# PAPER Pedestrian Detection for Counting Applications Using a Top-View Camera

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**SUMMARY** This paper presents a pedestrian detection framework using a top-view camera. The paper contains two novel contributions for the pedestrian detection task: 1. Using shape context method to estimate the pedestrian directions and normalizing the pedestrian regions. 2. Based on the locations of the extracted head candidates, system chooses the most adaptive classifier from several classifiers automatically. Our proposed methods may solve the difficulties on top-view pedestrian detection field. Experimental was performed on video sequences with different illumination and crowed conditions, the experimental results demonstrate the efficiency of our algorithm.

key words: pedestrian detection, top-view camera, people counting

## 1. Introduction

A functionality that can be provided by this video-based security system is counting the number of accesses to the edifice. A building that is able to control and adapt its functionalities according to the number of people in its rooms (i.e., adjusting air conditioning and ventilation) is certainly an example of ambient intelligence (AmI) and intelligent user interface, since the regulation of the settings of the building subsystems is performed in a way transparent to the users of the structure. Counting the number of people entering the edifice can also be useful for commercial purposes. This feature can be exploited, for example, by shops or malls to crosscheck the number of entering customers against the number of paying ones as a means to estimate the level of interest generated by the current goods or display. This is of course in the spirit of using technology to maximize revenues and to help attain financial objectives [1].

While infrared sensors and photocells can be used to detect someone entering a room (i.e., to switch on the lights), they do not provide the accuracy to distinguish the number of people. A more informative type of sensor is needed, and a camera is certainly a choice [1]–[7].

Some works [3]–[6], [13]–[18] introduce the estimating the number of people systems using the frontal placement of the camera or the oblique camera, due to the severe occlusion, it is difficult to estimate the number of people actually. To better cope with the problems given by occlusions in crowded rooms or corridors, a view from the top was chosen for the cameras. As can be seen in Fig. 1, a frontal placement of the camera generates partial and total

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occlusions. These occlusions in crowded environments are so severe that no tracking algorithm can handle them effectively even with a multi-camera approach.

Top view solves most of the problems given by occlusions normally generated in classical horizontal views by perspective projection. In order to count the number of the pedestrians accurately, especially in outdoor situation, it is necessary to consider some noises, such as the baggage, shadows, non-uniform illumination condition, and so on, distinguishing the pedestrians and the noises is important to achieve a robust counting application. In other words, the pedestrian detection is a necessary step for the counting applications. However, it's different between pedestrian detection on top-view image and pedestrian detection on horizontal view image due to following 2 reasons:

- When pedestrians stay at the different locations, the shape of the pedestrians will be changed as illustrated in Fig. 2.
- The features that can be extracted from the top-view pedestrian images are less than the horizontal view pedestrian images. In the original horizontal view pedestrian detection systems, the shape features of human body, upper-body, head region and cloth colors were always used to detect the pedestrians [3]–[12], however, as shown in Fig. 2, only few features can be extracted such as the head regions and shoulder regions from the pedestrians, it is more difficult to distinguish the human and non-human.

To our best knowledge, there has been no public report



Fig. 1 Input image of frontal camera.

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of reliable pedestrian detection algorithms for top-view image. For instance, most methods [1], [2] for top-view image achieved pedestrian detection via the motion regions (subtraction between the current image and the background), they used the area to judge how many people in one label. Only a simple idea was presented in [1], which is using Canny's edge-detection algorithm and the Hough transform to look for rigid bodies, and distinguish the people and the shopping cart. They did not consider the complicated environments on outdoor situation. Some literatures [6], [13], [17], [18] introduced a very popular method to segment and track of multiple humans in crowded environments - 3D model-based segmentation. They also used motion regions, and they proposed a method to reconstruct a 3D part-based human body model for segmentation the people from the motion regions. When the environments are complicated and sudden illumination changes occur, obviously, false positives (FPs) will increase using conventional method because they did not make people different from noises. Therefore, we propose a new pedestrian detection method using the top-view image, this method is suitable for counting applications. Testing was performed on indoor and outdoor video sequences with different illumination and crowed conditions. The novelties of this paper can be summarized as follows:

- As shown in Fig. 2, person A and person B's locations are close, since they have different directions, using the same detector can not detect both of them due to their different shapes, it is necessary to find a method to estimate the pedestrians' direction. We propose a method using the shape context descriptors to estimate each pedestrian's direction and normalizing the pedestrian region.
- Based on the location of the each extracted head candidate, system chooses the most adaptive classifier from several classifiers automatically.

The rest of this paper is organized as follows. In Sect. 2, our proposed method is described. In Sect. 3, proposed method is proved by the experiments where it is compared with the other methods and finally Sect. 4 presents the conclusion.



Fig. 2 Input image of top-view camera.

#### 2. Pedestrian Detection Method

The flow of our proposed approach is illustrated in Fig. 3.

### 2.1 Head Candidates Detection

The edges are extracted using Sobel operator, the extracted edge image is illustrated in Fig. 4. As shown in Fig. 4, all the head edges look like the circles, the hough transform algorithm is used to extract the circles from the edge image





Fig. 4 Example of extracted edge images.



Fig. 5 Extracted head candidates from Fig. 4.

as head candidates [19]. The results of the extracted head candidates are illustrated in Fig. 5.

The following process will be executed for each head candidate.

## 2.2 Estimation the Human Direction Using Shape Context Descriptor

There are also a lot of problems for top-view image pedestrian detection. For instance, as shown in Fig. 2, person A and person B's locations are close, but they have different directions, using the same detector (such as the original Histogram of Oriented Gradient (HOG) detector [10]) can not detect both of them. Therefore, it is necessary to find a method to estimate the pedestrians' direction, and normalize all the pedestrians to the same direction. In this paper, we propose a new method to estimate the pedestrians' direction.

#### 2.2.1 Shape Context Descriptors

Local Shape Context descriptors [8], [9] are histograms of gradient orientations sampled at edge points in a log-polar grid. In the implementation of [8] with 9 locations and 4 orientation bins and thus 36 dimensions were used. In this paper, because the inside of the head candidates' feature may be ignored, location is quantized into 8 bins of a log-polar coordinate system as displayed in Fig. 6 (b) with the radius set to r, 1.5r and 2.5r illustrated in Fig. 6 (c), where r is the radius of the head candidate whose rotation will be estimated, the orientation quantized into 6 bins (horizontal, 45 degree, vertical, 135 degree and two diagonals), therefore obtain a 48 dimensional descriptor (48 bins) illustrated in Fig. 6 (d). In our experiments we weight a point contribution to the histogram with the gradient magnitude, this has shown to give better results than using the same weight for all edge points. Note that the original shape context was computed for edge both point locations and orientations.

# 2.2.2 Shape Context Descriptors of Deferent Angle Templates

As shown in Fig. 7, templates of 0°, 45°, 90°, 135°, 180°,



**Fig.6** Shape context descriptors. (a) The edge image, (b) Diagram of log-polar histogram bins used in computing the shape contexts, (c) Shape context of the edge image, (d) Shape context descriptors.



Fig. 7 Templates of  $0^{o}$ ,  $45^{o}$ ,  $90^{o}$ ,  $135^{o}$ ,  $180^{o}$ ,  $225^{o}$ ,  $270^{o}$ , and  $315^{o}$  rotation angles.

225°, 270°, and 315° rotation angles are computed by training images, Shape Context descriptors of these 8 templates are computed.



Fig. 8 Compensation the rotation of the human candidate A.



Fig. 9 Compensation the rotation of the human candidate B.

#### 2.2.3 Estimation the Human Direction

The similarity of test image's shape context descriptors and *ith* template's shape context descriptors is calculated using the following Eq. (1)

$$\sum H_{test}(X_k) = 1 \quad and \quad 0 \le X_k \le 1$$

$$\sum H_{template_i}(X_k) = 1 \quad and \quad 0 \le X_k \le 1$$
similarity<sub>i</sub> =  $\sum_{k=0}^{48} ||\mathbf{H}_{test}(\mathbf{X}_k) - \mathbf{H}_{template_i}(\mathbf{X}_k)||$ 
(1)

Here,  $H_{test}(X_k)$  is the test image's shape context descriptors and  $H_{template_i}(X_k)$  is the *ith* template's shape context descriptors.

The template which is most similar to test image is selected as the rotation angle of this person.

We give three examples to explain the method of human direction estimation. The edge image of human A and the template which is most similar to the human A are illustrated in Fig. 8, and the edge image of human B and the template which is most similar to the human B are illustrated in Fig. 9. The edge image of human G and the template which is most similar to the human G are illustrated in Fig. 10. The shape contexts of the human A, B, G is most similar to the template  $0^{\circ}$ , the template  $45^{\circ}$  and the template  $315^{\circ}$ , respectively.



Fig. 10 Compensation the rotation of the human candidate G.

2.3 Compensation the Rotation of the Human Candidate and Extracting the Human Candidate Region

The rotation of each human candidate is compensated. We give three examples to explain the process of compensation the rotation of human candidate. As shown in Fig. 8, the rotation of the human candidate A is judged as  $0^{\circ}$ , therefore, that is not necessary to compensate. As shown in Fig. 9 and Fig. 10, the rotations of the human candidate B and human candidate G is judged as  $45^{\circ}$  and  $315^{\circ}$ , respectively. The human candidate B need to be rotated  $-45^{\circ}$  as illustrated in Fig. 9 (c), and the human candidate G need to be rotated  $45^{\circ}$  as illustrated in Fig. 10 (c). The compensated results of human candidate B and G are illustrated in Fig. 9.(d) and Fig. 10.(d).

Each human candidate region is extracted based on the head location. In order to determine the size of the human candidates in different locations, the method introduced in [7] is used in this paper. Considering a cuboid whose size is bigger than a normal man standing on the floor plane in real world, when the coordinate of upper cuboid's projection is near to the head candidate, the projection of this cuboid may be as human candidate region. The results of extracted human candidate regions are illustrated in Fig. 11.

2.4 Choose the Most Adaptive Classifier Based on the Head Candidate Location

As shown in Fig. 2, when pedestrians stay at the different locations, the shapes of the pedestrians are changing. Therefore, it is impossible to detect all the pedestrians using the same detector. In this paper, we create 3 kinds of classifier to classify pedestrian and no-pedestrians in each human candidate region, how to choose the most adaptive classifier is a important problem.



Fig. 12 Computing the angle  $\alpha$  for selection the most adaptive classifier.

Supposing the camera is set with  $\beta$  degree angle with the vertical. the coordinate of point of intersection (*X*, *Y*) between the normal line and the image plane is computed as follows:

$$X = X_{center} - H \cdot \tan \beta$$
$$Y = Y_{center}$$

Here,  $(X_{center}, Y_{center})$  is the image center coordinate, *H* is the camera's setting height.

Due to the shape of the pedestrians change based on the angle  $\alpha$  as shown in Fig. 12, angle  $\alpha$  is calculated using the following Eq. (2)

$$D_{hc} = \sqrt{X_{head} - X^{2} + (Y_{head} - Y)^{2}}$$
  

$$\alpha = \arctan\left(\frac{D_{hc}}{H}\right)$$
(2)

Here,  $(X_{head}, Y_{head})$  is the head candidate coordinate.

We construct 3 classifiers using different training images, the most adaptive classifier is selected using follows



Fig. 13 Examples of the most adaptive classifiers selection for the human candidate regions.

rules:

If  $\alpha \le \theta 1$ , Classifier-1 is the most adaptive, if  $\theta 1 < \alpha \le \theta 2$ , Classifier-2 is the most adaptive, if  $\theta 2 < \alpha \le \theta 3$ , Classifier-3 is the most adaptive,  $\theta 1, \theta 2, \theta 3$  are the thresholds selected by experience.

In order to achieve robust pedestrian detection, we adopt the HOG descriptors and cascade AdaBoost [10]–[12] classifier to construct 3 classifiers. The examples of selected the most adaptive classifiers for the human candidate regions are illustrated in Fig. 13.

It note that only the human candidates belonging to Classifier-1 should be estimated using the method presented in Sect. 2.2. Since we added a lot of training data with various orientations in the other classifiers, by analyzing a large number of experimental results, we find it is not very sensitive to the orientations of the humans except for the Classifier-1.

**Extraction HOG descriptors:** In this research, we used HOG descriptors. HOG descriptor [4] has several advantages. It captures the gradient structure that is characteristic of the human shape. First, magnitude and orientation of the gradients are computed. Each detection window is divided into cells of size  $5 \times 5$  pixels and each group of  $3 \times 3$  cells is integrated into a block in a sliding fashion, so that the blocks overlap with each other. Each cell consists of a 9-bin histogram of HOG features. Each block contains a concatenated vector of all its cells. The feature of one block (81 feature vectors) of block can represent feature vectors.

**Construction of classifier:** This section describes the construction of the classifier for human detection. The cascade AdaBoost classifier is used. The final strong classifier, H(x), is a linear combination of T weak classifiers,  $h_t(x)$ :





$$H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$$

Where  $\alpha_t$  is the weight of the training data, and *t* is number of round. The cascade AdaBoost classifier is used to reduce the number of false positives [10].

2.5 Combine the Results and Counting the Number of the Pedestrians

Sometime, the edges of inside pedestrians are extracted as head candidate mistakenly as shown in Fig. 14 (head candidate 2), In Fig. 14, pedestrian candidate region 1 and pedestrian candidate region 2 indicate the same person, and there is a big overlap region between them. In this paper, system combines the results of pedestrian candidate regions which have a big overlap region among them to one.

Counting all the human candidates detected as pedestrians, the number of the pedestrians is the final output of the countering system.

#### 3. Experiments

This section describes the experimental results of our method compared with those of the conventional method.

#### 3.1 Experimental Overview

The outdoor cameras were set around the building of Beijing Jiaotong University as illustrated in Fig. 15 (camera 1), the cameras were set with 5m height from the ground, and about 80° with the horizontal. Outdoor images have been recorded with 5 cameras at a resolution of 1280 by 720 pixels. The indoor cameras were set on the ceiling of the entrance hall of the building, the cameras set with the same height and angle with the outdoor cameras. Indoor images have been recorded with 2 cameras.

The human images were captured in Beijing Jiaotong University. We have selected a total of 800 human images for the experiment. These include 480 human images of indoor scenes, 320 human images of outdoor scenes. The maximum number of the pedestrians in each scene is 11, 108 pedestrians were captured on the crowed conditions (Fig. 16 (a)), and the number of each scenes is over 6; 120 pedestrians were captured when the sudden illumination changes occur (Fig. 16 (b)), and 52 humans were captured with the large luggage (Fig. 16 (c)). The samples in



Fig. 15 Input device using for experiment.



Fig. 16 Examples of experiment images.

our image database are illustrated in Fig. 16. The training data consisted of 5,000 positive images and 5,000 negative images for each classifier. The training data were captured on the different places with the test data, and the pedestrians in the training data and the test data were different too. It should be noted that the cameras used to capture the training data were set on the same camera height and angle with the camera used to capture the test data.

We compared 6 experiments: 1) only using Classifier-1 to detect the pedestrians, 2) only using Classifier-2 to detect the pedestrians, 3) only using Classifier-3 to detect the pedestrians. 4) using the moving regions method to detect the pedestrians [1], 5) using 3D model-based segmentation to detect the pedestrians [6], 6) using our proposed method to select the most adaptive classifier to classify.

- 3.2 Comparing with Other Methods
- 3.2.1 Using the Area of Moving Regions to Detect the Pedestrians

Because the image database used in [1] is not public database, we implement the same algorithm with the method presented in [1] to compare the performance with the proposed method using the data we collected. The approach of people counting system presented in [1] is presented as follows:

1. Three channels (hue saturation value) of the source color image are split with individually thresholded, and the resulting binary images are combined through a per pixel voting policy (or policy).

2. The size of the object captured from the top-view



**Fig. 17** Comparison experiment results between the proposed method and the others in [1] and [6]. (a) original image, (b) moving regions, (c) pedestrians detection results using the moving regions method, (d) pedestrians detection results using 3D model-based segmentation.

(d)

(C)

camera is the nearly constant, knowing the average area of a person from a given top view, it can be easily determined how many people from a given connected component. This average area for the person can be evaluated and chosen as threshold in the initial setup phase before putting the system into operation. We extracted 100 people appearing in the training images and computed the average value of their area as the average area for the person in this experiment.

3. Canny's edge-detection algorithm and the Hough transform are used to look for rigid bodies.

As shown in Fig. 17 (b), the size of the moving region was twice bigger than the average area for the person, therefore, the shadows or the large baggage are easy to be detected as the pedestrians.

# 3.2.2 Using 3D Model-Based Segmentation to Detect the Pedestrians

3D model-based segmentation approach is adopted in [6], [13], [17], [18], that is a very popular and effective method to estimate the number of people in crowed situation. In order to validate proposed algorithm, we implement the same algorithm with the 3D model based segmentation method presented in [6]. The solution of counter the number of people in one blob is defined to be the number of human objects and their associated parameters maximizing the posterior probability. The 3D model based segmentation approach presented in [6] is presented as follows:

1) A three-dimensional part-based human body model which enables the segmentation of humans in 3D and the







Fig. 19 Examples of miss detection and false positive detection.

inference of inter object occlusion naturally is structured.

2) The subtraction images of the foreground and standard background are computed.

3) A Bayesian framework that integrates segmentation based on a joint likelihood for the appearance of multiple objects is structured.

4) The segmentation result that maximizes the posterior probability defined is found.

Compared with the propose method, the major difference of the 3D model-based segmentation approach is that it is unable to judge whether there is a person or not in the subtraction images. As shown in Fig. 16 (b), because both the size and the shape of the shadow area might look like a person, the detection system based on that approach very likely would judge the shadow or the baggage as the pedestrian.

#### 3.3 Experimental Results

Figure 18 shows the experimental results. With a false positive rate of 10%, our method has a 11.5% lower miss rate than the system only using Classifier-1 to classify, has a 3.5% lower miss rate than the system only using Classifier-2 to classify, has a 4.75% lower miss rate than the system only using Classifier-3 to classify, has a 12.5% lower miss rate than the system using moving regions method to classify, and has a over 5% lower miss rate than the system using 3D model-based segmentation to classify, we can see that our proposed method has better accuracy compared to the other methods.

The examples of miss detection and false positive detection are illustrated in Fig. 19. Classifier-1 showed the poorer performance than the other classifiers as shown in Fig. 19 (a), (c), because only few features such as the head regions and the shoulder regions can be extracted from



Fig. 20 Examples of pedestrian detection results.

the pedestrian candidates belonging to the Classifier-1, it was more difficult to distinguish the pedestrians and nonpedestrian than the other classifiers. Figure 19 (b) shows a pedestrian walking pass the complicated background. Since too many useless features were extracted from complicated background to reduce the performance of pedestrian detection. The examples of pedestrian detection results are illustrated in Fig. 20. As shown from Fig. 20, using proposed method can detect the pedestrians accurately even in the different illumination and crowed conditions.

#### 3.4 Discussion

We try to use the other cameras (such as the camera 2 illustrated in Fig. 15) which were set on the 3.5 m height and 30° with the horizontal to collect the training data, however, the accuracy of the pedestrian detection has decreased obviously, especially almost the pedestrians belonging to the Classifier-1 have not been detected. The reason of low detection rate is the shapes of the pedestrians for training are not matching with the pedestrians for testing in each classifier. For instants, from the camera 2, the system can not collect enough training data for the Classifier-1. However, if just change the camera height and angle slightly, we expect that the system will not affect accuracy of detection.

#### 4. Conclusion

This paper presented a method of pedestrian detection using a top-view camera, which can improve the detection performance of pedestrian detection for counting applications. In this paper, we proposed 2 methods to solve the problems on top-view pedestrian detection systems, 1) we proposed a method to estimate each pedestrian's direction using the shape context method, 2) we constructed 3 classifiers to detect the pedestrians on different locations, and choose the most adaptive classifier to classify automatically. The experimental results demonstrated the efficiency of our algorithm.

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