ESANN 2018 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2018, i6doc.com publ., ISBN 978-287587047-6. Available from http://www.i6doc.com/en/.

Radar Based Pedestrian Detection using Support Vector Machine and the Micro Doppler Effect

João Victor Bruneti Severino[1,2], Alessandro Zimmer[2],
Leandro dos Santos Coelho[1,2], Roberto Zanetti Freire[1]

1- Pontifical Catholic University of Parana - PUCPR - Polytechnic School
Imaculada Conceição, 1155 - Postal Code: 80215-901 Curitiba, PR - Brazil
Industrial and Systems Engineering Graduate Program – PPGEPS
2- Federal University of Parana (UFPR) - Dept. of Electrical Engineering
Av. Cel. Francisco H. dos Santos, 210 - Postal Code: 82590-300 Curitiba, PR - Brazil
Electrical Engineering Graduate Program - PPGEE

Abstract. Based on alarming statistics related to both pedestrian fatalities and injuries in traffic accidents, this paper presents the development of a pedestrian detection method for an Advanced Driving Assistance System (ADAS). Using a 79GHz automotive radar, a signal processing application that can early identify pedestrians in short range situations using Support Vector Machine (SVM) was presented and evaluated in order to improve the velocity resolution for the micro Doppler effects extraction. By assuming pre-processing multiobjective optimization, promising results in terms of velocity resolution and measuring time were obtained, improving the accuracy of the classifier.

1 Introduction

Taking into account that 1.24 million people die every year in traffic accidents, and in the year of 2030, crashes will become the fifth leading cause of death worldwide, Advanced Driving Assistance System has being developed to reduce these statistics [1]. Only in Brazil, more than 12,000 pedestrian dies in traffic accidents every year, being more than 70% of these accidents attributed to human errors [2].

With the necessity of increasing vehicle's safety, machine learning techniques have being associated with different automotive sensors in order to predict accidents and help drivers [3-6]. A wide range of works using cameras, considering both deep learning and support vectors machines approaches to predict objects along the vehicles trajectory have been presented [3-4], while others focus in detecting pedestrians, assuming convolutional neural networks and boosting methods [5-6].

One of the main problems in the pedestrian detection is related to situations close to the moment of the impact, considered short distances. In these situations, prediction system must work fast. In this way, this work presents an approach to improve radar's velocity resolution without increasing measurement time, in order to extract the micro Doppler characteristics of the pedestrian movement. In a second step, SVM was adopted to early identify pedestrian in short-range distances.

ESANN 2018 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2018, i6doc.com publ., ISBN 978-287587047-6. Available from http://www.i6doc.com/en/.

The next section of this work shows an overview about the radar system adopted and its configuration. After, Section 3 presents the multiobjective optimization techniques used to improve the velocity resolution of the radar data in order to extract the pedestrian's micro Doppler effects. Section 4 explains the six test scenarios and how they were implemented in laboratory. In Section 5, the methods and characteristics to train the SVM models were explained and, in Section 6, the velocity resolution and the SVM classification results are presented. Finally, Section 7 reports the conclusion of this work and addresses possibilities for future researches.

2 Data acquisition with a radar system

The Radarlog, used in this work, is a radar system with maximum transmit frequency of 79GHz [7]. This radar works with Frequency Modulated Controlled Wave (FMCW), and a chirp modulation was adopted in order to reach the highest possible velocity resolution (Fig. 1).

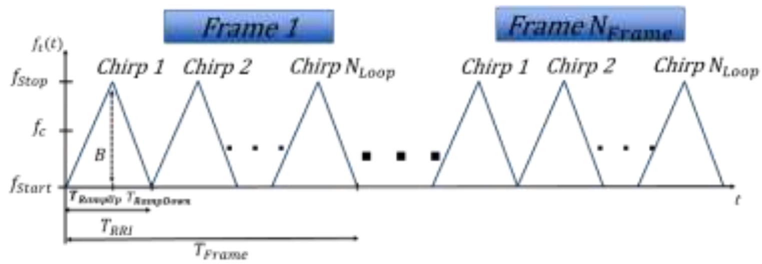


Fig. 1: Wave modulation.

The main parameters of the wave are the T_{rampup} and $T_{rampdown}$, those representing the duration time (in seconds) of the positive and the negative slopes, respectively. T_{RRI} is the duration time of one chirp, and T_{frame} the time of one frame (both in seconds). K is the number of chirps in one frame and B is the frequency bandwidth of the signal represented in hertz.

For the pedestrian classification problem presented in this work, there are two information that must be calculated using radar's signals: relative velocity and range. To compute the range, the time delay τ (in seconds) from the receiving wave and the velocity of light c (m/s) are considered, while for velocity the Doppler Effect is used. The latter happens when the pedestrian is moving to its source changing the frequency. When pedestrian and source move away from each other, the arrival time between successive waves is increased, reducing the frequency. When they approach to each other, the opposite occurs [8].

3 Improvement of velocity resolution

The velocity of human bodies are characterized by periodical movements of distinct body parts. These movements can be detected by the radar through Doppler effects of smaller intensities called micro Doppler effects. Taking into account these effects, it is possible to identify pedestrians in an easier and faster way, since most of traffic objects, as cars, are rigid bodies presenting one single movement characteristic.

In order to extract this information from the received signal, velocity resolution of the measured data must be optimized. To reach this goal a multiobjective optimization method was applied.

3.1 Multiobjective optimization of radar velocity

A single optimization of radar velocity resolution (Δv) is not possible, since the problem has more functions associated. Maximum measured velocity ($v_{r,max}$) maximum detectable range (r_{max}), and range resolution (Δr) are other goals that should be improved, or at least not worsened, in order to obtain a reasonable and feasible data. In addition, the radar system has restrictions, as measuring time T_{frame} (in seconds) and transmission data velocity D_{rate} (in Hz).

The problem has four objective functions J_i (Eqs. 1-4) and two inequations representing the constraints (Eqs. 5-6). The first constraint is to maintain the data acquisition faster than 100 ms per frame. The second one is to restrict the quantity of data per frame, since the radar can support at most 1,5 Gbits.

In general, there are six variables to be optimized based on the system: T_{Rampup}, B, T_{RRI}, K, N and N_{chn}, being the last two the number of measurements in one positive slope and the number of receiving channels by the radar, respectively.

$$J_1 = \min_{\Delta v \in \mathbb{R}^+} \Delta v, \text{ where } \Delta v = \frac{c}{2 f_c . T_{RRI} . K} \tag{1}$$

$$J_2 = \min_{\Delta r \in \mathbb{R}^+} \Delta r, \text{ where } \Delta r = \frac{c}{2B} \tag{2}$$

$$J_3 = \max_{v_{r,max} \in \mathbb{R}} v_{r,max}, \text{ where } v_{r,max} = \frac{c}{2 . T_{RRI} . 2 . f_c} \tag{3}$$

$$J_4 = \max_{r_{max} \in \mathbb{R}^+} r_{max}, \text{ where } r_{max} = \frac{T_{Rampup} . c . f_s}{4B} \tag{4}$$

$$T_{frame} = T_{RRI} . K < 10^{-1} \tag{5}$$

$$D_{rate} = \frac{N . K . N_{chn} . 16}{T_{frame}} < 15 . 10^8 \tag{6}$$

Both genetic algorithm (GA) [9] and random search (RS) methods were used to generate possible solutions J for this problem. In order to classify the best solutions, two ranking techniques were chosen, the Order of Preference by Similarity to Ideal Solution (TOPSIS) [10], and the Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) [11].

4 Test procedures

According to German In-Depth Accident Study (GIDAS) [12] more than 80% of the accidents involving pedestrians happens in six scenarios (Fig. 2). Based on that, these scenarios were assembled and measured inside an automotive track, using the previous mentioned radar system and a camera.

Fig. 2: Test procedures [12].

The radar and camera were fixed in a rigid structure, and this structure were positioned in the right lane. The radar parameters were configured considering the results obtained by the multiobjective optimization method, more information can be found in section 6 of this paper.

All scenarios were measured two times with different pedestrians, one male 1.85 m high and one female 1.65 m high. The tests were performed on the both sides of the road.

The pedestrians crossed the road considering three different speeds: normal walking (~1.5 m/s), fast walking (~2.5 m/s) and running (~4 m/s). In addition, the car approached the pedestrians with three different speeds: 3 m/s, 7 m/s and 10 m/s. For safety reasons, the velocity could not be higher than 10 m/s.

In the first scenario 54 data sets were captured, in the second one 27, in the third one also 27, in the fourth only 4, and the fifth and the sixth scenarios 54 to each, resulting in 220 tests gathered. Unfortunately, because of the project confidentiality the data is not available for independent verification.

5 Support Vector Machine Training

The gathered data resulted in 16,100 frames, and for each one, the radar signal were compared with the images from the camera. The signal representing the pedestrians and the other signals were labeled manually as positive and negative instances respectively. The positive and negative instances resulted in 66,580 labelled objects.

Each labeled signal was transformed into a matrix with the size based on the bigger matrix labeled, and then turned into a vector. Each vector has 8,115 values, also the velocity and distance information were added to them. Zeros were attributed to the negative instances and ones for the positive ones, resulting in a matrix of 66,580 lines per 8,118 columns. In Tab. 1 two lines of the matrix are presented.

Velocity (m/s)	Distance (m)	Signal (dB)	Instances
-0.508	15.04	1x8115 double	1
-1.012	14.97	1x8115 double	0

Table 1 – Data matrix example.

ESANN 2018 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2018, i6doc.com publ., ISBN 978-287587047-6. Available from http://www.i6doc.com/en/.

The data were divided in 70% for training and 30% for testing procedures. In addition, three kernels were adopted in the SVM method for comparisons: Linear, Polynomial and the Radial Basis Function (RBF).

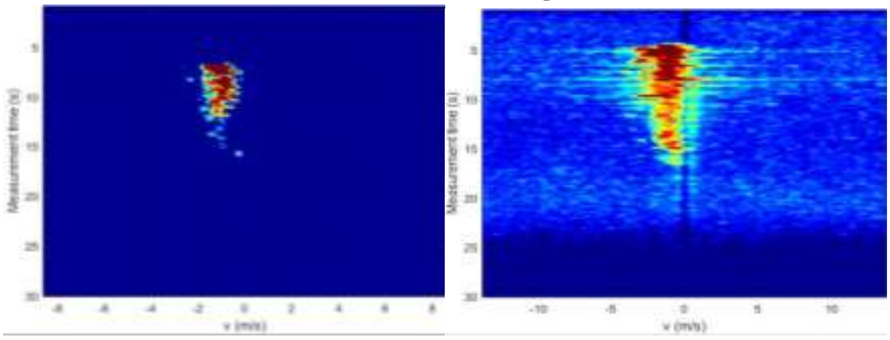
6 Results

The wave modulations parameters were defined based on the problem discussed in subsection 3.1. The chosen solution was the first position in both rankings. In Tab. 2 is presented a comparison between the optimized (Optm.) and original (Orig.) configuration of the radar.

	Objective Functions				Radar Parameters					
Config.	r_{max} (m)	$v_{r,max}$ (m/s)	Δv (m/s)	Δr (m)	T_{RampUp} (s)	B (Hz)	T (s)	K	N	N_{chn}
Optm.	33.9	7.56	0.12	0.13	1.01E-04	1.13E+09	1.2E-04	128	512	6
Orig.	33.4	13.77	0.43	0.15	0.51E-04	1.00E+09	0.7E-04	64	512	16

Table 2: Results and parameters.

Figures 2 (a) and (b) illustrate the pedestrian’s velocity in each second of the trajectory, before and after the optimization respectively. In (a), mainly the torso velocity can be seen (in red color), while in (b), for each measured time, smaller intensities of velocity (micro Doppler) are presented (yellow and green), representing also arms and legs of human movements. Considering the information presented in section 5, the results of the three SVM models are presented in Tab.3.



(a) (b)

Fig. 3: Micro Doppler Effect extraction.

	Linear	Polynomial	RBF
Accuracy	0.9698	0.9946	0.9915
False Positive	242	39	61
False Negative	362	69	109
Training duration (s)	1374.7	822.5	1150
Execution time (s)	0.5778	0.0558	0.0846

Table 3: SVM results.

7 Conclusion

The techniques for the velocity resolution optimization showed promising results, improving the velocity resolution three times. In consequence, a more visible micro Doppler effect in short time and range measurements could be obtained.

The clearer micro Doppler effects with the SVM models resulted in more accurate values, especially assuming the polynomial kernel. However, the execution time is not good enough for this application. The radar measured time plus the SVM execution time results in almost 150 ms in the best scenario. For traffic applications, the optimal time is around 60 ms.

For future works, micro controllers to capture data with the radar should be considered to reduce the measuring time. Additionally, more elaborated tests should be performed, increasing the velocity and including more pedestrians at the same time.

References

[1] World Health Organization, Global status report on road safety 2013: supporting a decade of action. Geneva: World Health Organization (WHO), 2013.

[2] Instituto Parar, Montadoras investem em segurança (*In Portuguese*). Brazil, 2016. Available at http://www.institutoparar.com.br/conteudo/278/montadoras-investem-em-seguranca.

[3] W. Ouyang, X. Wang. Joint Deep Learning for Pedestrian Detection, proceedings of the *IEEE International Conference on Computer Vision* (ICCV), 2013, pp. 2056-2063

[4] S. Giatti, R. Z. Freire, L. S. Coelho. Feature extraction for on-road vehicle detection based on support vector machine. *proceedings of the European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN 2017).* Bruges (Belgium), 26-28 April 2017

[5] M. Szarvas, A. Yoshizawa, M. Yamamoto and J. Ogata. Pedestrian detection with convolutional neural networks, *proceedings of the Intelligent Vehicles Symposium (IVS 2005),* 2005, pp. 224-229.

[6] D. Gray, H. Tao. Viewpoint on variant pedestrian recognition with an ensemble of localized features, *Computer Vision – ECCV 2008*. Lecture Notes in Computer Science, vol 5302. Berlin.

[7] INRAS GmbH. Radarlog User Manual. Linz, Austria: INRAS GmbH, April 2016, 6 pg.

[8] M. Skolnik. Introduction to radar systems, second edition. Singapore. Mcgraw-Hill Book Company, 1981.

[9] J. H. Holland, Adaptation in natural and artificial systems, *University of Michigan Press,* 1975.

[10] C. L. Hwang, K. Yoon, Multiple attribute decision making: methods and applications, New York: Springer-Verlag, 1981.

[11] J. P. Brans, P. H. Vincke, A Preference ranking organization method, *Management Science* 31(6):647-656, 1985.

[12] Unfallstruktur- und Wirkpotenzialanalysen zu den AKTIV-Applikationen auf der Basis von PkwHaftpflichtschaeden mit Personenschaden (*in German*), *Forschungsprojekt AKTIV-AS,* 2010.