# Risky Pedestrian Prediction at Night Based on Likelihood Combination

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*This paper introduces a system for predicting risky pedestrians at night to support an ADAS using a cheap IR lens camera. To predict risky pedestrian, the combination of likelihoods and spatiotemporal features of each pedestrian, such as the overlapping ratio, the pedestrian pose orientation, and distance ratio from camera are accessed. The proposed method was successfully applied to the KMU-RPC night driving dataset and the presented reasonable performance, with a shorter processing time.*

## 1. Introduction

According to a report of the road traffic authority of South Korea, most pedestrian-vehicle accidents occur between 6 p.m. and 8 a.m., and the rate of pedestrian fatalities is highest between 4 a.m. and 6 a.m. [1]. The four major causes of pedestrian-vehicle accidents at night are inebriated drivers, inebriated pedestrians, drowsiness, and poor visibility. Therefore, it is necessary to develop a supporting advanced driver assistance system (ADAS) to automatically prevent pedestrian-vehicle accidents especially for night.

Although pedestrian detection methods based on visible light images have already shown a reliable performance using color information when the illumination is constant and the target image quality is good [2], pedestrian detection in color images is ineffective in environments with poor illumination, such as at night, in darkened tunnels, or on rainy days. To resolve these limitations of visible camera, we use low-cost infrared (IR) lens camera that transmits infrared and visible light to produce relatively clear images even at night instead of expensive near IR camera or thermal camera.

Another important factor for an ADAS is the prediction of risky pedestrians before the pedestrians come into full view. Drivers should be alerted to a potential risky pedestrian as early as possible to avoid a collision. However, there has been far less research on risky pedestrian prediction when compared to pedestrian detection.

Therefore, we introduce algorithms for predicting risky pedestrians at night to support an ADAS using a cheap IR lens camera. To reduce the computational cost, a virtual reference line for a risky pedestrian decision is applied according to the driver's field of view instead of lane detection, and pedestrian detection is conducted within this line. For detecting multiple pedestrians, tiny-YOLO [3], a real-time object detection system was adopted as the pre-trained model to verify a pedestrian region. The risky pedestrian prediction is assessed based on the combination of likelihoods and spatiotemporal features of each pedestrian, such as the overlapping ratio, the pedestrian pose orientation, and distance ratio from camera. The proposed method was successfully applied to the KMU-RPC night driving dataset and the accuracy of the proposed risky pedestrian prediction method gave the reasonable results, with a shorter processing time.

## 2. Risky Pedestrian Prediction at Night

To predict a risky pedestrian, we propose three measurements relative to the virtual reference lines, i.e., the overlapping ratio (OR), pedestrian pose orientation (PPO), and distance ratio (Dist), inspired from [4]. These three ratios are then applied to the corresponding normal distribution, and the final decision is made using the likelihood estimation.

### 2.1. Overlapping Ratio

We first estimate the degree of overlap between a detected pedestrian and the virtual reference lines. When a pedestrian crosses a virtual reference line from the left or right side, the OR of pedestrian *i* (*OR (i)*) is defined.

### 2.2. Pedestrian Pose Orientation

Convolutional neural network (CNN) based pose orientation estimation requires large numbers of parameters and operations. Therefore, we apply the teacher–student algorithm to generate a compressed student model with high accuracy and compactness resembling that of the teacher model by combining a deep network with a random forest [5]. After the teacher model is generated using hard target data, the softened outputs (soft-target data) of the teacher model are used for training the student model. Moreover, the PPO has specific shape patterns, and a wavelet transform is applied to the input image as a preprocessing step owing to its good spatial frequency localization property and the ability to preserve both the

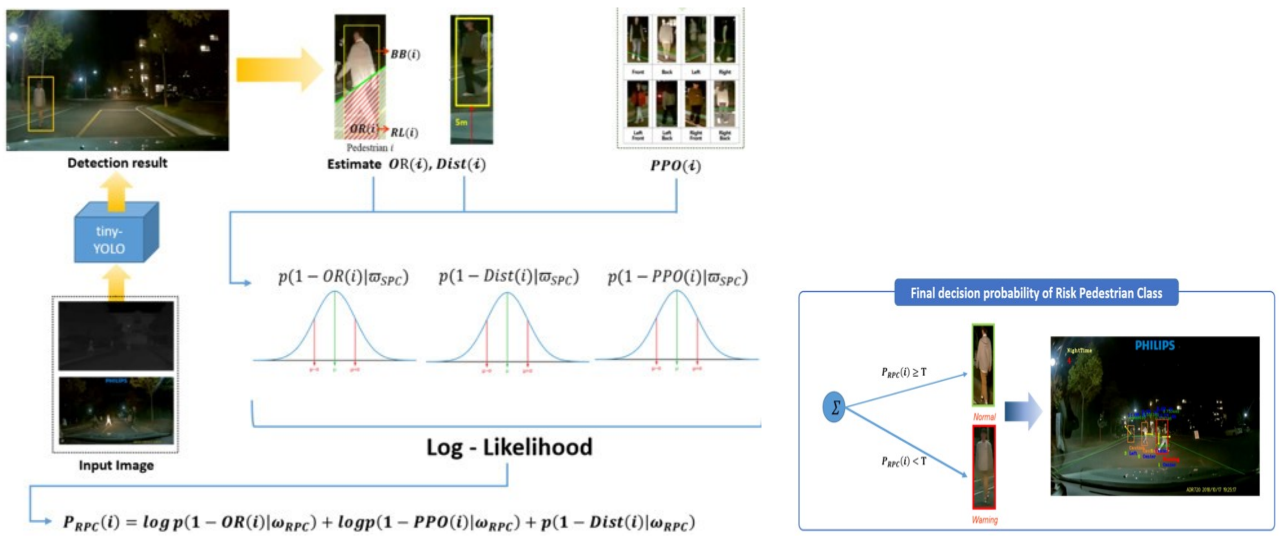


Figure 1. Risky pedestrian decision using candidate pedestrian, inverse ratio, and conditional probability estimation. The final decision of RPC is determined based on the results of $\mathrm{P}_{RPC}(\mathrm{i})$ .

spatial information and gradient information of an image. After estimating PPO within the bounding box of the pedestrian, the PPO ratio of pedestrian *i* (*PPO(i)*) is then computed.

### 2.3. Distance Ratio

Because the risk degree of a detected pedestrian differs depending on the distance even if the actual speeds are equal, we estimate the pedestrian distance ratio (*Dist (i)*) derived from the size of the *i*-th pedestrian's bounding box, as indicated in Fig. 2.

### 2.4. Risk Pedestrian Prediction

To assess the risky pedestrian, the proposed decision method evaluates the likelihood of such an event. After three ratios (*OR*, *PPO*, and *Dist*) are computed, we estimate the conditional probability of each ratio on the risky pedestrian class (*RPC*) based on the assumption that the three ratios have a normal distribution.

From the training data, we collect three ratio values from the dataset and estimate the normal distribution for each feature. Because the maximum value of the three ratios is 1 and the minimum value is 0, we take the inverse transform of all feature ratios and compute the inverse means $\mu_{1-OR}$, $\mu_{1-PPO}$, and $\mu_{1-Dist}$, and the standard deviations means $\sigma_{1-OR}$, $\sigma_{1-PPO}$, and $\sigma_{1-Dist}$, respectively. These three inverse ratios are normalized using a Gaussian normalization to follow an independent and identically distributed Gaussian distribution with zero mean and a single variance, $\mathrm{p}(1-\mathrm{OR},\mathrm{PPO},\mathrm{Dist}|\omega_{RPC}) \sim N(0,1)$. The probabilities of the three inverse ratios on the input features are then estimated from the three Gaussian distributions. The naïve Bayes can be changed to the log likelihood form of a semi-naïve Bayes.

$$\mathrm{P}_{RPC}(\mathrm{i}) = \log p(1-OR(i)|\omega_{RPC}) + logp(1-PPO(i)|\omega_{RPC}) + p(1-Dist(i)|\omega_{RPC}) \qquad (1)$$

Finally, if the final decision probability of the *RPC* exceeds the minimum *T* (0.5), it is accepted as an 'warning', as shown in Fig. 1.

## 3. Experimental Results and Conclusion

To evaluate the prediction of risky pedestrian at night, we generated training images from the KMU-RPC dataset using a low-cost IR lens camera. The KMU-RPC consists of 15 videos captured from moving vehicles (20 ~ 30 km/h) at night and each video sequence contains various unsafe pedestrian situations according to the scenario such as crossing the road and walking along the sidewalk.

Figure 2 shows examples of RPC prediction when applying our proposed method to the KMU-RPC dataset. As shown in Fig. 2, the proposed method can predict RPC although the light is low or far from the camera.

However, our method also produces false RPC predictions when the pedestrian is overlapped by other object, standing with the headlights of the vehicle coming from the other side, or light is relatively low (outer of headlight range). In the future, we plan to apply a RPC method based on pedestrian tracking to the current system to predict and be aware of pedestrian intentions in advance for collision avoidance.

Figure 2 Sample RPC prediction results using the proposed method. Red box, orange box, green box means ‘Warning’, ‘Caution’ and ‘Normal’ respectively. The arrows represent the orientation of pedestrian and numbers represent the distance pedestrians from the camera.

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