

# Pedestrian lane and obstacle detection for blind people

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**Abstract.** Pedestrian lane and obstacle detection have been a big problem for a blind person. The person has to use special tool or assistant to do daily activities. This work has utilized camera function, connected with data processing (mini PC) to process information captured by a camera. At first, RGB image, which was captured camera, was converted into XYZ colour system. This colour system was very useful to highlight pedestrian lane to reduce other objects. Then, colour filter was implemented to remove unnecessary objects, followed by close morphology to expose pedestrian lane. The result is white region which represent pedestrian lane. Major axis was then calculated using moments and its angle (calculated counter clockwise with reference to x-axis) was sent to the user to notify him/her which direction he/she can go. In the process of obstacle detection, some samples of RGB images has been used to train a neural network. The model was then used as obstacle detector. RGB images captured by camera were then used as test data. The result  $> 0.7$  was considered as obstacle. The experiment shows that under illumination of  $< 15000$  lux, the method can achieve 89.7 percentage accuracy on pedestrian lane detection and 100 percentage accuracy on obstacle detection.

## 1. Introduction

Previous efforts which worked on developing supporting stick to track pedestrian lane for blind people has been reported. The stick was equipped with ultrasonic or Infrared sensor, and accelerometer & PIT, or RFID to detect surrounding objects. Ultrasonic sensor was used to detect objects within 2 m distance, while infra-red sensor was used to detect living objects. Accelerometer & PIT was used to calculate motion direction and rotation. The whole information was then sent to a buzzer with different audible tones [1, 2], [4, 5]. Other work has added GSM-GPS modem to send the location of the blind user to relevant parties in case of emergencies [3]. Other works has proposed pedestrian lane tracking using camera [6, 7], [9-12], [14, 15]. The lane has been modified by adding 2 white lines at the crossroad. The method then tried to decide and verify the crossroad using statistic calculation. The geometric feature of the line was used for verification. The performance was evaluated by visual inspection. Another method was proposed to detect lane in unstructured environment. The method integrated the environment and the feature of lane boundary. Vanishing point was used to detect lane boundary based on colour edge orientation and pedestrian detection to handle occlusion. The method was evaluated on new data set using Convolutional Neural Network [8].

In this work, we proposed to implement 2 methods to detect pedestrian lane and to detect obstacle crossing the lane. RGB image captured by camera was fed to the system, processed by miniPC, and producing orientation  $\theta$  and obstacle detection for the user.



## 2. The Proposed Method

We proposed 2 data processing steps: pedestrian lane detection and obstacle detection. The input was a sequence of images taken from a camera.

2.1. *The pedestrian lane detection consists of several following steps:*

- RGB image input was converted to XYZ color system, using Equation (1):

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \frac{1}{0.17697} \begin{bmatrix} 0.49000 & 0.31000 & 0.20000 \\ 0.17697 & 0.81240 & 0.01063 \\ 0.00000 & 0.01000 & 0.90000 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

- Then, a color filter was implemented to isolate pedestrian lane from other unintended objects, producing only the lane. Equation (2) represents the filter:

$$bw = \begin{cases} 1 & x_l < X < x_u \\ & y_l < Y < y_u \\ & z_l < Z < z_u \\ 0 & \text{else} \end{cases} \quad (2)$$

- Image morphology was implemented to highlight the pedestrian lane as much as possible. Here, we proposed 'close' morphology with structured element  $s$ . The process was shown in Equation (3).

$$BW \cdot s = (BW \oplus s_{rot}) \ominus s_{rot} \quad (3)$$

- The result still contains several blobs with various sizes. Based on observation on the original image, the pedestrian lane was consistently being the blob with maximum size. Therefore, the next step was to select white blob with maximum size using Equation (4).

$$n = \arg \max_{1 \leq i \leq \text{numberofobjects}} Area(object(i)) \quad (4)$$

with  $n$  as maximum size object index,  $Area(i)$  as the size of  $object(i)$  in pixel unit and the object should be 8-connected.

- To calculate the blob's major axis and its orientation, we adopted inertial moment with refer to x-axis,  $I_x$ , y.axis  $I_y$ , and inertial multiplication against x-axis and y-axis  $I_{xy}$ . Orientation  $\theta$  was calculated counterclock-wise against x-axis using Equation (5). It was used to inform the user about his/her walking direction.

$$I_x = \int y \cdot dA$$

$$I_y = \int x \cdot dA$$

$$I_{xy} = \int x \cdot y \cdot dA$$

$$\theta = \frac{1}{2} \tan^{-1} \left[ \frac{2I_{xy}}{I_y - I_x} \right] \quad (5)$$

Figure 1 (a) and (b) shows the result of major axis and orientation calculation with  $(x_c, y_c)$  centroid as the origin point, and angle  $\theta$  as its orientation.

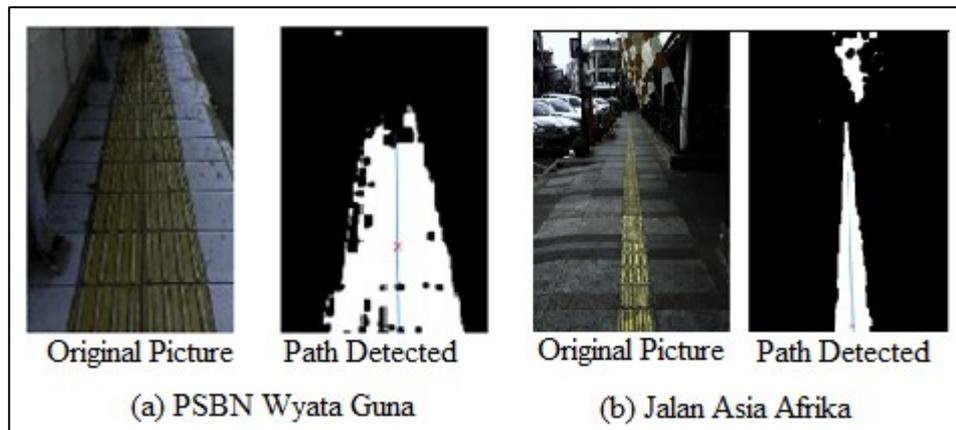


Figure 1. Video data.

2.2. The process of obstacle detection

Data training using backpropagation neural network, with 1 input layer, 1 hidden layer, and 1 output layer. The learning rate was set to 0.0001 and error tolerance was set 0.1 or the iteration has reached 10,000. RGB images as shown in Figure 2, was fed to the network input (*feedforward*). The images consists of 11 images with obstacle and 3 images without obstacle. In each iteration, the error was calculated during backpropagation. Then, its weights and bias was updated (*adjustment*). The model was verified using one of the training sample, with 0.7 threshold value. Above the threshold was considered as the obstacle.



Figure 2. Training pictures.

### 3. Results and analysis

The experiment of pedestrian lane detection was done using 2 videos with different patterns of pedestrian lanes and various obstacles such as waste basket, water hydrant, and city lamp poles. The videos was taken from 2 different locations: in Panti Sosial Bina Netra Wyata Guna pedestrian area, and in Asia Afrika Bandung street under good weather condition. Each video has different duration as shown in table 1. Measurement was done on orientation  $\theta$  with refer to x-axis ( with  $x_c, y_c$  as a reference point) using Equation (7).

$$Frame\ Result = \begin{cases} True & 40^\circ < \theta < 130^\circ \\ False & else \end{cases} \quad (6)$$

$$Accuracy = \frac{\sum True}{\sum Frame} \quad (7)$$

**Table 1.** Result of angle measurement.

File	Total Number of frames	Number of frames correctly measured	Accuracy (%)
File1 PSBN	386	343	88.8
File2 Asia Afrika	874	792	90.6
Total	1260	1135	89.7

The experiment used 11 images with obstacles and 3 images without obstacles. The system was run with 10000 maximum iteration or error tolerance of less than 0.0001, and learning rate ( $\alpha$ ) of 0.1. The result is shown in Table 2.

**Table 2.** Training result.

File	Target	Weight
Image 1	1	0.9999
Image 2	1	0.9996
Image 3	1	0.9985
Image 4	1	0.9999
Image 5	1	1
Image 6	1	1
Image 7	1	0.9999
Image 8	1	0.9999
Image 9	1	0.9988
Image 10	1	0.9999
Image 11	1	0.9987
Image 12	0	0.0006
Image 13	0	0.0022
Image 14	0	0.0018

The system was then tested RGB images with and without obstacles as shown in Figure 3.



**Figure 3** Testing pictures.

The result was shown in Table 3.

**Table 3.** Verification result.

File	Weight
Testing 1	0.3789
Testing 2	1
Testing 3	0.9573
Testing 4	0.9853

#### 4. Conclusions

Based on experiment and analysis on the implementation of the proposed system, it achieved 89.7% accuracy on pedestrian lane detection using image processing algorithm and 100% accuracy on obstacle detection using neural network under <15000 lux good weather condition.

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