Classification of Rush-Out Risk of Pedestrians in Blind Area Using 2.4 GHz FMCW Radar

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Abstract

In this study, basic experiments were conducted to detect pedestrians in a non-line-of-sight (NLOS) area behind a wall using a 2.4 GHz frequency modulated continuous wave (FMCW) radar and to classify their risk of rushing out. The experimental results showed that the pedestrians in the NLOS area were detected using only diffracted waves. Furthermore, the classification of pedestrian movements with different rush-out risks was achieved with 95% accuracy. The assumed movements were walking from the NLOS area toward the located radar (high rush-out risk) and walking toward the opposite side of the radar (low rush-out risk).

Keywords

Rush-out risk, NLOS (Non-line-of-sight) area, blind area, 2.4 GHz band, FMCW radar

1. Introduction

In Japan, the incidence of road accidents has declined in recent decades, partly due to the widespread adoption of collision avoidance technologies such as Advanced Driving Assistant Systems (ADAS). However, there has been an increase in the number of accidents involving blind areas, often referred to as non-line-of-sight (NLOS) areas, including collisions with pedestrians outside the driver's field of vision such as pedestrians behind walls and cars [1]. Current ADAS systems are primarily designed to monitor directly visible areas from the sensors embedded in vehicles and are inadequate for detecting pedestrians in NLOS areas.

To solve the above problems, a method has been proposed that utilizes a communication network between a pedestrian's mobile device and a car to detect the location of pedestrians in NLOS areas [2]. However, it should be noted that this method is limited in its ability to detect pedestrians who lack electronic devices capable of communicating with vehicles, such as mobile phones, or when such devices are powered off. Another approach involves direct vehicle-to-vehicle communication to detect pedestrians in NLOS areas [3]. This method can identify pedestrians in the blind area even when the vehicle is not in that area. However, in cases where two or more vehicles are present if one vehicle can see a pedestrian, the other vehicle may not be able to see the same pedestrian. In such situations, the system reports the presence of undetected pedestrians. Nonetheless, this approach also has its limitations, as detecting pedestrians in NLOS areas requires the presence of multiple vehicles and is thus not practical for use on heavily trafficked roads.

As another approach to detecting pedestrians existing in NLOS areas, microwave radar-based monitoring techniques have been proposed [4], [5], [6]. In our previous study [4], we used 24 GHz radar to classify the risk of pedestrians being run over based on multipath reflections. However, it proved difficult to use where there were no other walls or obstacles to multipath reflections. In [5], the detection capability for the targets in the NLOS range was investigated using only the diffracted waves of the 2.4

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GHz band radar. However, this study only considered signal detection and did not consider pedestrian motion detection. In [6], an efficient method for the detection of pedestrian rush-out using radar and stereo cameras was presented. However, this method does not sufficiently address the situation where the camera cannot detect the target pedestrian.

In this study, we investigate a classification of the rush-out risk of pedestrians in NLOS areas using the 2.4 GHz frequency modulated continuous wave (FMCW) to exploit the range information of diffracted waves. The possibility of detecting pedestrians behind walls using only diffracted waves was investigated. A rush-out risk classification method was then proposed and a high classification accuracy was demonstrated.

2. Experimental Setup

This study uses a 2.4 GHz FMCW radar. A sweeping signal in the 2.4 to 2.5 GHz frequency range is generated and transmitted from the transmitter antenna towards the target. Next, the receiver antenna picks up the reflected wave and the signal is amplified by a low-noise amplifier. The signal is then detected by multiplying the received signal with a delayed signal from the transmitter, and noise is removed by a low-pass filter to obtain the received signal. Because the bandwidth of the transmitting sweeping signals was 100 MHz, the range resolution of our FMCW radar was 1.5 m.

Figure 1 shows the system model of the experiments to measure pedestrians in a NLOS area, and Figure 2 depicts the experimental site. The pedestrian participant was behind an obstacle wall and was measured using diffractied waves from the left side of the obstacle. The height and width of the obstacle wall were 185 cm and 230 cm. The initial position of the participant was (x, y) = (0 m, 0 m), two types of motion are performed: 'Approaching the radar', walking from the origin to (x, y) = (-1.65 m, 0 m), and 'Going away from the radar', moving from the origin to (x, y) = (1.65 m, 0 m). The walking speed of the participants was approximately 0.6 m/s. We define two radar received signals as data0 and data1: the data0 was recorded at the start of the movement (0 s to 0.05115 s) and the data1 was recorded 1 second after the start of the movement (1 s to 1.05115 s). We performed each movement of approaching and moving away from the radar 80 times and collected data0 and data1 on each occasion. There were two participants (age: 22 and 23 years, height: 172cm and 173cm). Note that the distance between the radar and the back wall was 30 m and the radar echoes from the back wall were easily separated from those of the measured human target.

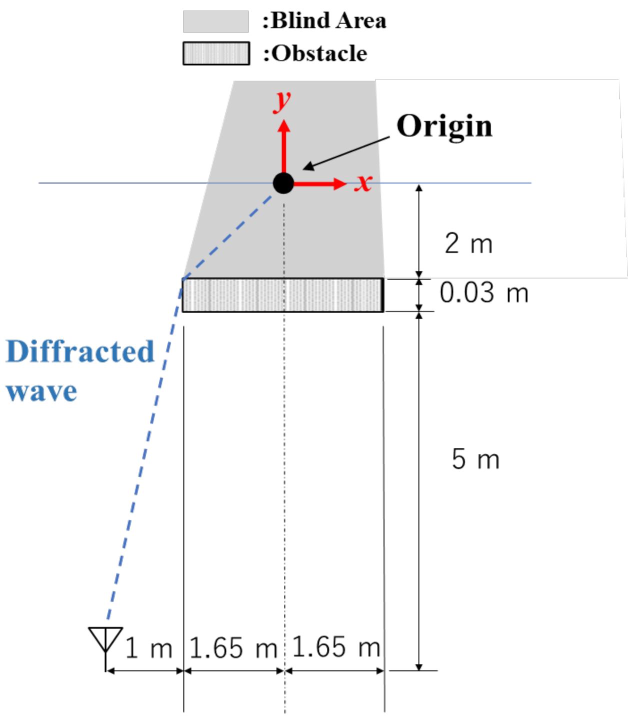


Figure 1: Radar measurement system model.

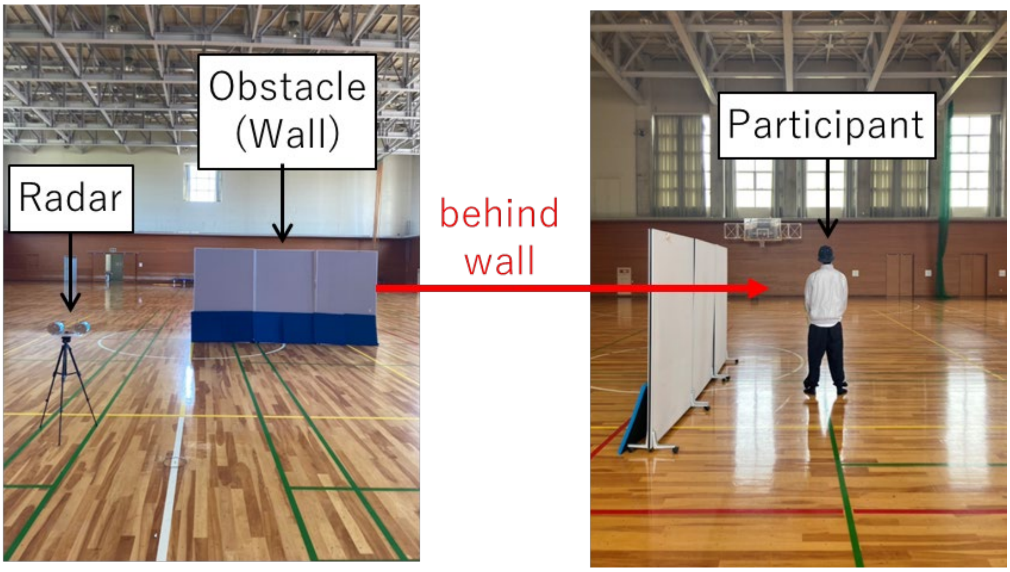
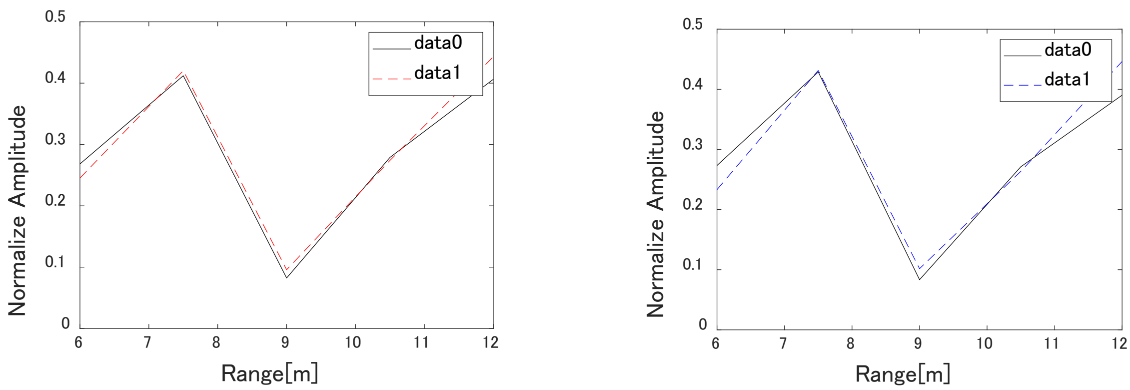


Figure 2: Experimental site.

3. Acquisition of Range Profiles

We obtained the range profiles of data0 and data1 by applying the Fourier transform to the received signals to confirm the detection capability of the pedestrians in the NLOS area and to classify their rush-out risks. Figure 3 shows an example of the range profiles of data0 and data1 for the two classes 'approaching the radar' and 'going away from the radar'. The vertical axis represents the radar received amplitude normalized to its maximum value, while the horizontal axis shows the range calculated from the beat frequency of the FMCW radar [7].

As indicated in Figure 3(a), the amplitude of the 7.5 m range of data1 increased compared with that of data0 for 'approaching the radar'. This increase in amplitude corresponds to the walking motion of the participant, as the path of the diffracted wave between the participant and the radar was approximately 8 m, as shown in Figure 1. In contrast, the amplitude of the 7.5 m range slightly decreased for the participants who were 'going away from the radar'. These results suggest that the range profile and its time-variation contain information about the small differences corresponding to the movements of the participants in the NLOS area, indicating the feasibility of pedestrian detection using diffracted waves and motion recognition of the detected pedestrians.

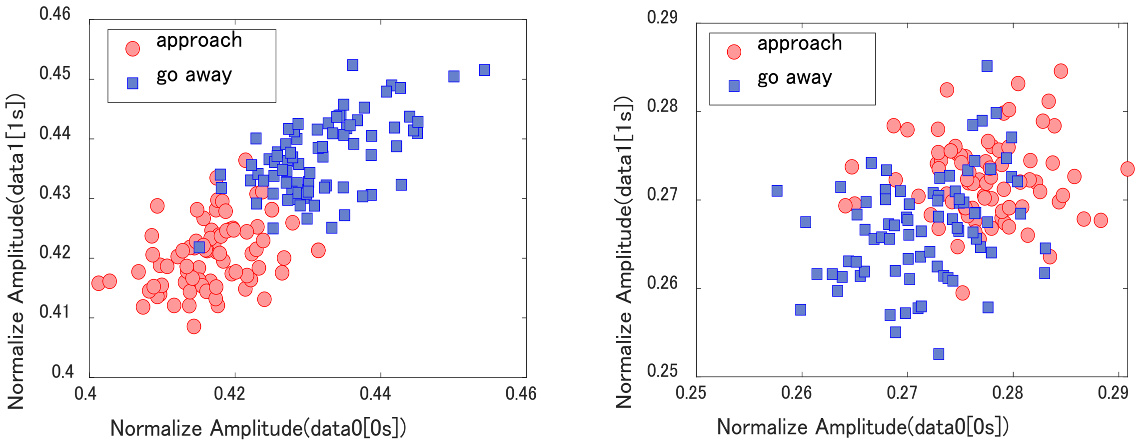


(a) 'Approaching the radar' (b) 'Going away from the radar'

Figure 3: Examples of range profiles.

4. Classification of Walking Motions with Different Rush-Out Risks

In this section, we present the results of the classification of the two types of walking motions with different rush-out risks based on the acquired range profiles. Firstly, we consider the efficient feature parameters in the range profiles. Figure 4 shows plots of the normalized received amplitude of data0 and data1 for 7.5 m and 10.5 m range bins, where the differences between the two classes were relatively clear. The 7.5 m range is the area where the pedestrian participant mainly exists. The 10.5 m range corresponds to the echoes of multiple reflections of the wall and the participant, and the slight differences corresponding to lateral movement relative to the radar can be detected at this range bin. Note that the data for other ranges did not show significant differences between the two classes.



(a) 7.5 m range

(b) 10.5 m range

Figure 4: Plots of amplitude data for the classification of rush-out risks.

For the classification, we used a support vector machine (SVM) [8] using the feature space shown in Figure 4. The SVM used a Gaussian kernel and the other hyperparameters were empirically optimized. The accuracy of the classification was evaluated using hold-out validation. 70% (112 data) of the acquired data (80 data × 2 people = 160 data) were used as training data to determine the SVM model, and the remaining 30% (48 data) were used as test data. The holdout validation was performed 10 times by randomly varying the training data selection.

Table 1 shows the confusion matrix for all 10 tests. The mean classification rate was 95.0%, indicating that the rush-out risk classification was performed with sufficient accuracy. Furthermore, it is important for practical purposes that the detected pedestrians having high rush-out risks are not misclassified as those with low risks. Thus, reproducibility is crucial and it was found to be 95.8%. Although these results indicate high performance in the classification of rush-out risks, better reproducibility is required for practical use.

Table 1
Confusion matrix of rush-out risk classification.

True\Predicted	Approaching	Going away
Approaching	95.8%	4.2%
Going away	5.8%	94.2%

5. Conclusion

This study aimed to assess the feasibility of using a 2.4 GHz band FMCW radar to classify the risk of pedestrian rush-out in the NLOS area behind the obstacle wall. Our results demonstrated that the classification accuracy of 95% and reproducibility of 95.8% were achieved based on the received signals corresponding to diffracted waves. Although more performance is required for the practical use of ADAS, our experiments indicated the feasibility of monitoring NLOS areas using low-frequency radar compared with well-used millimeter-wave automotive radars. To improve the accuracy, the use of bistatic array radar systems and more sophisticated classification method including deep learning approaches should be considered in our future study.

6. Acknowledgements

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