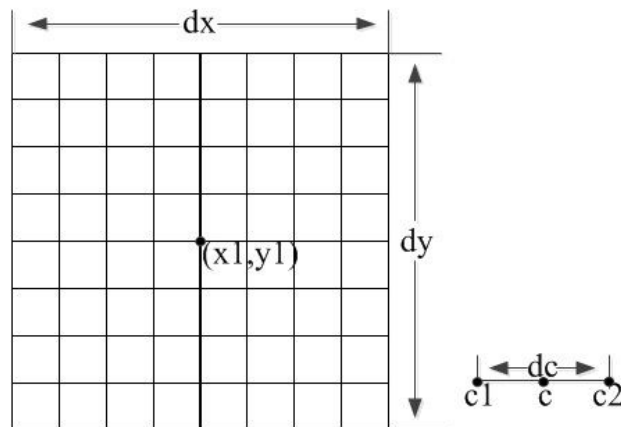

Figure 4.   Colors of three linear interpolation schemes

Now we can get 9 bins of color statistical histograms of each block:

$$R(i,j) = \left[chnl1(x_i,y_j,c_1),\cdots chnl3(x_i,y_j,c_3) \right] \quad (2)$$

In this paper, we use the size of the pedestrians' images as 64×128 to do the similarity calculation of pedestrians; Eq. (3) shows the composition of part01. We use Part01 to define the color histograms of head and shoulders as:

$$Part01 = \{R(i,j) \mid 2 \le i \le 4, 3 \le j \le 6\} \quad （3）$$

We use the Part02 to do the similarity calculation of pedestrians; Eq. (4) shows the composition of Part02. We use Part02 to define the color histograms of upper body as:

$$Part02 = \{R(i,j) \mid 5 \le i \le 8, 2 \le j \le 7\} \quad （4）$$

We use the Part03 to do the similarity calculation of pedestrians; Eq. (5) shows the composition of Part03. We use Part03 to define the color histograms of leg part as:

$$Part03 = \{R(i,j) \mid 9 \le i \le 15, 3 \le j \le 6\} \quad （5）$$

Step 4: Neighborhood constrain for computing the color similarity features of each part:

Figure 5.   Three symmetric distribution part of body diagram

Fig. 5 shows the symmetry distribution regions of pedestrian. The neighborhood constraint of similarity measurement is: measure similarity only with the same row blocks, so that head-shoulder part we can get $4 \times 3 / 2 \times 3 = 24$ dimension vectors and the upper body can get $6 \times 5 / 2 \times 4 = 60$ dimension vectors, the leg part can get $4 \times 3 / 2 \times 6 = 36$ dimension vectors. Above all, we finally get 24+60+36=120 dimension vectors.

Color similarity measure methods: there are many ways to measure histogram similarity, this article adopts the method of histogram intersection .The intersection method is proved to be the best, the measure method is as follows: $R(\text{k},l)$ and $R(m,n)$ are two histograms of nine bins, For convenient expression, we use M expression $R(i,j)$, N expresses $R(m,n)$, then each histogram components can be expressed as: $M(\text{i})$ and $N(i)$. Among them $i = 1,2,\ldots,9$, histogram intersection distance can be expressed as:

$$D(\text{M},N) = \sum_{i=1}^{9} \min(M(i), N(i)) \quad (6)$$

Step 5:The vectors of each part need to be normalized .Use $L2 - \text{norm}$ to do the normalization for the color similarity vector of each part, then combine vectors of each part ,

finally the three parts' vectors are consist of 120 dimensions vectors ,we call it LCSSF(Local Color Self-similarity Feature). So far we get 120 – dimensions' feature vectors, namely LCSSF, to describe pedestrians' color distribution features.

III.   RESULTS AND DISCUSSION

In this paper, for our evaluation, we focus on the INRIA [21] pedestrians dataset, it includes a number of 2416 images of pedestrians and contains 288 pedestrian images as test images, we use it mainly for comparing the performance and speed of the literature [18], we use our LCSSF feature with HOG instead of paper [18] using HOG with CSS. And according to the reality demand, the pedestrians in intelligent driving assistant system are almost upright walking before the car, to train a classify model needs more positive samples. There we combine datasets of pedestrian walking on street. We use Upright Front View Data (short of UFVD), the datasets are composed of standard database with a total number of 2786 positive samples of pedestrians, the datasets mix all Data of MIT [22] pedestrian walking on the street, 1862 positive images of CASIA GAIT [21] about walking pedestrians from 0 to 180 degrees relative to camera, some positive samples of CASIA GAIT image Data is shown in Fig. 6, mainly people are upright in road plane.

Figure 6.   Pedestrians different Angle relative to the camera

We also collect 266 walking pictures of pedestrians involving indoor pedestrians and outdoor pedestrians walking on the street as test images, the datasets including pedestrians that have an angle of 90 degrees toward camera as more difficult positive samples for classifier because of it is very different from the people standing along the direction of the capturing camera. To

use this kind of dataset to test the results of our method is more meaningful and is full of challenges.

In this paper, we adopt the method of cross validation method to select the penalty factor c of SVM for our feature, namely HOG with LCSSF. We randomly selected 2416 positive samples and 1218 negative samples of Inria datasets, as the table 1 shows below. We keep a positive and negative samples ratio 1:2, then we randomly divide 3634 samples into ten parts, we select one of ten parts as the test samples, the rest of the group as the training samples, Fig. 7 shows the experiments' curve about the relationship between the accuracy of the support vector and penalty factor parameter c , according to the Fig. 7,we can see that when the value of c gets above the 10 ,the accuracy of the SVM classifier increase slowly and the accuracy reaches above 96% already, so we choose c=10 for our classifier. The Fig. 8 also shows that when the c get above the 10, the support vector number also change little and little. So c=10 is a suitable value for our SVM classifier.

Table 1: The datasets for cross validation for SVM detector of HOG with LCSSF

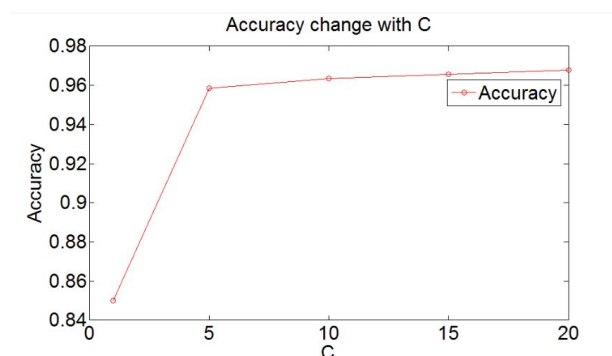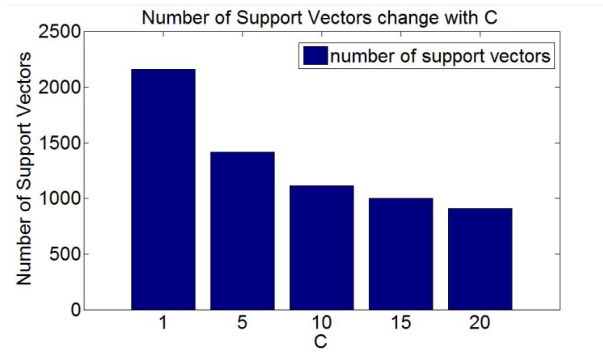|	Train samples
Positive samples	2416
Negative samples	1218

Figure 7.   The curve of Accuracy rate and C

Figure 8.   The bar of the relationship of penalty factor c and the support vector number

In this paper, the performance of the classifier tests in the INRIA pedestrians' datasets and a street pedestrian dataset. Similar to the performance evaluation of literature [13], we use the performance of testing by false negative Rate (Miss Rate) and the false positive per image (FPPI) using 10^{-2} points as reference point to compare. The platform for testing speed is laptop with CPU Intel Core i5-2410M. 2.3 GHz, 2 G Memory. Table 2-11 show the data of the experiments on the same situation of four kinds of feature detector in INRIA datasets .Fig. 9-12 shows the corresponding results of different features on the the same datasets. First we test the LCSSF affecting on the performance of classifier in RGB color space and HSV color space in the INRIA pedestrian database, its result is shown in Fig. 9, Fig. 9 shows our LCSSF classifier has better classification effect on INRIA datasets in HSV color space, using 0.1 FFPI points as a evaluating classification performance standard , from Fig. 9,we can see LCSSF in HSV color space has better classifier than in RGB color space with 5% miss rate decreasing, from Fig. 10 and Fig. 11, we can see that add color information on the HOG, at the reference point 10^{-1}, HOG with CSS get almost the same performance as HOG, but when the FPPI between the 10^{-3} and 10^{-1}, HOG with added color information feature can make a good performance in classifier. From Fig. 10 and Fig. 12, we can see that our classifier gets obviously good performance between the 10^{-3} and 10^{-1} part, at reference point 10^{-2}part, our classifier can get 5% miss rate decreased. During the 10^{-2} and 10^{-1} part, we can get the almost same performance as HOG. Compare Fig. 11 with Fig. 12, we can see that at reference point 10^{-2}, our classifier gets good performance than HOG with CSS, it is about 3% decreased at that point, CSS feature have good effects on the performance of classifier. So it is necessary to get an enough feature to do pedestrian detection. Table 2 shows the dataset we used for our

experiments, from table 3 we can see that only use HOG feature to detect the pedestrians have a high false alarming rate, HOG keeps a higher miss rate on the data. Table 6 and table 9 show the confusion matrix of the corresponding detectors of different kinds of features of pedestrians. From table 6 and table 9 , we can see that HOG with CSS classifier has almost the same accuracy with the HOG with LCSSF. But from table 4 and table 7 , we have less than 30% time in feature abstracting part, from table 5 and table 8 , we can see that our feature in training model time is lower almost 80% than the HOG with CSS, in the prediction part we can see our feature is almost saving 92% time than the HOG with CSS. Thus, it can be seen that the greater numbers of the pedestrians features, the higher time consuming of training a classifier and the more time consuming of predicting samples, too many features' dimensions can affect the real time predicting performance of classifier. From table 11, we can see the merits and shortcomings of different features in this paper; we can see that HOG with CSS has higher dimensions than HOG with LCSSF, so HOG with CSS is time consuming than HOG with LCSSF. HOG has a higher false positive rate, so it is necessary to combine another feature of pedestrians in the application. The HOG describes the contours of pedestrians, its shortcoming is time consuming and its merit is high detection rates. So it is necessary to change the contradiction between the high performance and the problem of the time consuming. From the performance of HOG with CSS feature in the detection rate and time computing, we know that the sufficient description of pedestrians is necessary, and it is also necessary to have features with less computing and higher performance. LCSSF only use 120 dimension vectors, but the CSS in literature [11] use 8128 dimensions vector. We can see that LCSSF with only 120 dimensions describes sufficient color features of pedestrians, LCSSF with the contour information of pedestrians, namely HOG feature, has a good performance on pedestrians' detection, and has higher speed than HOG with CSS.
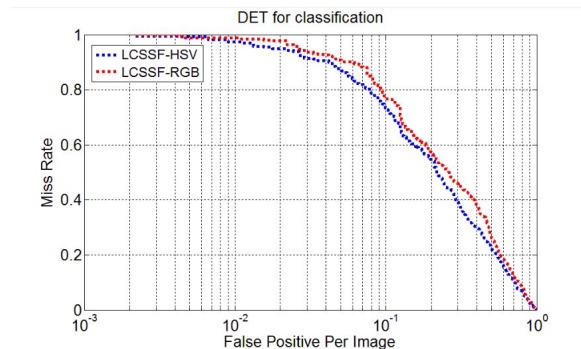
Figure 9.   The DET curve of LCSSF in Inria with different color spaces
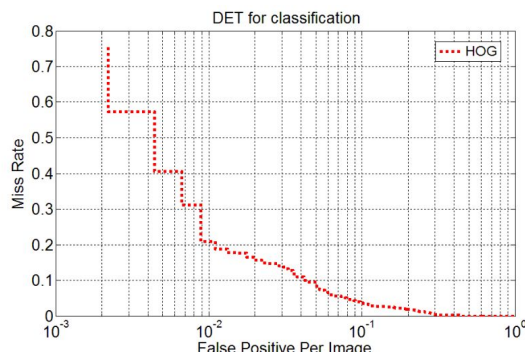

Figure 10.   The DET curve of HOG in INRIA database
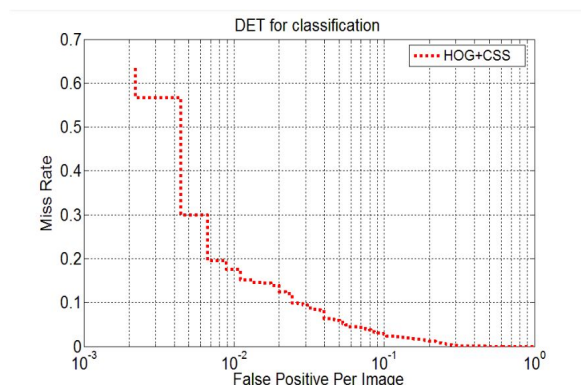

Figure 11.   The DET curve of Ref.[18] feature in INRIA database
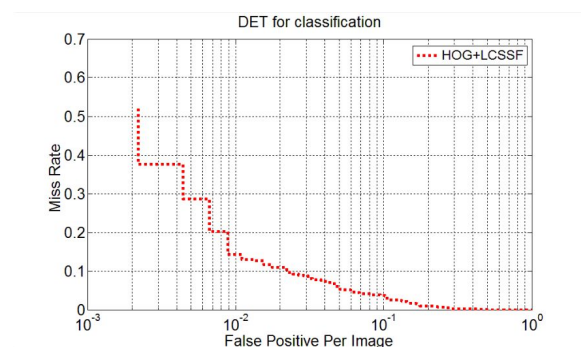

Figure 12.   The DET curve of HOG with LCSSF in INRIA database

The following tables are the experiments' data and results on the INRIA datasets.

Table 2: Data of Experiments

	Train samples	Test samples
Positive samples	2416	1126
Negative samples	1218	453

Table 3: HOG Confusion matrix

Accuracy = 85.6871% (1353/1579)

	Predicted as positive samples	Predicted as negative samples
Test positive samples	1126/1126	0/1126
Test negative samples	226/453	227/453

Table 4: Extraction time of HOG with CSS

	Train sample	Test samples
Positive samples	1408.1	658.3866
Negative samples	741.5820	260.6777

Table 5: Training model time and predicting time of HOG with CSS IN[18]

	Train samples	Test samples
Time	183.565628	80.912416

Table 6: Confusion matrix of HOG with CSS

Accuracy = 94.87% (1498/1579)

	Predicted as positive samples	Predicted as negative samples
Test positive samples	1102/1126	24/1126
Test negative samples	57/453	396/453

Table7: Extraction time of HOG with LCSSF

	Train sample	Test samples
Positive samples	956.6667	433.3691
Negative samples	477.5225	177.0022

Table 8: HOG with LCSSF training model time and predicting time

	Train samples	Test samples
Time	37.503011	15.706459

Table 9: Confusion matrix of HOG with LCSSF

Accuracy = 94.9335% (1499/1579)

	Predicted as positive samples	Predicted as negative samples
Test positive samples	1075/1126	51/1126
Test negative samples	29/453	424/453

In Inria dataset, we use 288 images to test our HOG with LCSSF and HOG with CSS, the size of tested image is 320×240 , the sliding window step is 16 pixels in horizontal and vertical directions of image, the experimental results of different detectors are as table 10. In this paper, we use sliding window detection, and use image resized with scale=1.0, 0.75, 0.5625. In the fusion of overlapping windows, we use the overlap regions of the windows as a fusion situation. If the overlap regions are more than 60% of each other, we treat these windows as a person, and we take the average size and locations of overlapping windows as the final position of the pedestrians.

Table 10: Comparison of different detectors

| Detector	Ref. [18]	Our method
Detecting time	120.04s	11.20s

Table 11: Contrast performance of different features

	merit	weakness	dimension
HOG[14]	Describe the contour features of the pedestrians	Time consuming,only contour features	3780
HOG with CSS in Ref. [18]	Contour and color information of pedestrians	With lots of useless information of contour and color, Time consuming	3780+8128
HOG with LCSSF	Describe the local region color symmetry and similarity	Only color information	3780+120

Fig. 13(A) shows the testing results of detector with only LCSSF of pedestrians on INRIA datasets and the images that we collect from indoor and outdoor images with pedestrians walking on the road plane. As the performance of DET curve shows, the LCSSF detector has a higher false negative rate, and from the Fig.13 (A), we can see that LCSSF has higher false alarm rate on the detector performance curve and the results of testing images, LCSSF feature detector mistakes some of the background objects (such as road, trees) as pedestrians, so LCSSF has shortcomings on false alarming. To improve the higher performance of LCSSF detector, we use HOG with LCSSF to build a classifier, Fig.13 (B) shows some detection results of HOG with LCSSF detector. We can see that LCSSF combined with the contour information of the pedestrian, the false positive rate gets down from the testing results on the images. The testing result shows that the detector with sufficient features can get better detection performance.
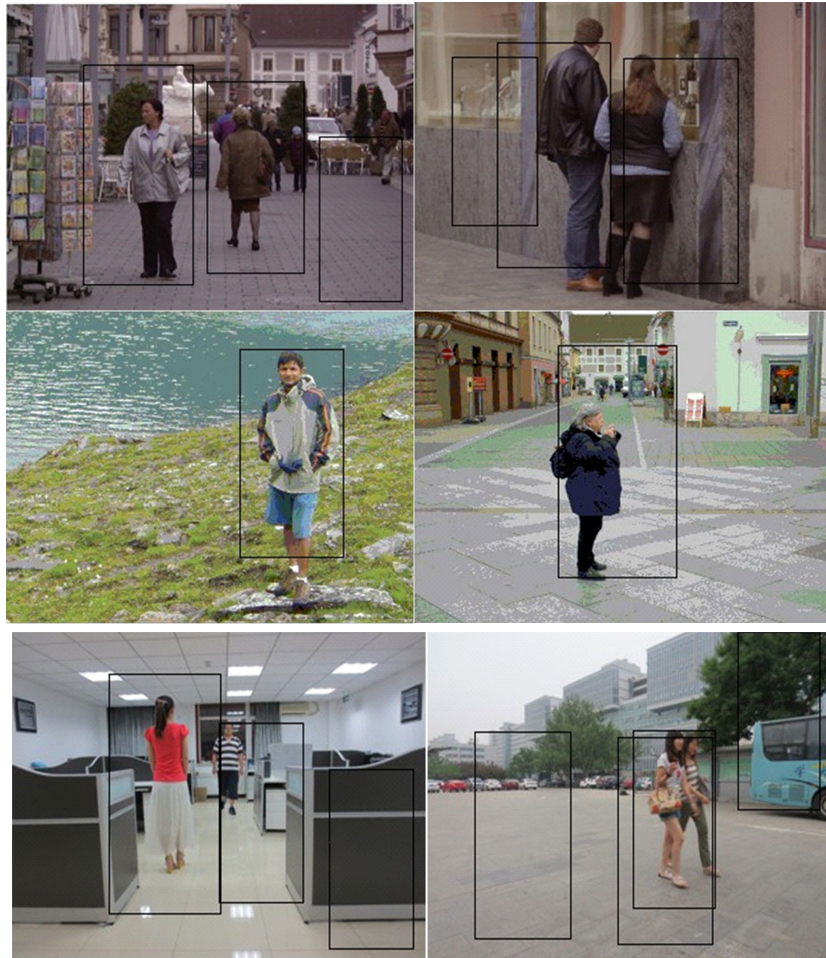
(A)   Testing results of Inria and some collection images inside and outside using LCSSF
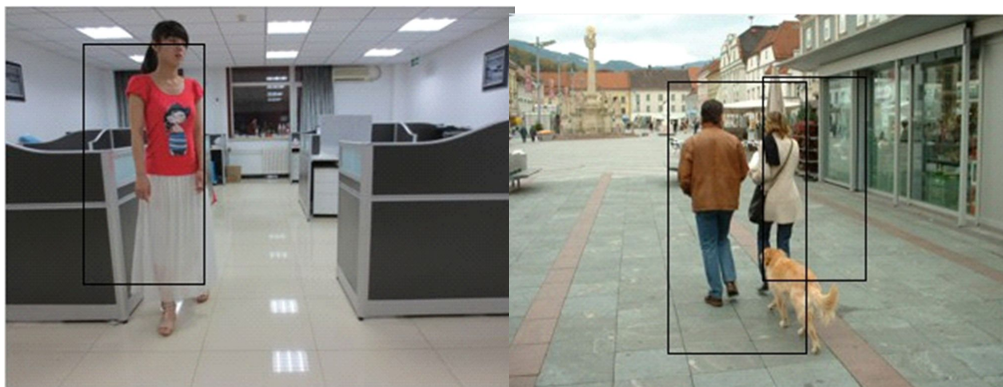
(B) Testing results of the Inria and some images inside and outside using HOG with LCSSF

Figure 13. Results of different kind of features on images

Figure 14. Failure tested samples

The Fig. 14 shows some failed detected positive and negative samples of HOG with LCSSF detector. The detector has a poorer classification of pedestrians walking with 90 degrees direction posture to camera, It is mainly because of no sufficient feature information of pedestrians in training database, maybe make the 90 degrees direction posture as another class can give a good classifier performance. May be through make a bigger pedestrian database with different person walking in different pose and different direction can make pedestrian detection more accuracy and more purposeful.

IV CONCLUSIONS

We used a dataset of upright walking datasets of pedestrians, it combines the standard pedestrian database MIT (which contains the images of pedestrians with the front and back of body in front of the camera) and CAISIA GAIT pedestrian standard dataset (pedestrians are walking on the ground plane and pedestrians are relative to the camera lens changing between 0-180 degrees), in this paper, the fusion of two datasets is aimed at providing more sufficient training and testing samples of walking pedestrians on the ground, it is more practical and standardized, it provides a more rich data for building detectors of intelligent driving system. The results of experiments show that the proposed HOG with LCSSF can build a high performance classifier, we can see that HOG with CSS classifier has almost the same

accuracy with the HOG with LCSSF, but our method has less than 30% time in feature abstracting part, our feature in training model time is lower almost 80% than the HOG with CSS, in the prediction part we can see that our feature is almost saving 92% time than the HOG with CSS. To build a pedestrian datasets of upright walking on the ground plane is necessary, and dividing the positive samples of different directions apart is also necessary, through this dataset, the researchers can use the different peculiarity of pedestrians to describe pedestrians walking on the street and the dataset is not just about people walking randomly and just upright, the people standing on the road and upright is more meaningful. In this paper, we propose a new feature of color, but if we only use the color information to train the classifier, it could not obtain sufficient information of pedestrians. As the experiment shows, HOG with LCSSF gets a good results, the feature is full of contours and color distribution information. In our future research, we will consider combining different kinds of features to do the pedestrian detection, we will consider the cyclical movement of pedestrians on the ground plane; maybe combination of multiple classifiers can get good performance of pedestrian detection. Thus, building a more sufficient pedestrian dataset is also an important work in the future.

ACKNOWLEDGEMENT

REFERENCES

[1] M Koplin and W Elmenreich, "State-of-the-Art Versus Time-Triggered Object Tracking in Advanced Driver Assistance Systems", International Journal Of Advanced Robotic Systems, September 2013.

[2]M.Z.Uddin, D.H.Kim, J.T.Kim and T.S.Kim, "An Indoor Human Activity Recognition System for Smart Home Using Local Binary Pattern Features with Hidden Markov Models", Indoor and Built Environment, 2013.

[3] R.C.Luo and O.Chen, "Wireless and Pyroelectric Sensory Fusion System for Indoor Human/Robot Localization and Monitoring", Mechatronics, IEEE/ASME Transactions on, 2013.

[4] P.Kohli and J.Shotton, "Key Developments in Human Pose Estimation for Kinect", Consumer Depth Cameras for Computer Vision, Springer London, pp.63-70, 2013.

[5] J.Gall, A.Yao and G.Van, "2D Action Recognition Serves 3D Human Pose Estimation", 11th European Conference on Computer Vision, pp.425-438, 2010.

[6]M.Takahashi, M.Naemura, M.Fujii, et.al, "Using Trajectory Features to Recognize Human Actions within Crowd Sequences of Real Surveillance Video", ITE Transactions on Media Technology and Applications, pp.118-126, 2013.

[7]S.M.Li , M.X.Wei, X.D.Miao, et.al, "Fast Pedestrian Detection for Intelligent Vehicle Based on FPGA and Monocular Vision", Advanced Materials Research, pp.784-788, 2013.

[8]M.W.Liu , S.Q.Cao, L.Z.Zhang, et.al. "Predicting Pedestrian Conflict Avoidance Behavior during School Commute Time", Applied Mechanics and Materials, 2013, 253: 1641-1644.

[9]B. Zhou, J.Cao, and J.Li, "An adaptive traffic light control scheme and its implementation in wsn-based its", The International Journal on Smart Sensing and Intelligent Systems, vol.6, no. 4, Setempber, 2013, pp.1559-1581.

[10] H.B. Wang, "The fast method for correction of distortion on infrared marker-based tracking system",The International Journal on Smart Sensing and Intelligent Systems, February 2013, pp. 259-277.

[11] S.Kwofie and N.Rahbar, "A fatigue driving stress approach to damage and life prediction under variable amplitude loading", International Journal of Damage Mechanics, 2013, pp. 393-404.

[12] M.Smeelen, P.B.W.Schwering, A.Toet, et.al, "Semi-hidden target recognition in gated viewer images fused with thermal IR images", Information Fusion, 2013.

[13]K.Arai, S.Akaisi, H.Miyazaki, et.al, "Regressive Analysis on Leaf Nitrogen Content and Near Infrared Reflectance and Its Application for Agricultural Farm Monitoring with Helicopter Mounted Near Infrared Camera", International Journal, 2013.

[14] N.Dala and B.Tfiggs, "Histograms of Oriented Gradients for Human Detection", Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, IEEE Press. pp. 886-893, 2005.

[15]S.B.Da , A.Braeken, E.H.Hollander , et.al, "Performance and Programming Environment

of a Combined GPU/FPGA Desktop", Presented at the 21st ACM/SIGDA International Symposium on Field-Programmable Gate Arrays, 2013.

[16]Q.Tian, B.Zhou,W.Zhao, et.al, "Human Detection using HOG Features of Head and Shoulder Based on Depth Map", Journal of Software, 2008, pp. 2223-2230.

[17] C.Zeng, H.Ma, "Robust Head-Shoulder Detection by PCA-Based Multilevel HOG-LBP Detector for People Counting", Proceedings of the 2010 20th International Conference on Pattern Recognition, pp. 2069-2072, 2010.

[18] W.Stefan, "New Features and Insights for Pedestrian Detection", Schiele in Computer Vision and Pattern Recognition, 2010 IEEE Conference on (June 2010), pp. 1030-1037, 2010.

[19]D.Gerónimo and A.M.López, "Datasets and Benchmarking", Vision-based Pedestrian Protection Systems for Intelligent Vehicles, Springer New York, 2014, pp.87-93.

[20] G.Othmezouri, I.Sakata, B.Schiele, et.al, "Detection of objects in an image using self similarities", U.S: Patent, 130,058,535, March, 07, 2013.

[21]INRIA Database, http://pascal.inrialpes.fr/data/human/.

[22]MIT Database, http://db.csail.mit.edu/.MIT-CBCL Pedestrian Database

[23]CASIA GAIT, http://www.cbsr.ia.ac.cn/english/Gait%20Databases.asp.