A Pedestrian Detection System Using Applied Log-Gabor Filters

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Abstract: - Pedestrian detection is one of the most important research contents of road safety. The crucial idea behind such pedestrian safety systems is to protect the driver and pedestrian from any accident. In this paper, a pedestrian feature extraction based on applied log-Gabor filters is presented. The resulting filtered images show desirable segmentation performance which allows support vector machines to be able to efficiently classify and recognize the pedestrian. The proposed system is capable of detecting multiple pedestrians from complex background and providing size and position information of pedestrians within the image. Pedestrians with different sizes, shapes, postures, and clothes can be detected effectively. Results and discussions are presented.

Key-Words: - pedestrian detection, pedestrian safety systems, applied log-Gabor filters, pedestrian feature extraction, support vector machines

1 Introduction

Pedestrian detection involves safety for both road drivers and pedestrians themselves. There are various kinds of technology for pedestrian detection using either hardware or software. From an application's point of view, the pedestrian detection system can be very useful for monitoring traffic flow, on-board and on-site vehicle drivers assisting system, or the intelligent pedestrian crossing system, etc. By using computer vision, pedestrians can be detected and segmented from complex background. This allows the system to locate both sizes and positions of pedestrians in the camera's field of view. Detecting of pedestrian details in an image, however, can be very complicated due to various postures and appearances of pedestrians, uncontrollable and unpredictable surroundings, and problems with illuminations of outdoor environments. In additions, complex backgrounds such as buildings, trees, traffic signs and vehicles, make this pedestrian detection even more challenging problem. Fig.1 displays such variations of pedestrians.

Methods of pedestrian detection can be mainly categorized into two concepts: motion analysis and shape analysis. By using of pedestrian motion [1-4], a continuous segmentation of pedestrian movement is analyzed. Although, these motion-based methods are efficient for reducing a rate of pedestrian false detection, there are still some limitations. They cannot detect motionless pedestrians or any unusual motions of pedestrian, e.g. jumping, crawling, etc. Also, pedestrian's legs must clearly appear in the image in order to search for patterns of pedestrian motions. Furthermore, a sequence of images is required for segmentation and recognition which cannot be done within a single image.

By using pedestrian shape, specific pedestrian characteristics are analyzed for segmentation and recognition [5,6]. Obviously, the advantage of these shape-based methods is no multiple images required. In [7], Radial Basis Functions, which is trained with pedestrian images, is deployed to analyze pedestrian shapes for detection and segmentation. Sparse Gabor filters has been used together with support vector machines in [8] for learning and recognizing pedestrian. Even though these shape-based pedestrian detection methods have been widely used, the various characteristics of pedestrian and illumination problem can increase false detection of pedestrians. In additions, this kind of method likely requires highly computational time.

Fig. 1 Examples of pedestrian with various shapes, postures, clothes and backgrounds (from [15])

From both motion-based and shape-based pedestrian detection, they all have some limitations. This work presents a shape-based pedestrian detection using applied log-Gabor filters for pedestrian feature extraction and support vector machines for recognition and segmentation of pedestrians. Details are described in the following sections.

2 Pedestrian Detection System

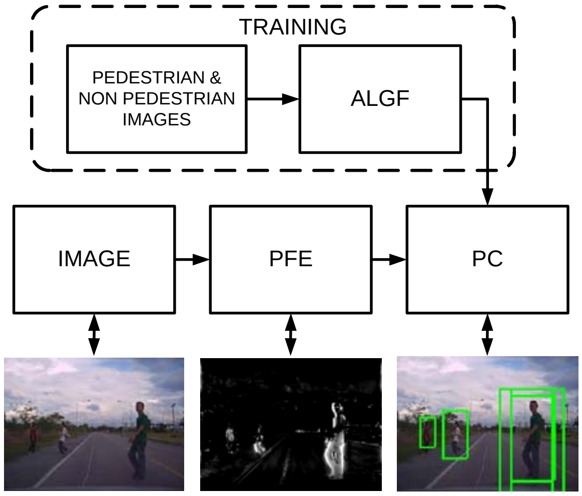

Fig. 2 Pedestrian detection system diagram

The proposed pedestrian system diagram is depicted in Fig.2. The system mainly consists of two parts: pedestrian feature extraction (PFE) and pedestrian classification (PC). The pedestrian feature extraction is achieved by filtering an image with applied log-Gabor filters (ALGF). The pedestrian classification is obtained by using support vector machines (SVMs) which are trained by both pedestrian and non-pedestrian images.

2.1 Pedestrian Feature Extraction

The proposed pedestrian feature extraction is based on log-Gabor filters (LGF). Input gray-scale images (Fig.3b) are pre-processed (PP) to adjust for brightness by using histogram equalization. These images are then filtered by LGF. Results from LGF provide salient features of pedestrians' pixels for both line and color features. The line feature extraction (LFE) is the part that looks for vertical responses from filtered images, i.e. extraction of vertical phase (VP) as seen in Fig.3f. It is obvious to consider vertical responses in the image because pedestrians' shapes tend to be vertical. Fig.3c and 3d are HSV image and its gray-scale image, respectively, used for color feature extraction. The color feature extraction (CFE) consists of both bright point symmetry phase (BPSP) and dark point symmetry phase (DPSP) as depicted in Fig.3g and 3h. By combining all responses, the result is total phase (TP) that responses to color of pedestrians' clothes (see Fig. 3i). Note that Fig.3e is vertical edges. It is used for a comparison purpose as described in the experimental result section.

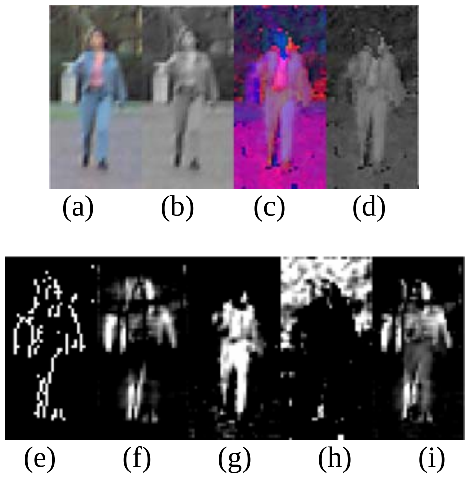

Fig. 3 Extraction of pedestrian features (a) RGB image (b) gray-scale image (c) HSV image (d) gray-scale from HSV image (e) vertical edges (f) vertical phase (g) bright point symmetry phase (h) dark point symmetry phase and (i) total phase

The pedestrian feature extraction (PFE) applies both LFE and CFE to extract salient features of pedestrians, hence, the name applied log-Gabor filters (ALGF) is introduced. Diagram of pedestrian feature extraction is displayed in Fig.4

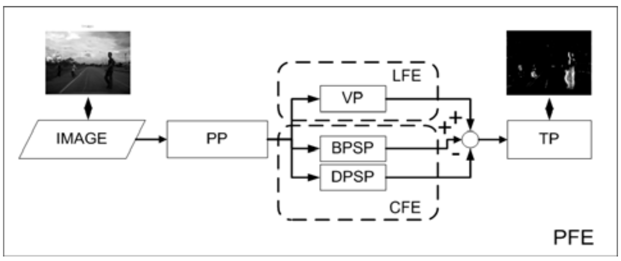

Fig. 4 Pedestrian feature extraction (PFE) diagram

Log-Gabor filters [9] (see Fig.5) used in this work is developed by [10] as formulated in the following equation.

$$\mathrm{LGF}(w) = \exp((-\log(w/w_0)^2)/(2(\log(\beta/w_0)^2))) \quad (1)$$

where w_0 is the filter's center frequency and β/w_0 is constant shape ratio filter.

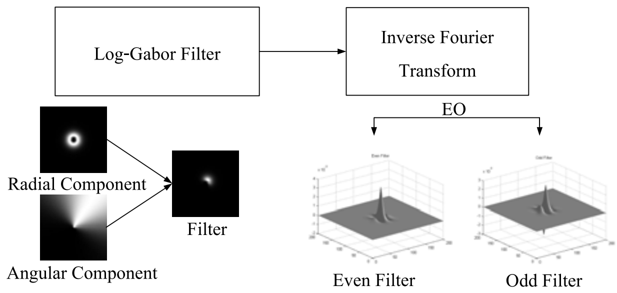

Fig. 5 Log-Gabor filters

The resulting filtered images are complex number. Each pixel x is composed of a real part $e(x)$ that has good responses to colors in the images and an imaginary part $o(x)$ that has good responses to edges in the images. The amplitude of filtered image at scale n is given by

$$A_n(x) = \sqrt{e_n{}^2(x) + o_n{}^2(x)} \quad (2)$$

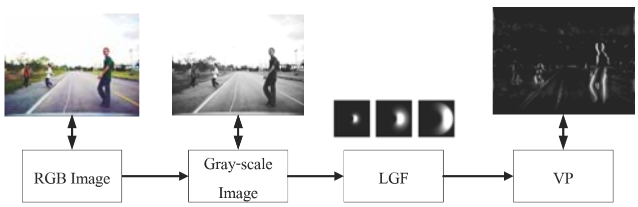

Fig. 6 Line feature extraction from vertical phase of a log-Gabor filtered image

In order to detect pedestrians in LFE part, a gray-scale image is filtered using $n = 3$ at 90 degree angle. This yields all vertical phases as given by

$$\mathrm{VP}(x) = \frac{\left(\left|\sum_n (o_n(x))\right|\right)}{\max\left(\left|\sum_n (o_n(x))\right|\right)} \quad (3)$$

where $\mathrm{VP}(x)$ is a vertical phase of pixel x. Pedestrian images that are filtered by these filters contain more salient lines and patterns than other images such as cars or trees. This is because pedestrians mostly appear in vertical angle (see Fig. 6).

For the color feature extraction (CFE) part, the hue and saturation components of the images are deployed. This HS image has a better response to pedestrian's appearance than the rest of the image. The symmetry phase (SP) [11] of the HS image is computed by the filter with $n = 6$ and 90 degree angle as given by

$$\mathrm{SP}(x) = \frac{\sum_n [|e_n(x)| - |o_n(x)|]}{\sum_n A_n(x) + \varepsilon} \quad (4)$$

where $\mathrm{SP}(x)$ is a symmetry phase of pixel x. In additions, this symmetry phase can be separately considered as bright point symmetry phase (BPSP) and dark point symmetry phase (DPSP). The BPSP provides well response for colors of pedestrians' clothes while the DPSP gives well response for colors of trees and background. The BPSP and DPSP are given by

$$\mathrm{BPSP(x)} = \frac{\sum_n [e_n(x) - |o_n(x)|]}{\sum_n A_n(x) + \varepsilon} \quad (5)$$

$$\mathrm{DPSP(x)} = \frac{\sum_n [-e_n(x) - |o_n(x)|]}{\sum_n A_n(x) + \varepsilon} \quad (6)$$

where $\mathrm{BPSP}(x)$ and $\mathrm{DPSP}(x)$ are the bright point symmetry phase and dark point symmetry phase of pixel x, respectively. Fig.7 depicts an example of responses from SP, BPSP, and DPSP.

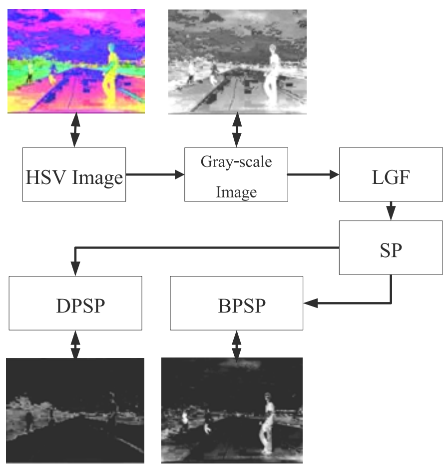

Fig. 7 Color feature extraction from symmetry phase of log-Gabor filtered image

The ALGF extracts salient features of pedestrians which are the vertical response (from VP) and the difference between colors of pedestrian (from BPSP) and colors of background (from DPSP). By adjusting with weighting factors and combining all features, the total phase (TP) is obtained as follow:

$$\mathrm{TP}(x)=\alpha*\mathrm{VP}(x)+\beta*\mathrm{BPSP}(x)-\gamma*\mathrm{DPSP}(x) \quad (7)$$

The results from TP contain salient features of pedestrians in the image for both lines and colors (see Fig.8). The total response of pedestrians in the image strongly appears in contrast with the background. Both types of responses are complement to each other allowing the better performance for segmenting pedestrians from the background. This leads to the improvement of pedestrian classification as described next.

Fig. 8 Total phase

2.2 Pedestrian Classification

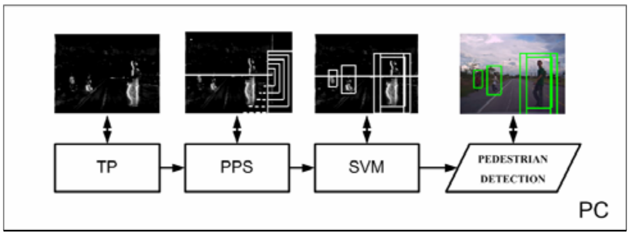

Fig. 9 Pedestrian classification system diagram

The main engine for pedestrian classification is support vector machines (SVMs), one of the most efficient tools for classification (see Fig.9). The ALGF filtered image is scanned at the proportion pedestrian size (PPS) area. Each resulting subimage is resized and sent to SVMs for classification. The SVMs are trained to classify pedestrian and non-pedestrian images. In order to overcome different sizes of pedestrians, the pedestrian's proportion can be determined by using relationship between distances from pedestrians to the camera [12] as given by the following equation.

$$y_i=\frac{h_i y_c}{v_i-v_0} \quad (9)$$

where y_i is a pedestrian height, h_i is a number of pixels of pedestrian in the image, y_c is a camera height, v_i is the last row of pedestrian's pixels in the image and v_0 is a vanishing line (see Fig.10)

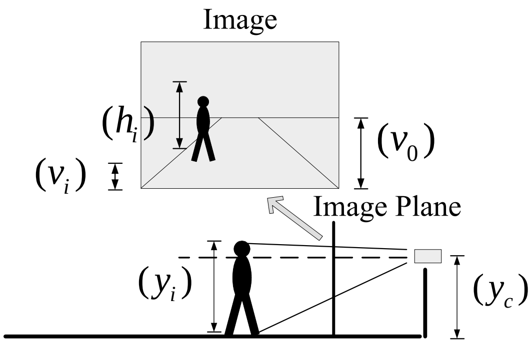

Fig. 10 Position and proportion of pedestrian in the real world and in the image plane

SVMs [13] can linearly and nonlinearly classify data into two classes. Its trained hyper plane is used to optimally separate both classes of data. Consider L data set, i.e. $(x_1,y_1)(x_2,y_2)...(x_L,y_L)$ where $x_L\in R^N$ and $y\in(-1,+1)$, the optimal hyper plane can be determined by

$$f(x)=\sum_{i=1}^{N} y_i\alpha_i k(x,x_i)+b \quad (10)$$

where α_i and b are the learning weight and $k(...)$ is a kernel function (in the work, the radial basis kernel function is deployed which is $k(x,y)=\exp\left(-\|x-y\|^2/(2\sigma^2)\right)$ where σ is parameter of the radial basis function).

3 Experimental Results

Fig. 11 Installation of a camera in a car

The proposed pedestrian system has been tested using various images with road environment from the camera that is installed in the car (see Fig.11). The size of the test images are 320 by 240 pixels. Fig.6 shows the example responses of vertical phase and Fig.7 depicts all responses of symmetry phase, bright point symmetry phase and dark point

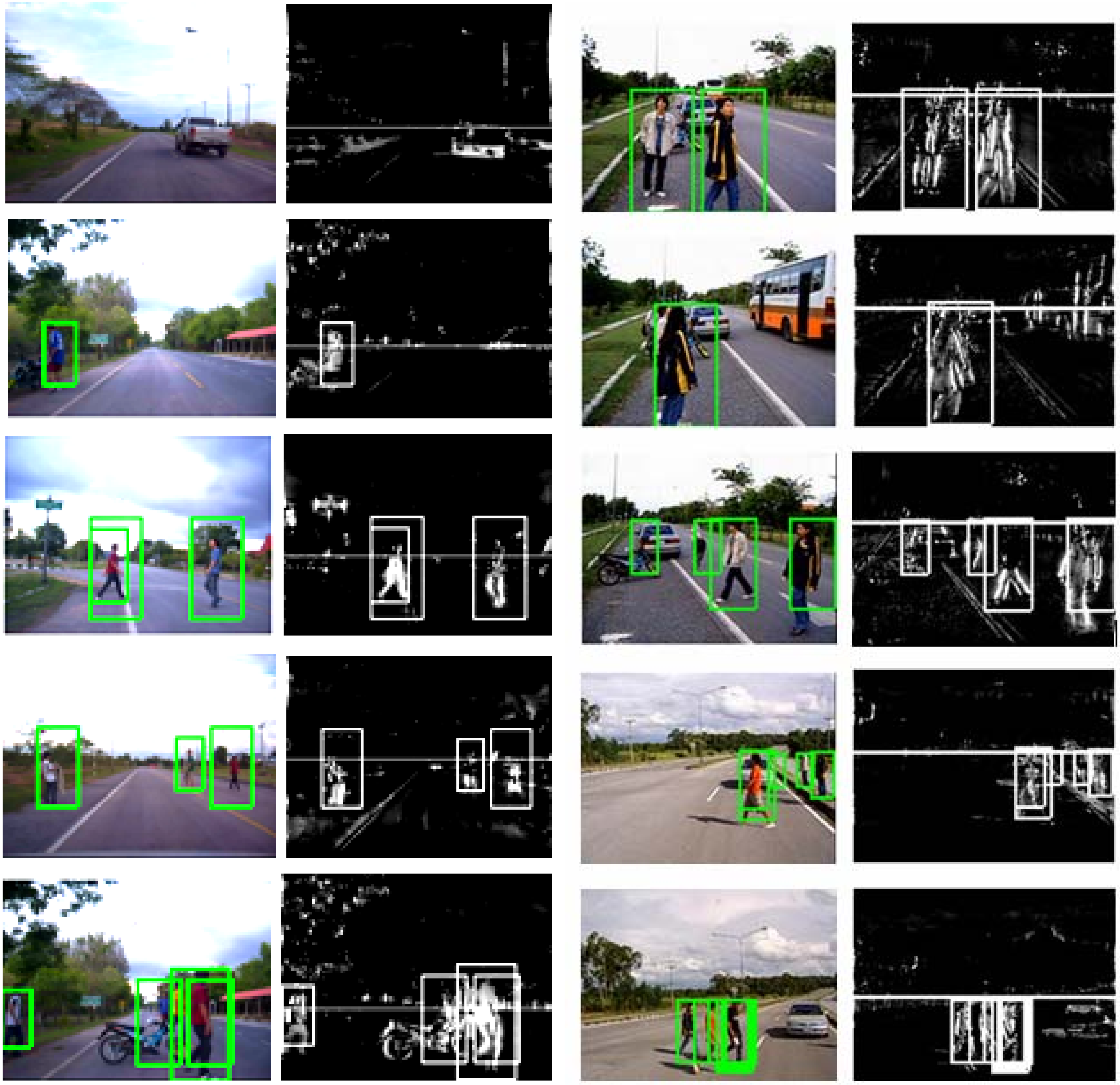

Fig. 12 Examples of pedestrian detection using applied log-Gabor filters

symmetry phase. The examples of total phase are displayed in Fig.8. Note that by comparing with individual phase, the total phase provides strongest responses to the pedestrian. The results clearly show that the ALGF is capable of extract pedestrian features. This yields the system to efficiently segment pedestrians from the image, locate and identify sizes of the pedestrian within the images, especially, when pedestrians' clothes have colors in contrast with the background and pedestrians have usual postures.

The pedestrian classification is trained with 500 pedestrian images and 500 non-pedestrian images [15]. The system is tested with 2,848 of untrained images [15]. Fig. 12 displays various examples of pedestrian detection using applied log-Gabor filters. Note that the proposed system is clearly capable of detecting multiple pedestrians in a single image. The performance of the system is measured by receiver operating characteristic graph (ROC) [14] which the y axis is true positive rate (TPR) and the x axis is false positive rate (FPR). The resulting ROC is displayed in Fig.13. Obviously, the pedestrian detection using total phase overcomes any detection that utilizes with one feature. The area under ROC curve of the total phase detection is as high as 0.9817.

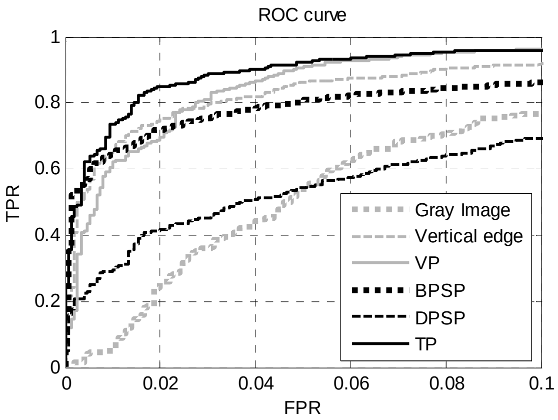

Fig. 13 Comparison of pedestrian detection using different features

4 Conclusion

This paper has presented pedestrian detection system using the applied log-Gabor filters. This filter efficiently provides both line feature extraction and color feature extraction for pedestrian feature extraction. This allows the pedestrian classification by support vector machines to be more effective. The proposed system is capable of detecting pedestrian with various kinds of postures, clothes, sizes, and shapes. The system, however, has some limitations for detecting partial pedestrian or pedestrian-alike objects in the image. With sufficient data for classification part, this system shows promising performance for using in real-world applications.

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