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Block-Based Hough Transform for Recognition of Zebra Crossing in Natural Scene Images

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ABSTRACT In this paper, a block-based Hough transform is proposed to recognize the zebra crossing in natural scene images. Overlapping blocks are laid on the region of interest (ROI) in each image. For each patch in the block, two processes are performed successively. First, preprocessing is adopted for edge detection, whereas the adaptive thresholding is used to minimize the effect of various shadows. Second, parallel lines detection is adapted to recognize the zebra crossing, whereas the Hough transform is used for straight lines detection. When all the blocks are processed, the angles of parallel lines are averaged to provide the direction of the zebra crossing, and the accumulative scores are synthesized to provide the position of the zebra crossing. The performance of the proposed method is evaluated by testing results based on numerous images.

INDEX TERMS Accumulative scoring evaluation, block-based Hough transform, zebra crossing recognition.

I. INTRODUCTION

The zebra crossing is an important traffic sign that provides a safe passage for pedestrians at intersections [1]. Focusing on helping the visually impaired to recognize this sign, several research works have been reported in the field. In [2] the Hough transform is adopted to detect straight lines and the vanishing point constraint is adopted to verify concurrency of the zebra crossing. In [3] bipolarity is proposed to detect the bipolar patterns of the zebra crossing. The prototype "Crosswatch" runs on a camera phone and provides information about the zebra crossing in voice [4], [5]. In [6] a framework to recognize zebra crossings, stairs, and traffic signals with RGB-D (red, green, blue, and depth) images is developed. In the prototype "ZebraRecognizer", the projection distortion of the zebra crossing is rectified to improve the accuracy of recognition [7]. The prototype is parallel implemented on the GPU for acceleration [8]. In [9] the Hough transform and logical constrains are adopted to detect the zebra crossing in the mobile LIDAR data. Recently, machine learning methods are used to classify zebra crossings [10], [11]. In these works, large-scale data are automatically acquired on electronic maps, and deep-learning-based models are trained on the data for classification. In [12], satellite images are captured from an electronic map, and an SVM classifier is trained to recognize the zebra crossing.

In this paper, a similar solution of Hough transform is adopted to detect straight lines of the zebra crossing. Instead of processing the entire image, herein a block-based Hough transform is proposed. Specifically, the region of interest (ROI) in each image is segmented by overlapping blocks, and the patch in each block is handled by two processes successively. Firstly, preprocessing is adopted to detect edges. Secondly, the Hough transform is improved for parallel lines detection. Once all the blocks are processed, the angles of parallel lines and the accumulative scores are synthesized to provide the information of the zebra crossing.

Different from the existing works, the proposed method can provide both the position and direction of zebra crossings in nearby regions. For safety reasons, the proposed system should be carried out simultaneously with the pedestrian traffic light detection, which is discussed in our previous works [13], [14]. The combination of the various information will help the visually impaired to make a good decision. The rest of this paper is organized as follows. In Section 2, problems and restrictions to recognize the zebra crossing in natural scenes are specified. In Section 3, the architecture of the proposed system is introduced. Experiment results are shown in Section 4. Conclusions are presented in Section 5.

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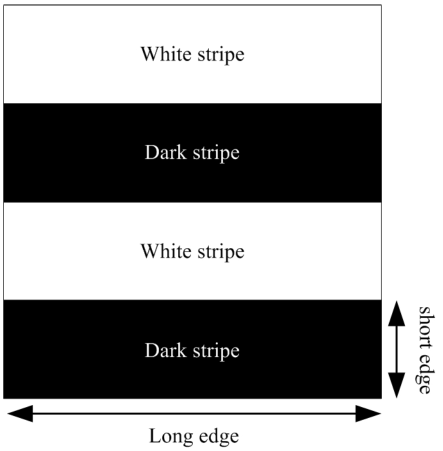

FIGURE 1. The standard zebra crossing. It is composed of white stripes and dark stripes. Each stripe is rectangular.

II. PROBLEM SPECIFICATION

In this section, problems of recognizing zebra crossings in natural scenes are discussed. In addition, images of these scenes are captured and stored for further analysis.

A. PROBLEMS AND RESTRICTIONS

The standard zebra crossing is composed of white stripes and dark stripes, which is shown in Fig.1. The stripes are rectangluar. The color of dark stripes is always similar to the road below. The zebra crossing has two distinguishing properties:

- The long edges of the stripes are parallel [2].
- The intensity has bipolar characteristics [3].

However, these properities become insignificant in natural scenes, as shown in Fig.2. These problems are summarized as following:

- The number of stripes changes along various intersections [e.g. Fig.2(a)-(j)].
- The illumination condition changes from morning till night [e.g. glare lighting in Fig.2(a), low illumination in Fig.2(g)].
- Irregular shadows offen appear on the zebra crossing [e.g. shadow of tree in Fig.2(a), shadow of car in Fig.2(i)].
- White strips sometimes are indistinct [e.g. faded stripes in Fig.2(b), destroyed stripes in Fig.2(c)].
- The zebra crossing is partly occluded [e.g. leaves in Fig.2(d), sewage in Fig.2(e), pedestrian in Fig.2(h)].
- The direction of the zebra crossing changes within a certain range [e.g. Fig.2(f)].
- The color of dark stripes is not unique [e.g. red stripes in Fig.2(j)].
- The minority of the zebra crossing is visible from this perspective [e.g. Fig.2(j)].
- The road surface is uneven [e.g. repair in Fig.2(c), slope in Fig.2(f), seam in Fig.2(j)].

B. DATASET

In order to analyze the actual situation encountered by the visually impaired, we capture images standing on blind bricks, keeping the camera upright. This is based on the reality that the visually impaired can find intersections through blind bricks. Totally, 742 videos are captured during the day and 84 videos are captured at night. The resolution of each video is 4032×3024. In these videos, 2940 frames of daytime and 396 frames of night are captured to form a dataset. These images are scaled to 640×480, since the computation of Hough transform has a linear complexity with the number of pixels [4]. As shown in Fig.2, the images in the dataset have four characteristics: 1) the zebra crossing is captured in natural scenes; 2) the zebra crossing occupies a local region tightly; 3) The angle between the zebra crossing and the horizontal line does not exceed 10°; 4) some short edges of the zebra crossing are not captured since a close perspective.

III. THE PROPOSED METHOD

To recognize the zebra crossing in natural scene images, a block-based Hough transform is proposed in this section. The proposed method consists of two processes: 1) block-based recognition, 2) synthesize. Its framework is shown in Fig.3. The top 50% of the image is out of consideration since it represents a region in a long distance, where the visually imparied cannot step into. At the bottom of the image, the ROI is laid by overlapping blocks with a spacing stride of one. The size of the ROI is 320×480, and the size of each block is 320×120. If parallel lines are detected in a block, the angle of parallel lines is estimated, and the score of every pixel plus one. After all of the blocks are detected, the angles are averaged to calculate the direction of the zebra crossing, and the accumulative scores are synthesized to find the position of the zebra crossing. These messages can be provided in the form of sound or vibration. To represent them visually in this paper, the direction is given at top left of the image, and the accumulative scores are labeled colorfully.

A. BLOCK-BASED RECOGNITION

The block-based recognition includes preprocessing and parallel lines detection. It is used to calculate angles of parallel lines and record scores of pixels in blocks.

1) PREPROCESSING

In the preprocessing, each patch of blocks is transformed to grayscale. This is because the zebra crossing is composed of light and dark stripes in the grayscale image [3]. Then the adaptive thresholding method [15] is adopted to minimize the effect of shadows. The six steps of the preprocessing are summarized as following:

Step 1. The patch in the block is transformed to grayscale.

Step 2. The adaptive thresholding method is adopted for binaryzation.

Step 3. Filtering is processed to eliminate the noise.

FIGURE 2. Challenges of recognizing the zebra crossing in natural scenes. (a) Glare lighting. (b), (c) Indistinct stripes. (d), (e), (h) Occlusions. (f) Uncertain direction. (g) Low illumination. (i) Irregular shadows. (j) Red stripes.

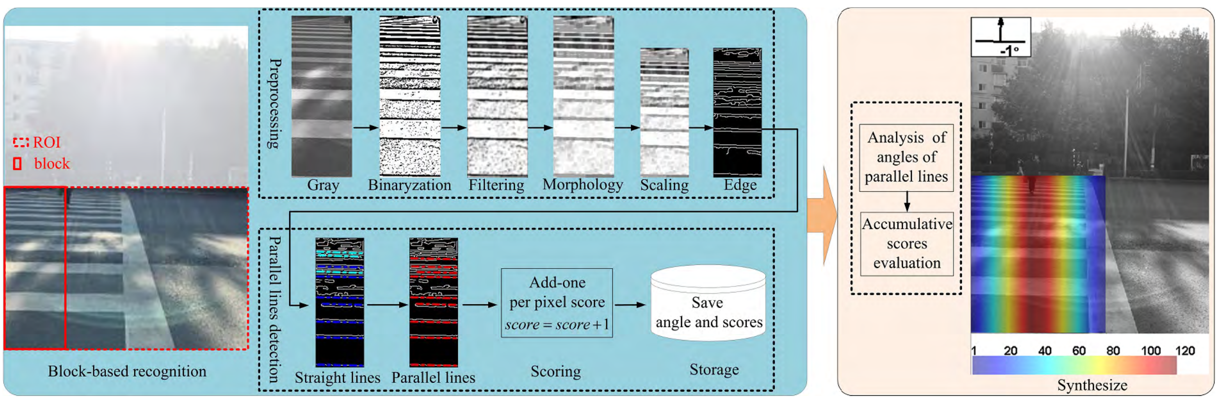

FIGURE 3. Overview of the block-based Hough transform for recognition of the zebra crossing in natural scene images. The ROI is laid by overlapping blocks. If parallel lines are detected in a block, the angle of parallel lines is estimated, and the score of every pixel plus one. After all the blocks are processed, the angles are analyzed to calculate the direction of the zebra crossing, and the accumulative scores are evaluated to provide a region of high safety for traveling.

Step 4. Dilation and erosion are adopted to smooth the boundary.

Step 5. The patch is scaled with a factor.

Step 6. The Canny edge detector is used to compute the edges in the patch.

2) PARALLEL LINES DETECTION

The block-based Hough transform is adopted to detect parallel lines. In the transformation, the local origin is set at the top left of the block and non-zero edge pixels are transformed from the Cartesian space to the polar coordinate space, as below:

$$\rho = x \cos\theta + y \sin\theta. \quad (1)$$

where the radial coordinate ρ represents the distance from the local origin to the straight line passing though (x, y), and the angular coordinate θ represents the angle between the normal of the line and the x-axis. The range of θ is $[-\pi/2, \pi/2)$, which can be narrowed with the prior knowledge of the direction of the zebra crossing.

According to their polar coordinates, the edge pixels vote for an accumulator array. The advantage of the block-based

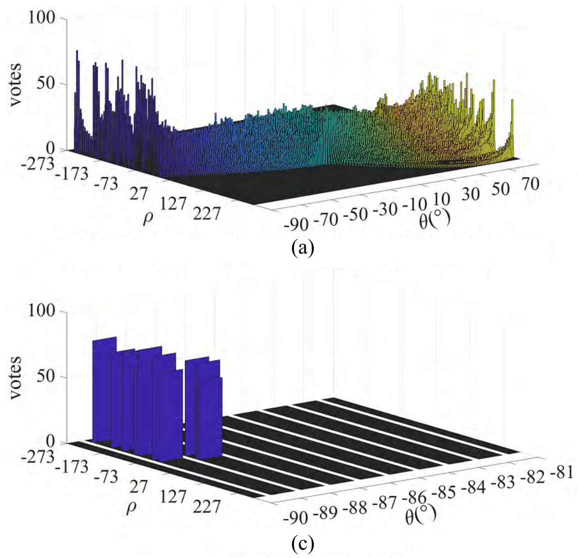

FIGURE 4. **Illustration of block-based Hough transform for parallel lines detection. The advantage of the block-based Hough transform is that the spurious maxima votes caused by noise are suppressed. In (a), each bar with large votes represents an individual straight line. In (b), the range of θ is limited to [−90°, −80°], [80°, 90°) for simplification. In (c), ten maximal votes are selected. The majority votes ($\theta = -89°$) are considered as candidate parallel lines. In (d), the original voting branch ($\theta = -89°$) is used to confirm the parallelism.**

Hough transform is that the spurious maxima votes caused by noise are suppressed. This is because the edge pixels of zebra crossings in blocks are dominant and dense. As shown in Fig.4, the steps of the parallel lines detection are as following:

Step 1. In each block, the edge pixels vote for the bins marked by their polar coordinates. Each bin with more votes represents an individual straight line.

Step 2. The angular value is limited to [−90°, −80°], [80°, 90°), since the angle between the zebra crossing and the horizontal line does not exceed 10°.

Step 3. Ten maximal votes are selected. The angular value of the majority votes is selected as the value of the angle between the normal of candidate parallel lines and x-axis.

Step 4. The original voting branch of the selected angular value is extracted. The parallelism is confirmed if there are at least three straight lines, whose votes are greater than 60.

B. SYNTHESIZE

After all the blocks are processed, the angles of parallel lines are analyzed to calculate the direction of the zebra crossing, and the accumulative scores of pixels are evaluated to provide a region of high safety for traveling. As shown in Fig.3, the value of angle between the zebra crossing and the horizontal line is given to indicate the direction, and the accumulative scores are shown colorfully for visual presentation. The range of scores is [1, 120]. A higher score represents higher safety. The relation between the score and color is given under each image.

IV. EXPERIMENTS AND RESULTS

To verify the effectiveness of the proposed method, the tests are analyzed in this section. Experiments of the proposed method are described in details. Then the experimental results are compared with the results of other methods. Finally, the limitations of the proposed method are presented.

To evaluate the performance of each experiment, three indices are defined as below:

$$precision = \frac{TP}{TP + FP}. \tag{2}$$

$$recall = \frac{TP}{TP + FN}. \tag{3}$$

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall}. \tag{4}$$

where TP, FP, FN are the number of true positives, false positives and false negatives, respectively. In (2), *precision* represents the fraction of true positives among the predicted positives. In (3), *recall* represents the fraction of true positives among the actual positives. In (4), F_1 score is the harmonic average of the *precision* and *recall*, and it reaches one with perfect *precision* and *recall*.

A. EXPERIMENTS OF THE PROPOSED METHOD

In the preprocessing, it is found the adaptive thresholding is effective to handle shadows, which are unavoidable in natural scenes. The various shadows can be categorized into two types: 1) umbra, and 2) penumbra [16]. As shown in Fig.5, the umbra of buildings is captured in (a), (c) and (e), the umbra of cars is captured in (d), and the penumbra of trees is captured in (b) and (e). In order to eliminate the interference of these shadows, the global thresholding method OTSU and the adaptive thresholding method are adopted separately. The binary images of the two methods are shown in Fig.5. It can be seen that, the adaptive thresholding method performs better.

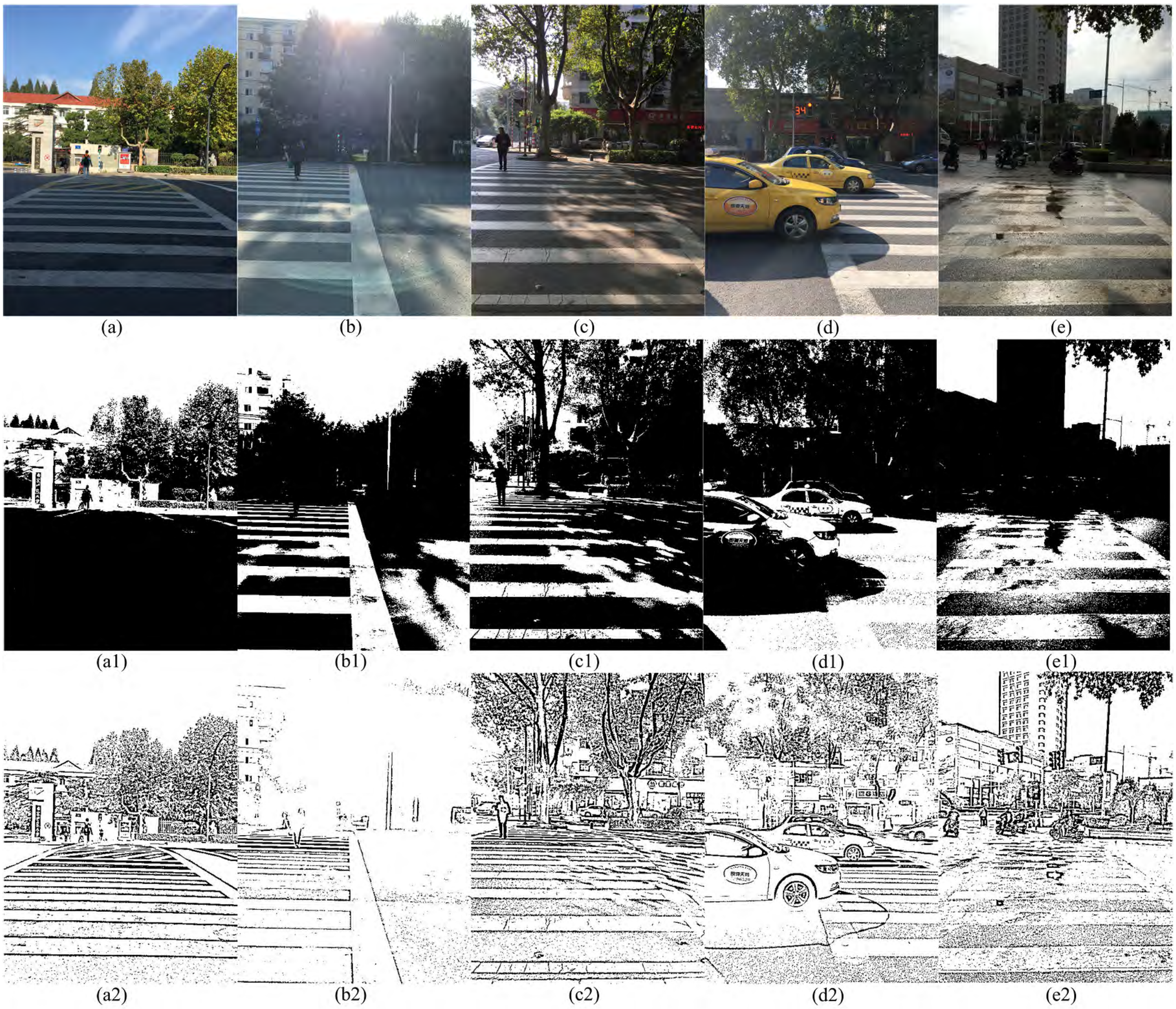

FIGURE 5. Comparsions between OTSU and the adaptive thresholding method. (a1)-(e1) are the binary images using OTSU. (a2)-(e2) are the binary images using the adaptive thresholding method.

It can remove the umbra completely, and it can decrease the noise transmitted to the next step.

In the parallel lines detection, the performance of the proposed method mainly depends on three parameters, the width of the block (*block_w*), the block spacing stride (*step_w*), and the factor of scaling (s). To determine these parameters, 300 images in the dataset are used for evaluation [17]. Specifically, the *block_w* takes different values [40, 80, 120, 160, 200, 240], the *step_w* takes different values [1, *block_w*/2, *block_w*], and the s takes different values [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1]. The $precision - recall$ curve of the proposed method is shown in Fig.6. Totally, the parameter setting ($block\_w = 120$, $step\_w = 1$, $s = 0.8$) yields an optimal performance with a *precision* of 98.0% and a *recall* of 99.7%.

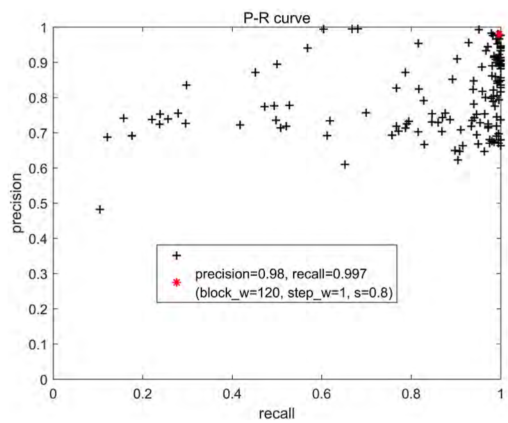

FIGURE 6. The $precision - recall$ curve of the proposed method. The parameter setting ($block\_w = 120$, $step\_w = 1$, $s = 0.8$) yields an optimal performance with a *precision* of 98.0% and a *recall* of 99.7%.

Some recognition results of zebra crossings are shown in Fig.7. As shown in (a), no zebra crossing is recognized since stripes fade seriously. In (b), the partially damaged zebra crossing is well recognized. Although the zebra crossings in (c), (d), (h), (i) and (j) are partly occluded, the safe regions on each zebra crossing are recognized. In addition, the proposed method can provide safe routes to avoid collision with other pedestrian. In (e), the zebra

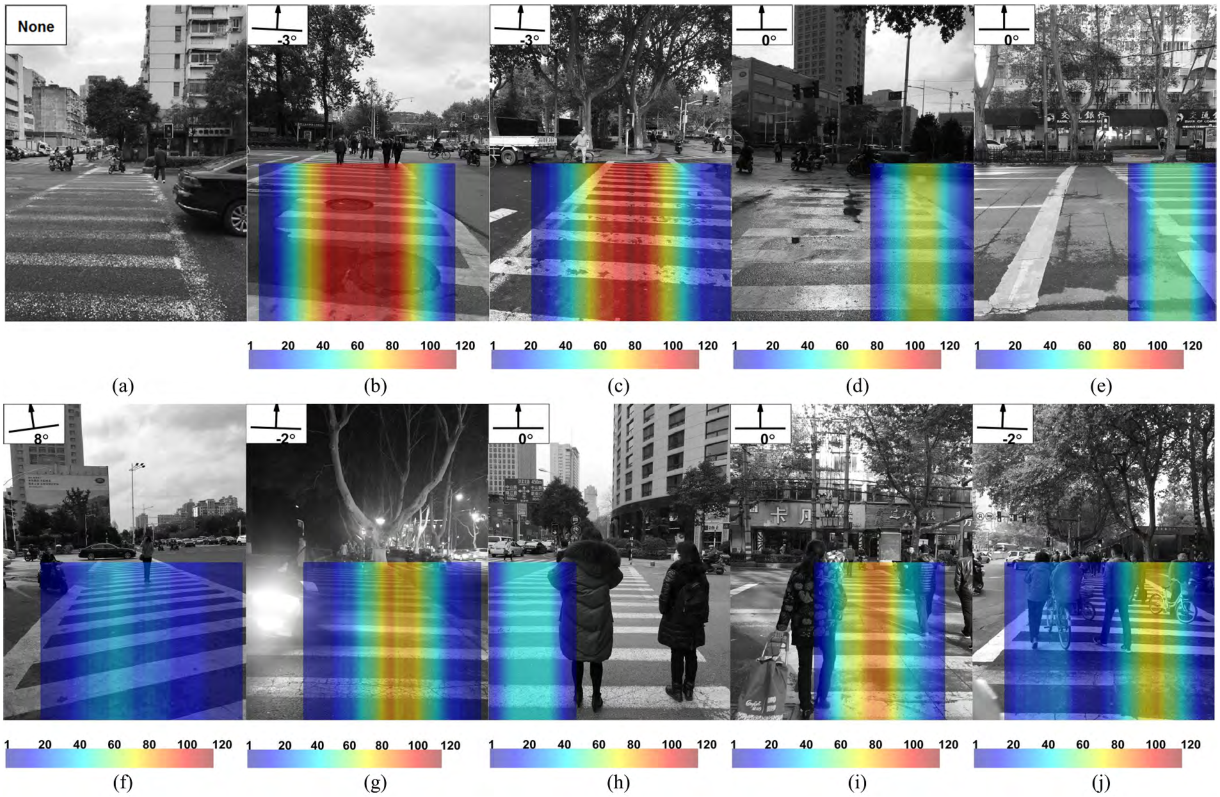

FIGURE 7. Results of the zebra crossing recognition. The value of angle between the zebra crossing and the horizontal line is given at top left. The range of the accumulative scores is [1, 120]. A higher score represents higher safety.

crossing consisting of red stripes is recognized. The direction of the zebra crossing in (f) is 8°. The zebra crossing captured at night is recognized in (g).

B. COMPARISON OF DIFFERENT METHODS

To evaluate the facility of the proposed method, it is compared with the traditional Hough transform, bipolarity and deep learning methods. The process of the traditional Hough transform method is similar to the proposed method, except it is implemented on the entire ROI. The size of the ROI is 320×480. Since the bipolarity method and the deep learning method require a post processor to calculate the direction of the zebra crossing, these methods are only compared in terms of recognizing zebra crossings.

In the bipolarity method, the ROI is laid by blocks of 160×120 with a spacing stride in width of 1 and in height of 160. In each block, the Gaussian Mixture Model (GMM) is adopted to group pixel intensity values into two normally distributed clusters: $N(\mu_1, \sigma_1^2)$, $N(\mu_2, \sigma_2^2)$. Where μ_1, μ_2 are expectations and σ_1^2, σ_2^2 are variances. Then the bipolarity γ [3] is calculated as below:

$$\gamma = \frac{1}{\sigma_0^2}\{\alpha(1-\alpha)(\mu_1-\mu_2)^2\}. \tag{5}$$

where α is the mixing proportion of $N(\mu_1, \sigma_1^2)$, σ_0^2 represents the variance of all pixel intensity values in the block. If the value of γ is greater than 0.8, the block is recognized as a patch of the zebra crossing. The score of each pixel in the block adds one.

In the deep learning methods, two small networks are adopted and evaluated, including the LeNet [18] and AlexNet [19]. In the architecture of AlexNet, the feature maps of each layer are reduced by 50% to simplify the computation. In order to tune the parameters in these networks, 300 images used to determine parameters in the proposed method are adopted to make labeled samples for training. Specifically, blocks of zebra crossings and blocks of background are cropped as positive and negative samples separately. The size of each block is 320×120. In all, 6780 positive samples and 7375 negative samples are acquired. These samples are preprocessed as in the proposed method and then fed to train the convolution neural network. During the testing process, the ROI in each image is laid by blocks of size 320×120. Each block is preprocessed and fed to the network for prediction. The score of each pixel in the block is increased by one if the prediction is positive.

These methods are implemented on CPU except the deep learning methods. Due to massive operations, the deep learning methods are implemented on GPU for accelerating. The parameters of each method are summarized in Table 1, and the recognition results are summarized in Table 2. The LeNet yields much worse results compared with others. The performance of the AlexNet is best, but it becomes much worse if the neurons in the architecture continue to

TABLE 1. Summary of parameters of each method.

Method	Block size	Stride in width	Stride in height
The proposed method	320 × 120	1	-
Hough transform	-	-	-
Bipolarity	160 × 120	1	160
Deep learning	320 × 120	1	-

TABLE 2. Summary of recognition results on the dataset.

Method	$Precision(\%)$	$Recall(\%)$	$F_1(\%)$
Block-based Hough transform	99.0	93.4	96.1
Hough transform	99.0	73.1	84.1
Bipolarity	91.7	88.4	90.0
AlexNet	99.2	94.7	96.9

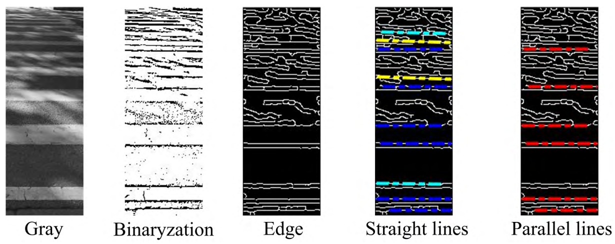

FIGURE 8. Robustness of the block-based Hough transform. In the binaryzation process, some noise remains and affects the edge image. In the noisy edge image, the block-based Hough transform can detect most of the straight lines, which is helpful to select parallel lines of the zebra crossing.

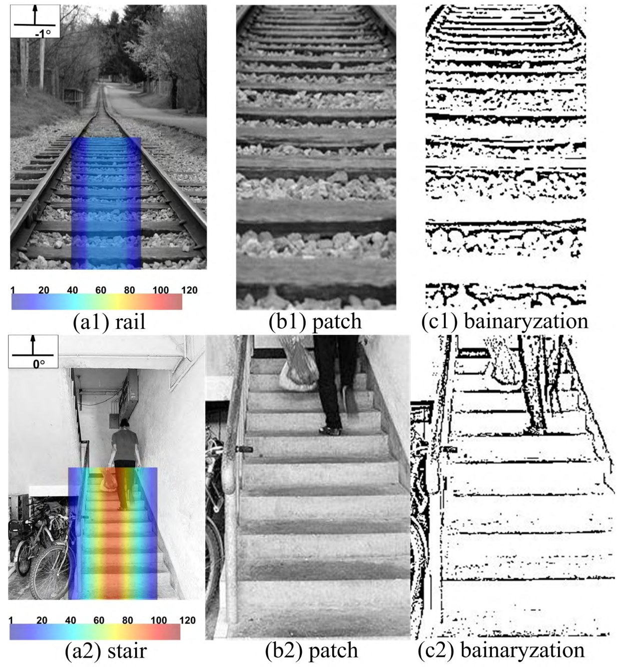

FIGURE 9. Limitations of the proposed method. The parallel stairs and rail lines are similar to the zebra crossing in patches without contexts. The depth information should be provided by the white cane.

be decreased. The proposed method is simple and has a good performance. Furthermore, it can calculate the direction of the zebra crossing straightforwardly.

C. ROBUSTNESS AND LIMITATIONS

The block-based Hough transform is robust to detect straight lines, which is shown in Fig. 8. Although some noise remains in the binary image and has an effect on the edge image, the block-based Hough transform can detect most of the straight lines. This is helpful to select parallel lines of the zebra crossing. In addition, the block-based Hough transform can be applied to detect and measure lines in remote sensing images and integrated circuits.

Notwithstanding the good performance in the recognition of the zebra crossing, the proposed method cannot distinguish the parallel stairs and rail lines. As shown in Fig. 9, the stairs and rail lines in patches without contexts are similar to the zebra crossing. The lack of depth information in 2D image makes them confusing. In this case, the visually impaired needs to get aware of the surroundings with the white cane. In the future, the binocular camera will be applied to get the depth information in vision-based methods.

V. CONCLUSIONS

In this paper, the block-based Hough transform is proposed to calculate the position and direction of the zebra crossing in natural scenes. In the block-based Hough transform, the spurious maxima votes caused by noise are decreased in the accumulator array. The contributions of the paper including:

- A simple implementation of Hough transform for parallel lines detection in overlapping blocks is proposed.
- The recognized parallel lines in blocks are cross validated by their adjacent blocks in the accumulative scoring evaluation.

The future work is to implement the proposed method on a binocular camera, in order to solve the problem of lack of depth information.

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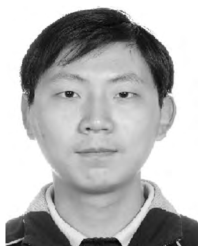

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