# NIGHTTIME PEDESTRIAN DETECTION BY ONBOARD MONOCULAR CAMERA

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**ABSTRACT**

In recent Japan, traffic accidents have been reduced by safety improvement of vehicles. However pedestrian accidents have not been so. Pedestrian accident occurs 70% at night. Currently, devices which are equipped with pedestrian detection technology have begun to install for the safety of pedestrians. These devices are equipped using an infrared camera for the night environment. Because of high cost, these have an issue that consumers are difficult to introduce them. If the nighttime pedestrian recognition is possible by inexpensive monocular camera, consumers are able to introduce it easily. Therefore this paper proposes a detection method of nighttime pedestrian by the monocular camera.

We select pedestrian candidate regions by distinguishing optical flow of the legs and background in the image. The pedestrian candidate region is selected by erasing small optical flows and quantizing the direction. However, if only optical flow is used, whole other moving objects are captured. Therefore this study focused on that the change of the legs of the pedestrian shape. Vertical edge histograms of legs of the pedestrian greatly change because the shapes of the legs change for walking. We clarify the pedestrian shape by applying a local normalization to less visible upper body shape of the pedestrian candidate region. Local normalization to clarify the fine changes by expanding the brightness range that represents the image. We extract the pedestrian like shape by binarization on the normalized area. By estimating the human similarity of the extracted shape, we classify the pedestrian.

## 1. INTRODUCTION

In Japan, incidence of traffic accidents has been reduced by the improved safety of the car. Since the number of fatalities due to accidents during the ride has been greatly reduced, now the fatalities had accidents while walking has become the most as shown Fig.1.1. The characteristic of pedestrian fatalities is that about 70 percent has occurred at night. In addition, the situation of the accident is accounted for about 70% by the crossing road as shown in Figure 1.2.Especially, the case which has the accidents in outside of crosswalk in where street light are less is account for over 50%.

Therefore, there is a need for safety measures for pedestrians who cross the outside of crosswalks at night. Currently, technologies detecting pedestrians for pedestrians safety has become widespread.

The conventional method using a monocular camera mainly uses the pedestrian upper body shape. However only legs of a pedestrian illuminated by host headlamps are visible at night, therefore conventional method cannot apply to nighttime.

Pedestrian recognition technology using an infrared camera as a countermeasure of the nighttime environment has been developed. Because of high cost, it is difficult for consumers to introduce these. Therefore, the spread of the pedestrian detection techniques can be expected by using an inexpensive monocular camera.

This paper proposes the method of pedestrian detection at night using the leg of the movement of pedestrians. Below, this paper describes the conventional method and the proposed method, and effectiveness of the proposed method by experiment.

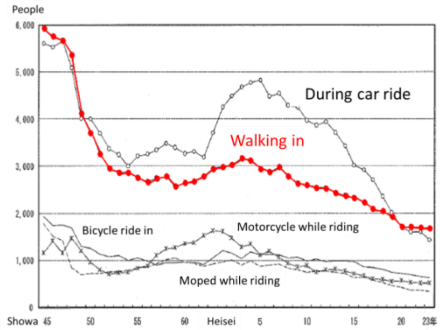


Fig.1.1 the number of traffic fatalities by state

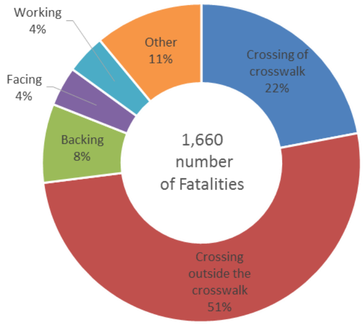


Fig.1.2 Accident situation

## 2. Conventional method

### 2.1. HOG

The current pedestrian recognition methods use Histogram of Oriented Gradients (NavneetDala, 2005) generally. Since HOG is based on the distribution of the direction of the brightness, HOG has less computational costs. HOG is robust to illumination changes because features are normalized. HOG is possible to represent the approximate shape of the object. Visualized HOG is shown in Figure 2.1.

Fig.2.1 HOG

### 2.2 Classification by AdaBoost

AdaBoost (Yoav Freund, 1996) is a representative algorithm of the boosting. The AdaBoost uses pedestrians and non-pedestrian images in Fig.2.2 as the training data, to create classifiers by learning the pedestrian-specific HOG. The created classifier determines as a pedestrian if HOG of input data is close to the pedestrians.


Fig.2.2 Training data

### 2.3 Issue of conventional methods

Only legs of a pedestrian which illuminated by host car headlamps are visible at night, as shown in Fig.2.3. Therefore, it is impossible for HOG to extract the shape of pedestrians at night as well as in the day. In addition, the classifier learned by daytime images cannot detect pedestrians at night. More explanations

Fig.2.3 Nighttime situation

## 3. Proposed Method

3.1 Detection of the moving object by the optical flow

Optical flow (BK Horn, 1981) is calculated from two frames obtained by the camera. Used Optical flow method is a block matching of 10 × 10 pixel. Visualized optical flow is shown in Figure 3.1.At this time, small optical flow is eliminated by some thresholds.

For simplicity, angles of optical flow is quantized to 6 bins from 0~180 degrees. Big clusters which have close angle optical flow is removed. The remaining optical flow area is a pedestrian candidate region.

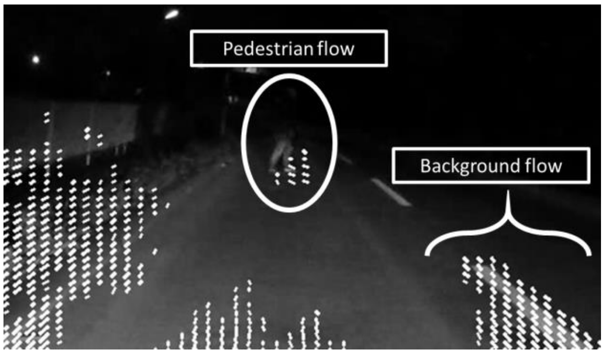


Fig.3.1 Opticalflow

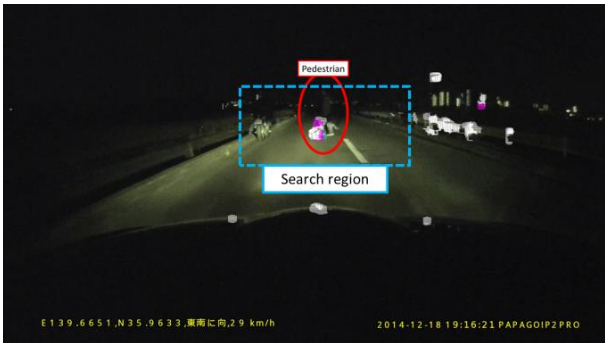


Fig.3.2 Search region

Table 3.1 Rectangle size

| Pixels \ Distance | 10m | 20m | 30m | 40m |
|---|---|---|---|---|
| Pedestrian position | 586 | 622 | 651 | 673 |
| Pedestrian width | 90 | 60 | 48 | 30 |
| 2m height | 180 | 112 | 76 | 54 |

### 3.2 Classification of pedestrian leg by histogram

Further, the region obtained by optical flow is narrowed down. Shapes of pedestrian legs are extending in the vertical direction and changed by moving. Therefore the classification of the legs and the stationary object uses the vertical edge histogram. A histogram of legs greatly change against a histogram of stationary objects almost never change. Therefore, to distinguish legs and other objects by comparing the histograms. The Region obtained by the optical flow is differentiated vertically and the histogram is computed by stacking density as shown in Fig.2.3. The vertical differentiation process uses the Sobel filter. When abscissa is x and the ordinate is y, the shape of Sobel filter is shown in Figure 3.4.

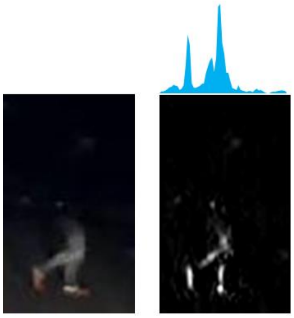

Fig.3.3 Vertical edge image

| | x−1 | x | x+1 |
|---|---|---|---|
| y−1 | −1 | 0 | 1 |
| y | −2 | 0 | 2 |
| y+1 | −1 | 0 | 1 |

Fig.3.4 Sobel filter

The comparison between frames uses the inconsistency degree D calculated by the equation (1). The average of inconsistency degree of pedestrians was 30.1% and stationary objects was 65.8%. If the inconsistency degree is less than 40%, the region is excluded from the candidate. Bt is

$$D = \sum_{x=0}^{Xsize} \left| \frac{B_t(x)}{B_a(t)} - \frac{B_{t-1}(x)}{B_a(t-1)} \right| \times 100 \qquad (1)$$

Since the location of the object is changed to between frames, search window is shifted as shown in Figure 3.4.

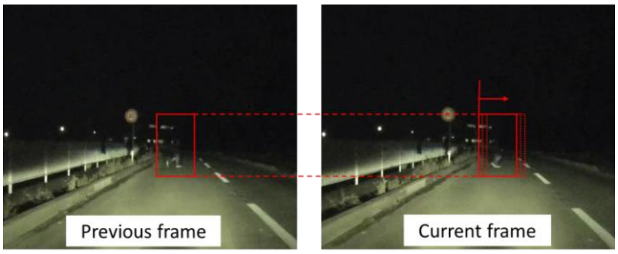


Fig.3.4 Rectangle shift

### 3.3. Local normalization

For the clarification of the shape, the local normalization applies to the region in which pedestrian shape is disappeared. The normalization is to clarify the fine shape by expanding the range of brightness used in the image as shown in Fig.3.5.When a processed pixel density is I (x, y) , a maximum density is Max and a minimum density is Min, a normalized density I '(x, y) is expressed by equation (2).

$$I'(x,y) = 255\frac{I(x,y) - Min}{Max - Min} \qquad (2)$$

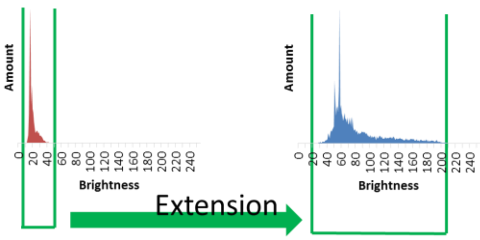


Fig.3.5 Normalized histogram

Fig.3.6 Local normalization

### 3.4. Binarization

The local normalized region is binarized to extract the shape as shown in Figure 3.7. The extracted shape is decided whether similar to a pedestrian by classifier created in the conventional method. Up to section 3.2 pedestrians can be detected to some extension. Therefore if object exist on legs, the region can be decided as pedestrian. If binarized image even slightly similar to a pedestrian by AdaBoost learned daytime images, the region is decided as pedestrian as shown in Fig.3.8.

Fig.3.7 Binarization

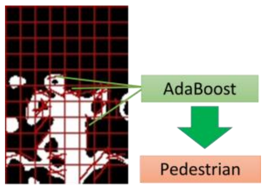


Fig.3.8 Pedestrian discrimination

## 4. Experimental Results

The detection rate of the proposal method was verified using actual video images taken by an on-board monocular camera. A drive recorder was installed in the windshield of the car with a 1m height from the ground and the optical axis of it is parallel to the ground. The drive recorder is named PAPAGO P2PRO, which has 1920 × 1080pixels and the field of view is 130°[degree].

This experiment targets single pedestrian. The detection rate is values which were obtained by dividing the number of frames which accurately detecting pedestrian by the number of all frames. From fig.4.2, the proposal method has about from 70 to 80% detection rate against the conventional method has low detection rate at night.

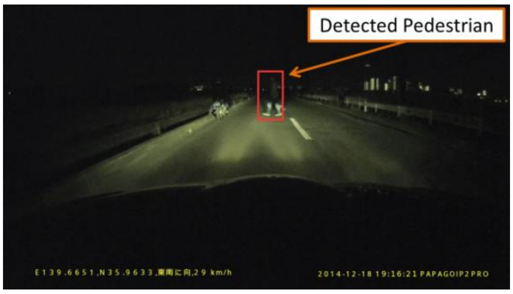


Fig.4.1 Detection result

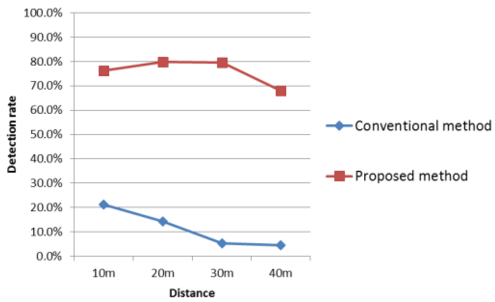


Fig.4.2 Detection rate

Since proposal method is able to detect a pedestrian at the distance of 40 meters, this is possible to prevent accidents of pedestrians. One of the reason why proposal method could not detect the pedestrian is considered that the vibrations of the car cause blur between images by the unevenness of the road surface. There is also a need for verification of other causes in the future.

Table 4.1 Detection accuracy

| Distance | 10m | 20m | 30m | 40m |
|---|---|---|---|---|
| Max | 594 | 626 | 654 | 675 |
| Min | 579 | 617 | 649 | 669 |
| Average | 586.5 | 622.0 | 651.0 | 672.8 |
| Varianc | 11.9 | 4.5 | 1.6 | 1.7 |

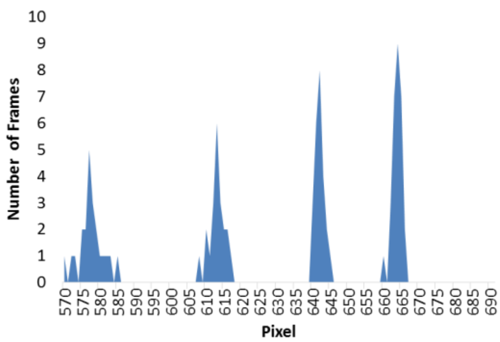


Fig.4.3 Detection accuracy

By this method, a pedestrian who was at the distance 40m from the car was detectable. The car speed which causes pedestrian fatalities is many in middle-speed range from 40 to 60km/h.

At here, we think that the accident was occurred in the general road. The driver has 2 seconds to collide the pedestrian in 50km/h and the 30m distance. Generally, 0.8 seconds are needed for that the driver would notice and step on the brake. If the avoidance operation is done at the remaining 1.2 seconds it is possible to avoid the accident. Therefore detection distance according to the present experiment is meaningful.

## 5. CONCLUSION

This paper proposed nighttime pedestrian detection by onboard monocular camera. The proposed method uses the movement of the pedestrian legs. This method distinguishes the movement of the pedestrian legs from the background by the optical flow. In addition, the classification of the legs and the stationary object uses inconsistency degree of the vertical edge histogram. The shape of the upper body part in the candidate region is extracted by normalization and binarization. The extracted shape is determined whether the similar to pedestrian shape by classifier created in the conventional methods.

The detection rate of applying for the obtained image from a drive recorder became about 80% in distance 10m, 20m, 30m and about 70% in distance 40m. This method is assumed single pedestrian crossing the straight road. Future tasks are that this method applies to other road shapes and plural pedestrians. Also complementing blur which cause detection failure and verifying other causes will be performed.

## REFERENCES

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