Optical Camera Based Pedestrian Detection in Rainy Or Snowy Weather

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Abstract. Optical camera based detection method is a popular system to fulfill pedestrian detection; however, it is difficult to be used to detect pedestrians in complicated environment (e.g. rainy or snowy weather conditions). The difficulties mainly include: (1) The light is much weaker than in sunny days, therefore it is more difficult to design an efficient classification mechanism; (2) Since a pedestrian always be partly covered, only using its global features (e.g. appearance or motion) may be mis-detected; (3) The mirror images on wet road will cause a lot of false alarms. In this paper, based on our pervious work, we introduce a new system for pedestrian detection in rainy or snowy weather. Firstly, we propose a cascaded classification mechanism; and then, in order to improve detection rate, we adopt local appearance features of head, body and leg as well as global features. Besides that, a specific classifier is designed to detect mirror images in order to reduce false positive rate. The experiments in a single optical camera based pedestrian detection system show the effeteness of the proposed system.

1 Introduction

Most existing pedestrian detection systems (PDS) [1] [2] [3] [4] [5] are designed for sunny weather; however, a practical PDS should also work well in rainy or snowy weather. One way to solve this problem is to adopt infrared camera based systems [4] [5] or radar/laser based systems [6] which do not affected by rain or snow (it means an infrared camera based PDS works the same in both sunny and rainy/snowy days.); these systems are high cost and maybe affected by other factors. Another way is to design a suitable optical camera based PDS, the system is low cost, simple and having irreplaceable advantages. Compared with an infrared camera based PDS, an optical camera based PDS has much wider detection range and it is not affected by environment temperature.

To an optical camera based PDS, rainy and snowy weather causes following additional difficulties: (1) Brightness of the original images is weaker than in sunny days,

L. Wang et al. (Eds.): FSKD 2006, LNAI 4223, pp. 1182 – 1191, 2006.

and we found that color information can hardly be used according to many experiments, therefore pedestrians are harder to distinguished from the environment; (2) In rainy or snowy weather, a pedestrian might be partly covered by umbrella or raincoat, if take the same way of pedestrian detection in sunny weather which only using global features(e.g. appearance or motion) of pedestrian, a lot of pedestrians will be misdetected; (3) In rainy or snowy days, the wet road becomes a huge mirror, this makes the images much more complicated, the mirror images of many objects (such as pedestrians and trees) will cause a lot of false alarms.

We have designed a system to detect pedestrians in sunny weather using a two-step method. It firstly used both global appearance features and motion features to select candidates with an AdaBoost classifier; and then a decomposed SVM classifier was used to make accurate classification. [2]

However, to fulfill pedestrian detection in rainy or snowy weather, it is necessary to design a better classification mechanism and efficient classifiers. Based on our previous work for sunny weather [2], new features need to be introduced, and additional measures need to be taken in order to reduce false alarms; however, the detection speed also needs to be guaranteed.

More and more features have been adopted for pedestrian detection; however, most of the existing PDS systems only use pedestrian's global features (features of entire human body) to detect pedestrian. The most widely used global features are appearance or motion features. For instants, Paul Viola et al. took both advantages of global appearance and motion features to detect pedestrian in static scene [1]. Until now, only a few PDS considers using local features to detect pedestrian or to assist detection. For example, Shashua Amnon et al. proposed another PDS which took nine main parts of a human body and their position relations as key features to detect pedestrian [3].

Moreover, since the introduction of new features probably slows down the detection speed, we present a three-stage method.

The remainder of the paper is arranged as follows: Section 2 describes detection and training procedures of the system in detail. Section 3 introduces the validation experiment and shows the results. Section 4 concludes this paper.

2 Procedure of the System

2.1 Detection Procedure

As shown in Figure 1, the whole detection procedure consists of three main stages: candidate selection (stage 1), further confirmation (stage 2) and false alarm reduction (stage 3). Each stage contains one or a group of classifier(s).

To solve the problems caused by rainy or snowy weather, it is necessary to design an efficient classification mechanism and pertinent classifiers. In the system, we improved our two-cascade architecture, adding a new module to solve the false alarm problem caused by specifically weather condition; and more complicated further confirmation layer is designed to solve the problem of being partly covered.

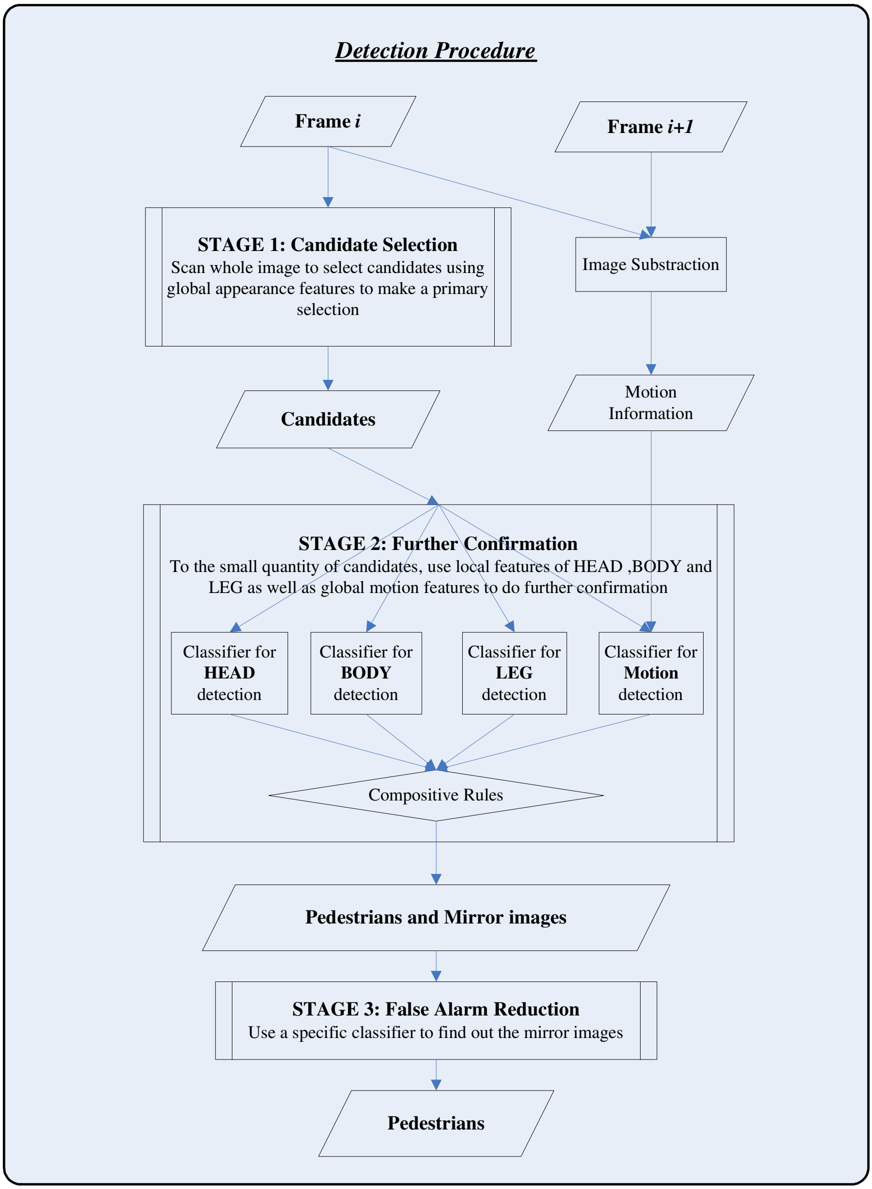

Fig. 1. Detection procedure of the system

2.2 Classification Mechanism and Classifiers

To such a classification based PDS, the classification mechanism and performance of each classifiers are most important. There are six classifiers in the system, the detail of them are listed in Table 1.

Table 1. Detail of all classifiers in the system

Stage	Classifiers / Training algorithm	Features		Training Samples	
		Type	Number	Positive	Negative
1	Candidate selection / AdaBoost	Global Appearance	280	Pedestrians	Non-pedestrians
2	Head detection / AdaBoost	Local appearance	80	Head/ umbrella	Others
	Body detection / AdaBoost	Local appearance	120	Coat/ raincoat	Others
	Leg detection / AdaBoost	Local appearance	160	Legs	Trees and others
	Motion detection / AdaBoost	Global motion	160	Motion	Others
3	Mirror image detection / SVM	Global appearance and motion	160 + 120 (ap. + mo.)	Mirror images	Pedestrians

Candidate selection classifier is designed to quickly wash out most of non-pedestrian objects at first. Hence there is ample time for further confirmation and false alarm reduction. Similar to our previous work [2], zoom-image and slide-window techniques are applied to perform exhaustive search over the whole images at different scale; to each window, the candidate selection classifier is used to decide whether there might be a pedestrian in it.

The classifier is only based on global appearance features in order to get higher detection speed; however, according to our experience and experimental results, only using appearance features is enough if about two times candidates are selected than in our previous system for sunny weather [2].

As shown in Figure 2, four classifiers work in parallel to make further confirmation to the candidates. There are about 100-400 candidates selected, to each candidate, we use local features of a pedestrian's three main parts and global motion features to make further confirmation as following steps:

(1) To get motion information of the candidate region, and then use an AdaBoost classifier to get the probability *P(motion)* that whether the candidates is a pedestrian.

(2) To get the top 1/4 region of the candidate, and then use an 8×8 pixel slide window to scan this area for head with a classifier. The outcome of this classifier is *P(head)* which describes the probability of the region contains a head; it is also a real number between 0 and 1.

(3) To get the middle 1/2 region of the candidate, and then use a well trained classifier to determine whether it contains a human body. The probability is expressed as *P(leg)*.

(4) Similar to previous step, to estimate the probability *P(leg)* that whether the bottom 1/2 region contains a pair of human legs.

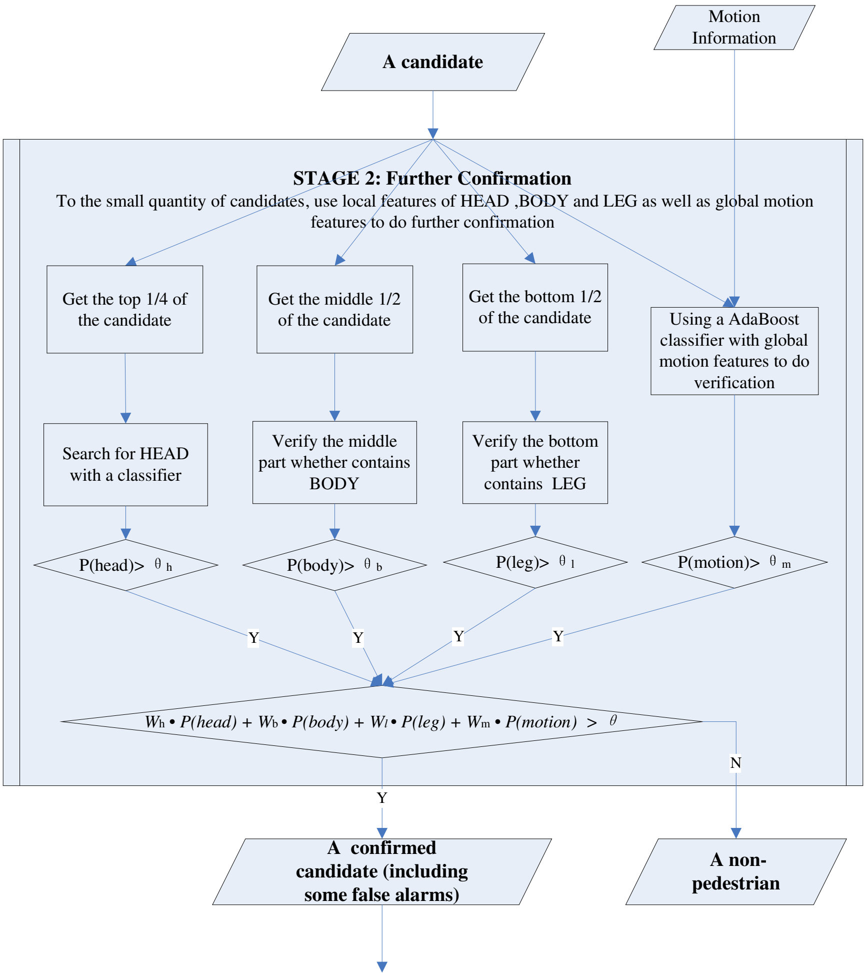

Fig. 2. Detail of further confirmation

(5) To make following computation to make a decision:

① if $P(motion) \le \theta_m$, then $P(motion) = 0$; Others are similar to this.

② if $W_h \bullet P(head) + W_b \bullet P(body) + W_l \bullet P(leg) + W_m \bullet P(motion) > \theta$, then the candidate is judged as a pedestrian in this stage and it will be verified by next stage; Else it is a non-pedestrian.

The four classifiers are all trained by AdaBoost algorithm [1] [7], and all the parameters can be obtained at the same time of training. However, we adjust the eight parameters θ_m, θ_h, θ_b, θ_l, W_m, W_h, W_b, and W_l manually according to the experimental results, because this can increase the training speed great a lot and the performance is also acceptable.

After further confirmation, there are only 10-50 confirmed candidates. Some of them are real pedestrians, and usually more than a half of them are mirror images and other false alarms according to the experimental results, and almost the remainder false alarms are mirror images. To each confirmed candidate, a specific classifier is adopted to judge whether it is a mirror image, if it is not, then it is a pedestrian. (Figure 3)

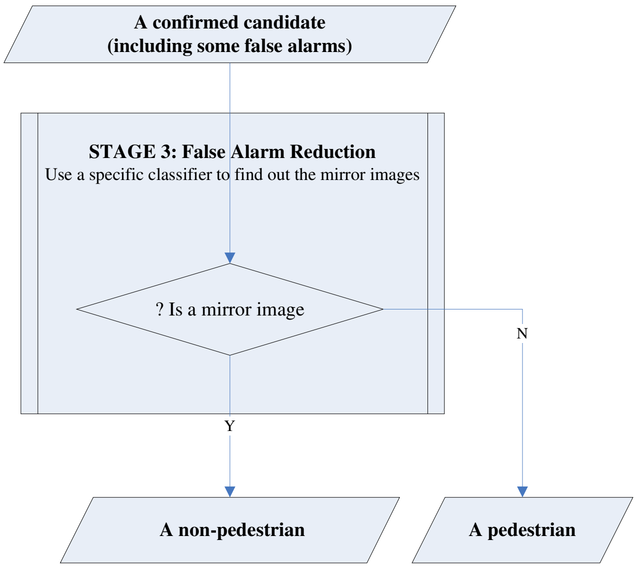

Fig. 3. A classifier to reduce false alarms caused by mirror images

Different from others, mirror image detection classifier takes non-pedestrian (mirror images) as positive samples, and takes pedestrian as negative samples; whilst other classifier take pedestrian as positive one.

2.3 Classifier Training: Samples and Features

As listed in Table 1, we train most of the classifiers with quick and effective AdaBoost algorithm [1] [7]. This algorithm can finish key feature selection and classifier training at the same time. Mirror image detection classifier in stage 3 is trained with SVM ^{light} algorithm proposed by Joachims [8] [9]. Furthermore, different kinds of classifiers aim at different purpose; therefore each classifier is trained separately with its own target. Classifier in stage 1 should be as fast as possible and the false negative rate must be extremely low. Classifiers in stage 2 and 3 should have high positive rate, the detection speed is ignored to them.

To get a well trained classifier, various high quality samples and proper features are most important. Part of the samples of entire pedestrian we used to train the

Fig. 4. Some positive samples of entire pedestrian (32×16 pixel)

candidate selection classifier is shown in Figure 4. We totally select 2400 positive samples and 3000 high-quality negative samples.

Definitions of the each main part of a pedestrian is shown in Figure 5, therefore samples of body and leg can be obtained from samples of entire pedestrian automatically. However, we only select clear ones as positive samples. Some of the leg samples are shown in Figure 6. Head samples are manually made from videos captured in rainy or snowy weather; and the head includes human head and umbrella.

A classifier's performance is also strongly depends on its feature set; in the system, we mainly use haar features. Similar to Paul Viola's work [1] and our previous work [2], appearance information can be got from the anterior original gray-scale image. Motion information can be obtained by subtracting two consecutive frames.

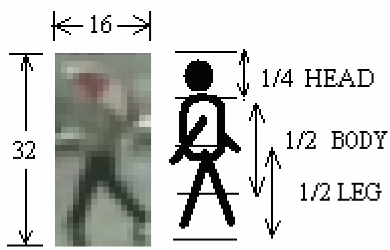

Fig. 5. Definitions of three main parts of a pedestrian

Candidate selection only takes advantages of global appearance features [2] to get higher processing speed. Haar features of head, body and leg are of the similar kinds; however, we choose them according to the character of each part, and only typical features are chosen. Five selected features of leg are shown in Figure 7. We also apply AdaBoost algorithm to choose proper features.

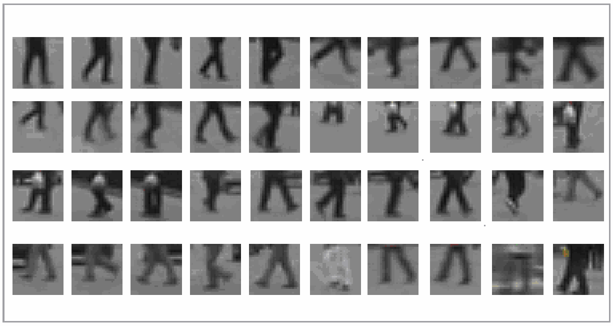

Fig. 6. Some positive samples of leg (16×16 pixel)

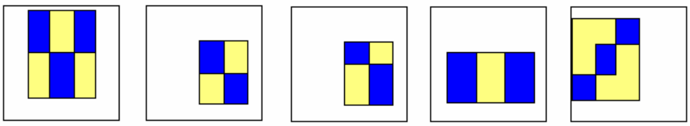

Fig. 7. Five example appearance local features of leg (16×16)

3 Experimental Results

In order to validate the detection ability of our system, we carried out several tests on a high performance PC which equipped a Pentium IV 3.0G CPU and 1G DDR2 RAM. Sixteen test videos (eight of rainy days and eight of snowy days) were captured at a 320×240 resolution with 15fps on a moving vehicle in real city traffic environment and the vehicle speed is 50 km/h in average. Each video has 225 frames (15 seconds). The average result of pedestrian detection for verification videos is listed in Table 2.

Table 2. Average system performance in rainy and snowy weather

Average System performance	Rainy	Snowy
Detection rate	75.2%	83.3%
False positive rate	1. 2%	0.65%
Detection speed	13.3 fps	14.8 fps

Table 2 indicates that:

(1) The system both gets good performance in rainy and snowy weather.

(2) The system performs better in snowy weather than in rainy weather. As shown in Figure 8, the light is weaker in rainy weather because of thick rain cloud, this leads to lower detection rate in rainy weather. The system has a lower false positive rate and a higher speed because of that the road is drier in snowy weather; therefore less mirror image need to be processed.

If other local features are adopted, the system can be easily modified to detect other kind of objects such as bicycle rider (only change local features of leg to features of bicycle). Additionally, we train another PDS for sunny days use similar samples in sunny days and drop body local features. Five random selected test video captured in sunny days show that the average performance is also better than our previous work [2]. Especially the detection speed reaches 15.5fps which is more suitable for real-time vehicular detection in urban area.

Fig. 8. Pedestrian detection in snowy (left) and rainy (right) weather

4 Conclusions

This paper proposed a fast pedestrian detection system for rainy or snowy weather, and the idea and system architecture are also suit for PDS in other weather condition. The experimental results show that the system is suit for real-time detection in city traffic, and if we design a weather judgment module, and for each weather condition train a cascaded classifier which having the same input and output, then a self-reacting PDS can be obtained. Of course this is one of our future works.

Only few optical camera based pedestrian detection system for rainy or snowy weather is proposed; however, infrared (IR) camera based PDS has good performance in rainy or snowy weather, comparing with these systems [4] [5], our system mainly has the following features:

(1) With optical zoom camera (three times max), the system can detect pedestrian in the range of 4.5-90 meters; whilst the infrared camera based system can detect pedestrians within 15 meters.

(2) Bertozzi M. et al. proposed an IR stereo vision based PDS [4]. This PDS worked on single frame and took seven steps to detect pedestrian; it only took shape features to select candidates, and morphological characteristics based head detection was adopted to verify the candidates. The detection speed of our system is much faster than Bertozzi M. et al.'s. (It is about 500 to 600 times faster than theirs if not mention the differences between computers); hence our system is more suitable for a real-time vehicular pedestrian detection.

Acknowledgement

This work was supported by National Natural Science Foundation of China (60204009), and Open Foundation of The Key Laboratory of Complex Systems and Intelligence Science, Chinese Academy of Sciences (20040104).

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