SVM-BASED HUMAN DETECTION COMBINING SELF-QUOTIENT ε-FILTER AND HISTOGRAMS OF ORIENTED GRADIENTS

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Abstract: This paper describes a noise robust SVM-based human detection combining self-quotient ε-filter (SQEF) and histograms of oriented gradients (HOG). Although human detection combining HOG and SVM is a powerful approach, as it uses local intensity gradients, it is difficult to handle noise corrupted images. To handle noise corrupted images, we introduce self-quotient ε-filter (SQEF), and implement it in human detection combining HOG and SVM. SQEF is an advanced self-quotient filter (SQF), and can clearly extract features from the images not only when they have illumination variations but also when they are corrupted with noise. The new approach gives a robust human detection from noise corrupted images using the data trained by intact images without noise.

1 INTRODUCTION

Detecting human from images is a challenging task in owing to their variable appearance and the wide range of poses that they can adopt. The important requirement is to extract the feature from the images clearly, even in backgrounds under different illumination. Histogram of Oriented Gradients (HOG) algorithm is a useful approach to match this requirement (Dalal and Triggs, 2005). It can extract the feature clearly compared to other existing feature sets including wavelets (Mohan et al., 2001; Viola et al., 2003). The approach is related to edge orientation (Freeman and Roth, 1995; Freeman et al., 1996), SIFT descriptors (Lowe, 2004) and shape contexts (Belongie et al., 2001). Although locally normalized HOG detectors are attractive approaches to detect the human from the image, it is difficult to detect them from the noise corrupted images because it uses local intensity gradients.

To handle the problems, this paper introduces self-quotient ε-filter (SQEF), which is an advanced noise robust self-quotient filter (SQF) and propose a noise robust SVM-based human detection combining SQEF and HOG. Self-quotient filter (SQF) is a simple nonlinear filter and can extract the feature from an image with light variation (Wang et al., 2004a; Wang et al., 2004b). It needs only an image, and can extract intrinsic lighting invariant property of an image, while removing extrinsic factor corresponding to the lighting. Feature extraction using SQF is simpler than that using multi-scale smoothing (Gooch et al., 2004). It can extract the outline of the objects independent of shadow region. However, it is difficult to extract the shape and texture when the noise damages the image as SQF assumes that the image does not include noise. The noise influence becomes large due to the self-quotient effect of SQF.

Self-quotient ε-filter (SQEF) (Matsumoto, 2010) is a nonlinear filter combining the idea of SQF and ε-filter (Arakawa and Okada, 2005). Although many studies have been reported to reduce the small amplitude noise while preserving the edge (Himayat and Kassam, 1993; Tomasi and Manduchi, 1998), it is considered that ε-filter is a promising approach due to its simple design. It does not need to have the signal and noise models in advance. It is easy to be designed and the calculation cost is small because it requires only switching and linear operation. We can clearly extract the feature from noise corrupted image images by defining SQEF as the ratio of two different ε-filters. In this paper, we aim to reduce the noise influence by employing SQEF as preprocessing of HOG.

This paper is organized as follows. In section 2, we briefy introduce SQEF, and discuss the merits of SQEF compared to SQF. We also describe the algorithm of SVM-based human detection combining

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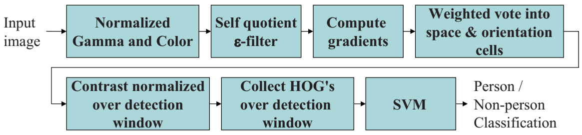


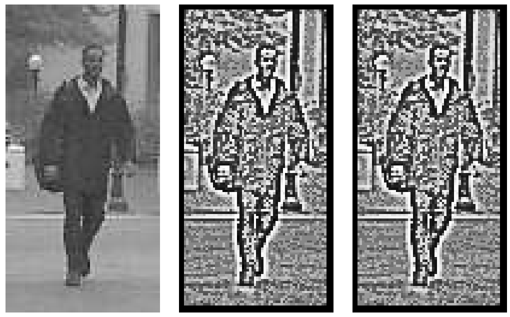
Figure 1: An overview of our feature extraction and object detect chain.

SQEF and HOG. Experimental results are shown to clarify the effectiveness of the proposed method for human detection from noise corrupted images compared to other approaches in section 3. A libsvm (Chang and Lin, 2001), MIT pedestrian test set (Oren et al., 1997; Papageorgiou et al., 1998; Mohan et al., 2001; Papageorgiou and Poggio, 2000) and standard image database (SIDBA) are used as a SVM classifier, positive sample images and negative sample images, respectively throughout the experiments. Conclusion is given in section 4.

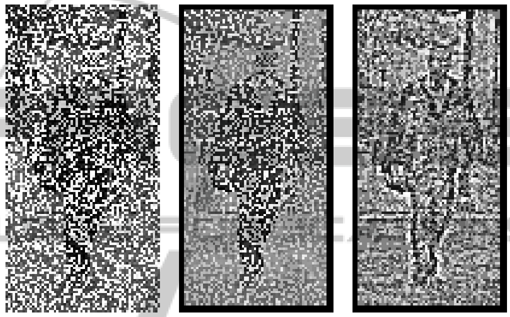
2 PROPOSED ALGORITHM

In this section, we describe the proposed algorithm. Figure 1 shows the procedure of our approaches. In the proposed method, we first extract the feature from the noise corrupted image by using self-quotient ε-filter (SQEF) to eliminate not only illumination variations but also noise influence. Some examples are shown to clarify the difference between self-quotient filter (SQF) (Wang et al., 2004a; Wang et al., 2004b) and SQEF. Figure 2 shows the examples of filter output of SQEF to show its robust feature extraction from noise corrupted images. We also show the filter output of self-quotient filter (SQF). Fig.2(a) shows a sample image from MIT pedestrian database (Oren et al., 1997; Papageorgiou et al., 1998; Mohan et al., 2001; Papageorgiou and Poggio, 2000). Figs.2(b) and 2(c) show the filter outputs of SQF and SQEF, respectively when we used the original image. On the other hand, Fig.2(d) shows the sample image corrupted with 40% impulse noise. Figs.2(e) and 2(f) show the filter outputs of SQF and SQEF, respectively when we used the impulse noise corrupted image. As shown in Fig.2, both SQF and SQEF can extract the feature from the original image. However, SQF cannot extract its feature from the impulse noise corrupted image, while SQEF can extract the feature from the impulse noise corrupted image.

Let $x(i_1,i_2)$ be the image intensity at the point $\mathbf{i} = (i_1,i_2)$ in the image. The aim of SQF is to separate the intrinsic property and the extrinsic factor, and to remove the extrinsic factor. To handle the problem, SQF assumes that a smoothed version of an image has approximately the same illumination as the original



(a) A sample image from MIT pedestrian database (file name: per00008.pgm)
(b) Filter output of SQF when we used original image
(c) Filter output of SQEF when we used original image



(d) Impulse noise corrupted image (40% impulse noise)
(e) Filter output of SQF when we used impulse noise corrupted image
(f) Filter output of SQEF when we used impulse noise corrupted image

Figure 2: Self-quotient image and self-quotient ε-filter from original image and impulse noise corrupted image

one. In SQF, we first calculate the following equation:

$$y(i_1,i_2) = \frac{x(i_1,i_2)}{F[x(i_1,i_2)]}, \quad (1)$$

where $x(i_1,i_2)$ is the original image and F is the smoothing function. Due to the process of Eq.1, the texture and edge can be extracted because the original image is divided by the smoothed image. However, SQF assumes that the image does not include the noise. When we consider the noise corrupted image, the noise is reduced in the smoothed images $F[x(i_1,i_2)]$, while the original image $x(i_1,i_2)$ includes the noise. As a result, the influence from the noise in SQF is emphasized very much as shown in Fig.2 due to the self-quotient effect of SQF in Eq.1.

A simple idea to solve the noise influence in SQF is to use two smoothed filters instead of original image as follows:

$$y(i_1,i_2) = \frac{F_1[x(i_1,i_2)]}{F_2[x(i_1,i_2)]}. \quad (2)$$

F_1 and F_2 should be different because the output always becomes 1 if F_1 and F_2 are the same smoothed filter.

However, even if we design SQF by using two different smoothed filters, not only the noise is smoothed but also the texture and shape are blurred. As the blur level of one smoothed filter is different from the other, it is also difficult to handle impulsive noise. Hence, we need to employ alternative filters, which can reduce the small amplitude noise effectively, while preserving the texture and shape information instead of simple smoothed filter. The alternative filters should be simple to keep the simplicity of SQF.

Based on the above prospects, self-quotient ε-filter (SQEF) is designed as follows:

$$y(i_1,i_2) = \frac{\Phi_{\varepsilon_1}[x(i_1,i_2)]}{\Phi_{\varepsilon_2}[x(i_1,i_2)]}, \tag{3}$$

where Φ_ε represents ε-filter described as follows:

$$\begin{aligned} z(i_1,i_2) &= \\ \Phi_\varepsilon[x(i_1,i_2)] &= x(i_1,i_2) + \\ &\sum_{j_1=-K}^{K}\sum_{j_2=-K}^{K} a(j_1,j_2)F(x(i_1+j_1,i_2+j_2)-x(i_1,i_2)), \end{aligned} \tag{4}$$

where $a(j_1,j_2)$ represents the filter coefficient. $a(j_1,j_2)$ is usually constrained as follows:

$$\sum_{j_1=-K}^{K}\sum_{j_2=-K}^{K} a(j_1,j_2) = 1. \tag{5}$$

$F(x)$ is the nonlinear function described as follows:

$$|F(x)| \le \varepsilon : -\infty \le x \le \infty, \tag{6}$$

where ε is a constant number constrained as follows.

$$0 \le \varepsilon. \tag{7}$$

It should be noted that calculation cost of ε-filter is small because it requires only switching and linear operation. See the references (Arakawa and Okada, 2005) if the reader would like to know the details about ε-filter.

When we apply SQEF to impulse noise corrupted image, it is considered that both ε-filters in SQEF keep the impulse noise in the image unlike when two smoothed filters are employed. Hence, when one filter output in SQEF is divided by the other filter in SQEF, the impulse noise effect is reduced by the self-quotient effects.

We next apply HOG procedure to SQEF output. Figure 3 shows the procedure of HOG from SQEF outputs. The method is based on evaluating well-normalized local histograms of image gradient orientations in a dense grid. As local object appearance and shape are kept in SQEF output, the gradient intensity and the gradient direction of SQEF are calculated for all the pixels as follows:

$$f_{i_1}(i_1,i_2) = y(i_1+1,i_2) - y(i_1-1,i_2) \tag{8}$$

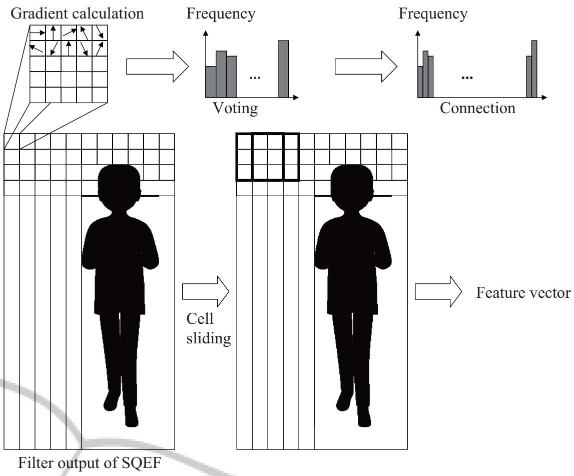


Figure 3: Procedure of Histogram of Oriented Gradients (HOG) from SQEF output.

$$f_{i_2}(i_1,i_2) = y(i_1,i_2+1) - y(i_1,i_2-1) \tag{9}$$

$$m(i_1,i_2) = \sqrt{f_{i_1}^2 + f_{i_2}^2} \tag{10}$$

$$\theta(i_1,i_2) = \arctan\frac{f_{i_2}}{f_{i_1}} \tag{11}$$

The basic idea of HOG is that local object appearance and shape can often be characterized rather well by the distribution of local intensity gradients or edge directions, even without precise knowledge of the corresponding gradient or edge positions (Dalal and Triggs, 2005). In practice, this is implemented by dividing the filter output into small spatial regions ("cells"), for each cell accumulating a local 1-D histogram of gradient directions or edge orientations over the pixels of cell. The obtained direction θ ($0^\circ \le \theta \le 180^\circ$) is divided with 20° intervals. 9 dimensional feature vector is generated by adding the gradient intensity $m(i_1,i_2)$. We then regard 3×3 cells as "Block" and generate many blocks by sliding on a pixel to pixel basis. The feature vector is finally obtained by combining all the feature vector. The obtained feature vector is adopted to SVM.

3 EXPERIMENTS

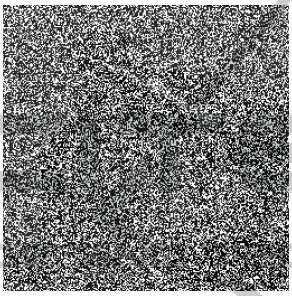
We conducted the recognition experiments using impulse noise corrupted images to show the effectiveness of the proposed method.

MIT pedestrian database and SIDBA were employed as image database. MIT pedestrian database contains 900 images. The size is 64 pixel × 128 pixel. Some non person images were selected from standard image database (SIDBA). 900 64 pixel × 128 pixel

(a) Person image from MIT pedestrian database (per00001.pgm)

(b) Non-person image from SIDBA (Airplane)

(c) Person image from MIT pedestrian database with 40% impulse image (per00001.pgm)



(d) non-person image from SIDBA with 40% impulse noise (Airplane)

Figure 4: Sample images of person image and non-person image (Original and noise corrupted images).

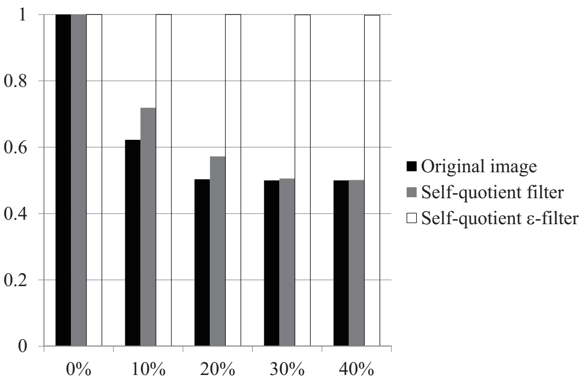


Figure 5: Experimental results of human detection from impulse noise corrupted image.

images were cut from them. We also prepared impulsive noise corrupted images by adding the impulse noise to the above 1800 images. Noise percentage changed from 10% to 40% with 10% intervals. Figure 4 shows original person / non-person images and its noise-corrupted version. Our aim is to detect human from these types of noise corrupted images not by using the data trained by the impulse noise corrupted image but by using the data trained by intact images without noise. As a SVM tool, we used libsvm, a library for support vector machines (Chang and Lin, 2001), and employed default setting and parameters throughout the experiments for simplicity.

In the experiments, we used original 450 pedestrian images from MIT pedestrian database and 450 non-person images from SIDBA. We tried to classify the impulse noise corrupted image by using the training data. The test images are the remaining 450 pedestrian images from MIT pedestrian database and the remaining 450 non-person images from SIDBA with impulse noise, which are different from the training images. For comparison, we also tested to classify them using the method combining HOG and SVM, and the method combining SQF, HOG and SVM. Figure 5 shows the recognition results. As shown in Fig.5, it was difficult to classify the images using the method combining HOG and SVM when the image was corrupted with the impulse noise. The results were still bad even when we used the method combining SQF, HOG and SVM. On the other hand, the proposed approach could detect human from noise corrupted images over 90% using training data with intact images without noise.

4 CONCLUSIONS

This paper proposed a noise robust SVM-based human detection combining self-quotient ε-filter and histogram of oriented gradients. We compared the results of our approach to the results of HOG and SVM, and the results of SQF, HOG and SVM. Throughout the experiments, the proposed method could robustly detect pedestrians from noise corrupted images using the training data with the clean image without noise, while it is difficult to detect pedestrians using other approaches. Future works include the applications of our method to robot vision. Detailed study of effects of the parameters should also be required. We also would like to apply the proposed method to medical images to detect disease site from noise corrupted images.

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REFERENCES

Arakawa, K. and Okada, T. (2005). ε-separating nonlinear filter bank and its application to face image beautification. In *IEICE Transactions on Fundamentals*, pages 1216–1225. IEICE.

Belongie, S., Malik, J., and Puzicha, J. (2001). Matching shapes. In *Proc. of Int'l Conf. on Computer Vision*, pages 454–461. IEEE.

Chang, C.-C. and Lin, C.-J. (2001). LIBSVM: a library for support vector machines. In *http://www.csie.ntu.edu.tw/ cjlin/libsvm*.

Dalal, N. and Triggs, B. (2005). Histograms of oriented gradients for human detection. In *Proc. of Int'l Conf. on Computer Vision and Pattern Recognition.*, pages 886–893. IEEE.

Freeman, W. T. and Roth, M. (1995). Orientation histograms for hand gesture recognition. In *Proc. of Int'l Workshop on Automatic Face and Gesture Recognition*, pages 296–301. IEEE.

Freeman, W. T., Tanaka, K., Ohta, J., and Kyuma, K. (1996). Computer vision for computer games. In *Proc. of Int'l Conf. on Automatic Face and Gesture Recognition*, pages 100–105. IEEE.

Gooch, B., Reinhard, E., and Gooch, A. (2004). Human facial illustrations: Creations and psychological evaluation. In *ACM transactions on Graphics*, pages 27–44. ACM.

Himayat, N. and Kassam, S. (1993). Approximate performance analysis of edge preserving filters. In *IEEE Trans. on Signal Processing.*, pages 2764–2777. IEEE.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. In *Int'l Journal of Computer Vision*, volume 60, pages 91–110. Springer.

Matsumoto, M. (2010). Feature extraction from noisy face image using self-quotient ε-filter. *Proc. of Int'l Conf. on Computer Engineering and Technology*, pages 395–399.

Mohan, A., Papageorgiou, C., and Poggio, T. (2001). Example-based object detection in images by components. In *IEEE Trans. on PAMI.*, volume 23, pages 349–361. IEEE.

Oren, M., Papageorgiou, C., Sinha, P., Osuna, E., and Poggio, T. (1997). Pedestrian detection using wavelet templates. In *Proc. of IEEE Conf. on Computer Vision and Pattern Recognition*, pages 193–199. IEEE.

Papageorgiou, C., Oren, M., and Poggio, T. (1998). A general framework for object detection. In *Proc. of Int'l Conf. on Computer Vision*, pages 555–562. IEEE.

Papageorgiou, C. and Poggio, T. (2000). A trainable system for object detection. In *Int'l Journal of Computer Vision*, volume 38, pages 15–33. Springer.

Tomasi, C. and Manduchi, R. (1998). Bilateral filtering for gray and color images. In *Proc. of Int'l Conf. on Computer Vision*. IEEE.

Viola, P., Jones, M. J., and Snow, D. (2003). Detecting pedestrians using patterns of motion and appearance. In *Proc. of Int'l Conf. on Computer Vision*, volume 1, pages 734–741. IEEE.

Wang, H., Li., S. Z., and Wang, Y. (2004a). Face recognition under varying lighting conditions using self quotient image. In *Proc. of Int'l Conf. on Automation Face and Gesture Recognition*. IEEE.

Wang, H., Zhang, J. J., Li., S. Z., and Wang, Y. (2004b). Shape and texture preserved non-photorealistic rendering. In *Computer animation and virtual worlds*, pages 453–461. John Wiley and Sons, Ltd.