Design of Short-Range S-band Radar Sensing System for Autonomous Object Classification

Filip Turčinović, Marin Erny, Vedran Zoričić, Nino Poletan, Marko Bosiljevac
* University of Zagreb Faculty of Electrical Engineering and Computing, Zagreb, Croatia

e-mail: filip.turcinovic@fer.hr, marko.bosiljevac@fer.hr

***Abstract* - Remote environmental and industrial sensing based on multi-spectral or radar imaging today plays an important role in ensuring sustainability and protection of natural resources, in saving time and energy in industry and agriculture, and in many other applications. Numerous examples of such systems exist which provide information like product quality to manufacturers, crops growth parameters to farmers or structural integrity details to civil engineers. With recent developments in electromagnetic millimetre-wave (mm-wave) technology and artificial intelligence implementation, short range mm-wave remote sensing is experiencing strong growth with the market dictating new applications with increasingly higher levels of system autonomy. The objective of this paper is to demonstrate methodology and hardware used in short-range radar sensing and use it to build-up a database of scattering images which will allow us the extraction of key signal parameters for particular objects and subsequently allow autonomous object classification using machine learning principles.**

Keywords – short-range radar, FMCW radar, radar imaging, object classification

I. INTRODUCTION

The idea of short-range microwave radar systems with IoT communication possibilities has the potential to improve the quality of service in many areas ranging from security and surveillance to healthcare, agriculture and infrastructure monitoring. Technology of these radar systems is developed primarily in connection to certain fields of application and major advances have been made in detection of vital signs [1–4], structural health monitoring [5-7], different kinds of gesture detection and characterization [8,9] and in all kinds of ranging and tracking applications [10,11] where radars for autonomous vehicles are the most common example [12-14]. Significant advancements are related also to synthetic aperture radar (SAR) and inverse synthetic aperture radar (ISAR) which are being used not only in classic terrain imaging applications, but also in indoor localization, target tracking, fall detection, etc. [15,16]

These advancements have been further enhanced by increased use of conventional machine learning (ML) [17-19] algorithms to optimize the desired application. Most commonly used algorithms were support vector machine (SVM) [20], dynamic time warping (DTW) [21] or random forest classifier [18]. However, the drawbacks of ML approaches such as lack of robustness, required high level of apriori knowledge and dependability on the quality of the original dataset, have prompted recently increased interest in deep learning (DL) approaches [22], which can avoid these limitations. Through hierarchical architectures DL approaches extract different problem features automatically and by doing so apriori specific knowledge is not necessary. Deep learning techniques have accelerated development in numerous fields [23] and even very complex problems related to difficult classifications and similar can be tackled [24,25].

Our aim is to develop a low-cost short-range radar system for autonomous object classification using frequency modulated continuous wave (FMCW) radar system. In order to apply deep learning techniques for classification it is still necessary to build a comprehensive database of radar scattering images and this is the focus of this paper where we will demonstrate the basic design of the radar itself, modifications with respect to classic FMCW architectures and obtained scattering images. Several databases are mentioned in the literature [26,27], however, due to differences in used equipment, lack of normalization, different frequency ranges, etc., it is difficult to combine and use these results in new studies.

The paper is organized in the following way; in Section II, an overview of the used FMCW architecture is given with the highlight on the used polarimetric diversity, followed by Section III where results of the measurements are presented and analysed, again with a special focus on results obtained for different polarizations. Finally, the obtained results are discussed with the perspective of future work in Conclusion.

II. PRINCIPLES OF FMCW RADAR

Classic CW radar system uses a known microwave frequency signal, transmits it in the desired direction and captures the reflection of the signal from the objects which are present in the radar field-of-view. Depending on the desired application, the signal can be purely continuous (unmodulated) or modulated, which leads to two most common types of radars, Doppler mode radar and frequency modulated continuous wave (FMCW) radar.

Doppler radars are based on single frequency signal which thanks to Doppler effect is shifted in reception when the target is moving. This type of radar can be realized at very low-cost and it is found in many devices and applications which require detecting moving objects or for measuring object velocity. However, Doppler radars cannot determine the distance from the object or measure certain parameters of an object (size, composition, etc.). For this reason, we will focus on FMCW architecture as the basis of our radar system.

FMCW based radar transmits a signal with a known frequency modulation, typically triangle, sawtooth, or sinusoidal. Local oscillator (LO) signal is transmitted and when reflected from a target it is received with a delay with respect to the original LO signal. Using principle of homodyne detection, the delayed reflected signal and LO signal are mixed in the receiver producing baseband signal corresponding to the frequency shift (so called beat frequency Δf or f_B). Beat frequency is then proportional to the time delay Δt knowing that

$$\Delta f = \frac{\Delta t B}{T}, \qquad (1)$$

where T is the modulation period and B is the sweep bandwidth. The range to target can then be expressed as

$$R = \frac{cT\Delta f}{2B} \qquad (2)$$

Complete architecture of the FMCW system is shown in Fig. 1. Depending on the application this baseband signal is then processed further, either in analogue or digital domain.

In our case, the FMCW radar is based on the well known MIT scheme developed by G. Charvat [28] operating at 2.4 GHz. With respect to the classic measurement scheme, we also employ polarization change (both Tx and Rx polarizations can be manually changed, and any linear polarization can be achieved) in order to acquire more information on the target object/objects which will lead to a more successful classification later. Used FMCW radar system was built using commercial components and it works at 2.4 GHz with sweep bandwidth of 200 MHz (based on this sweep bandwidth, the expected range resolution of the system is $\Delta R = c/(2\Delta f) = 0.75$m).

All components were separately tested to ensure the required sweep bandwidth and to set the output power to 10 dBm. This limits the maximum range of the radar due to signal loss to approximately 40m in our test cases. Obtained baseband signal is passed through AD converter and recorded as audio stream for further processing. In the detection process, the received signal is multiplied by the window function and transformed into frequency domain by utilizing the FFT operation. This gives us the beat frequencies corresponding to the range of the target.

III. Results

Primary objective of this work is to acquire a series of radar scattering images for different objects and polarizations in order to form a database which will serve in developing and training the classification algorithms. The goal is to test the system with the same objects in a closed laboratory environment with minimum interference and open space scenario where different interfering signals and reflections are possible.

First recording session in the lab environment (semi-closed anechoic chamber) revealed the limitations of the space since there was not enough room to position the radar at a reasonable distance from the objects. Fig. 2. shows the momentary IFFT spectrum for a large metal box placed 2 m from the radar antennas.

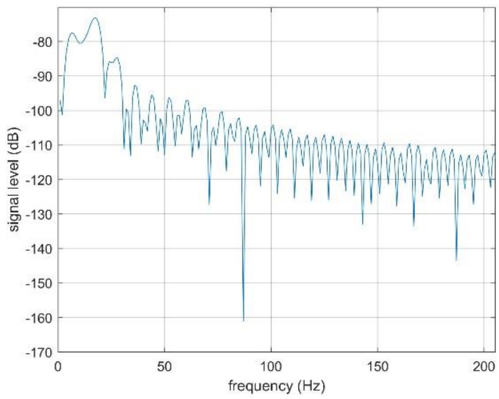


Fig. 2. Output from the IFFT block in FMCW processing showing the detected beat frequencies in baseband for measurement in the lab environment.

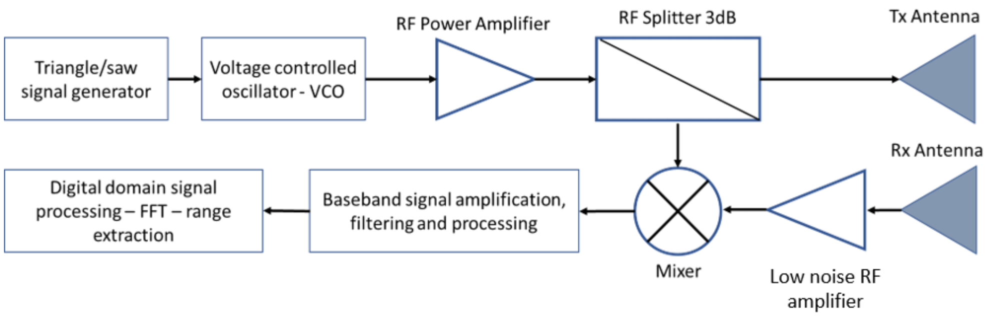


Fig. 1. FMCW radar principal components and layout

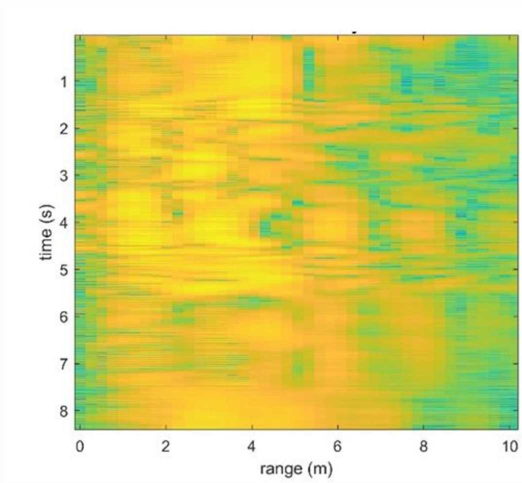
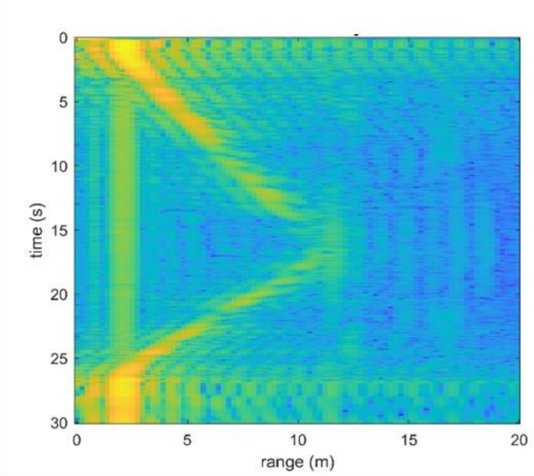


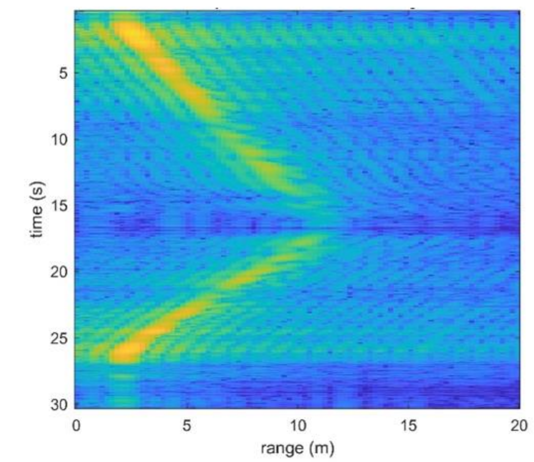
Fig. 3. Range diagram for a stationary object in indoor environment (horizontal polarization).

When the beat frequency is translated into range and plotted vs. time we obtain Fig. 3. where it is very difficult to detect any information due to high level of clutter and noise. This can be mitigated to some level by using certain processing techniques, different kinds of windowing and similar. One commonly used is coherent change detection (CCD) [28,29] which is applied to improve detection of moving objects by subtracting the previous signal from the current one. That way only changes in the recording are identified and it is easier to detect moving objects. This is visualized in Fig. 4. where the object (metal box) is moving away and towards the radar in outdoor environment. The first image Fig. 4.a shows the case when no CCD is applied, and Fig. 4.b. shows the results with CCD, clearly showing the benefit of such processing since a significant clutter reduction is achieved. If the application requires the image in Fig. 4.b. can be analyzed further and also the speed of the object can be easily determined from the slope in this range vs. time display.

The results so far were a reconstruction of similar tests from the literature in order to verify the functionality of the developed radar system and data processing. The following recordings reveal the added information which can be gained by using multiple polarizations which in return should enable the upcoming steps related to object classification.



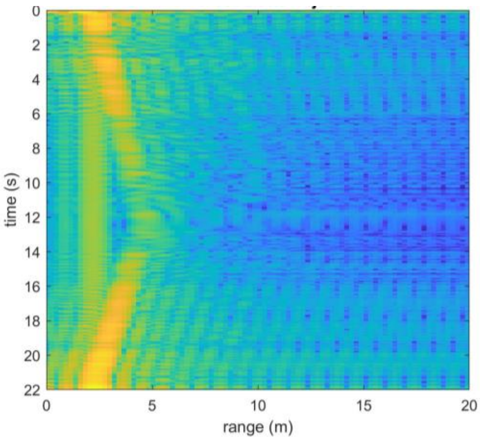
(a)



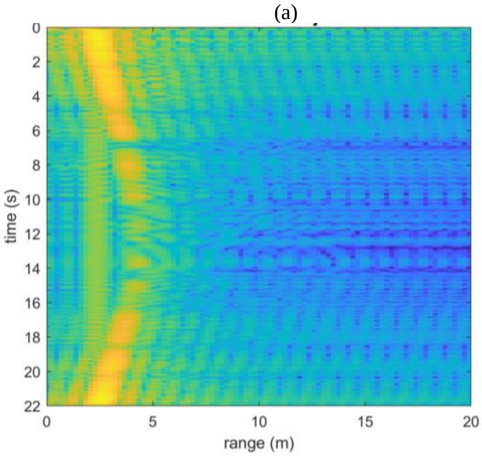
(b)

Fig. 4. Range detection (horizontal polarization) for a moving object; (a) without CCD, (b) with CCD.

Fig. 5. reveals the difference between the horizontal and vertical polarization recordings when a person is walking away and towards the radar for the case when no CCD processing is applied. The same is repeated in Fig. 6. with CCD applied. Although the difference between polarizations is quite small there is a visible difference which can be extracted and our preliminary testing with different objects has revealed that particular shapes will have a dominant relation between polarization results which will be used in our classification process.



(a)

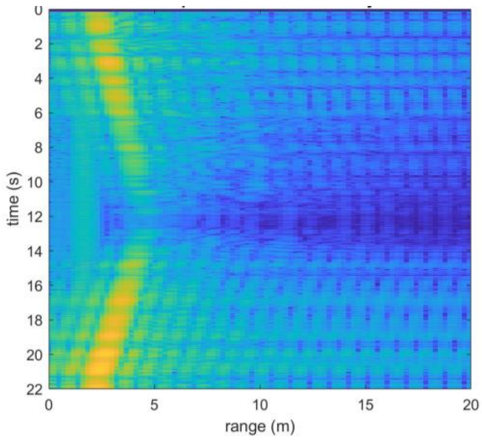


(b)

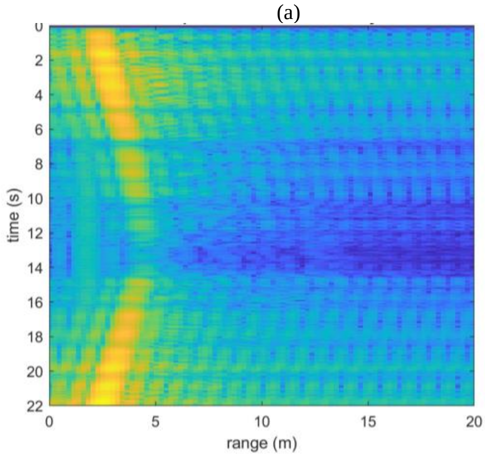
Fig. 5. Range detection for a moving object; (a) horizontal polarization without CCD, (b) vertical polarization without CCD.

IV. CONCLUSION

As indicated in the Introduction there is a growing interest for using radar sensing in various applications other than automotive industry and terrain mapping. With the increased availability of required electronics and reduced prices, even low-cost devices are becoming possible, and in this paper our first goal was to demonstrate the basic principle of low-cost FMCW radar in S-band that can be applied in various application scenarios. In particular, we focus on building a database of moving objects recorded using FMCW radar with various antenna polarizations. Several radar recordings are shown here indicating small, but visible differences between results obtained using different polarizations. These and other recorded signals will be utilized in future steps to autonomously classify different objects and the knowledge gathered in these scenarios will be used in radar sensing at higher mm-wave bands.



(a)



(b)

Fig. 6. Range detection for a moving object; (a) horizontal polarization with CCD, (b) vertical polarization with CCD.

ACKNOWLEDGMENT

This work was supported in part by Croatian Science Foundation (HRZZ) under the project number IP-2019-04-1064.

REFERENCES

[1] J. C. Lin, "Microwave sensing of physiological movement and volume change: A review," Bioelectromagnetics, vol. 13, no. 6, pp. 557–565, 1992.

[2] A. D. Droitcour, O. Boric-Lubecke, V. M. Lubecke, J. Lin, and G. T. A. Kovacs, "Range correlation and I/Q performance benefits in single-chip silicon Doppler radars for noncontact cardiopulmonary monitoring," IEEE Trans. Microw. Theory Techn., vol. 52, no. 3, pp. 838–848, Mar. 2004.

[3] C. Li, V. M. Lubecke, O. Boric-Lubecke, and J. Lin, "A review on recent advances in Doppler radar sensors for noncontact healthcare monitoring," IEEE Trans. Microw. Theory Techn., vol. 61, no. 5, pp. 2046–2060, May 2013.

[4] F. K. Wang, Y. R. Chou, Y. C. Chiu, and T. S. Horng, "Chest-worn health monitor based on a bistatic self-injection-locked radar," IEEE Trans. Biomed. Eng., vol. 62, no. 12, pp. 2931–2940, Dec. 2015.

[5] J. A. Rice, C. Li, C. Gu, and J. Hernandez, "A wireless multifunctional radar-based displacement sensor for structural health monitoring," Proc. SPIE, vol. 7981, p. 79810K, Apr. 2010.

[6] S. Guan, J. A. Rice, C. Li, Y. Li, and G.Wang, "Structural displacement measurements using DC coupled radar with active transponder," Struct. Control Health Monitor., Jan. 2016.

[7] B. Spencer, Jr., S. Cho, and S.-H. Sim, “Wireless monitoring of civil infrastructure comes of age,” Structure Mag., vol. 13, pp. 12–16, Oct. 2011.

[8] Y. Wang and A. E. Fathy, “Micro-Doppler signatures for intelligent human gait recognition using a UWB impulse radar,” in Proc. IEEE Int. Symp. Antennas Propag. (APSURSI), Jul. 2011, pp. 2103–2106.

[9] J. Lien et al., “Soli: Ubiquitous gesture sensing with millimeter wave radar,” ACM Trans. Graph., vol. 35, no. 4, pp. 1–19, Jul. 2016.

[10] A. Koelpin, F. Lurz, S. Linz, S. Mann, C. Will, and S. Lindner, “Sixport based interferometry for precise radar and sensing applications,”Sensors, vol. 16, no. 10, p. 1556, 2016.

[11] G. Vinci, S. Lindner, F. Barbon, R. Weigel, and A. Koelpin, “Promise of a better position,” IEEE Microw. Mag., vol. 13, no. 7, pp. S41–S49, Dec. 2012.

[12] B.-H. Ku et al., “A 77-81-GHz 16-element phased-array receiver with ±50° beam scanning for advanced automotive radars,” IEEE Trans. Microw. Theory Techn., vol. 62, no. 11, pp. 2823–2832, Nov. 2014.

[13] J. Hatch, A. Topak, R. Schnabel, T. Zwick, R. Weigel, and C. Waldschmidt, “Millimeter-wave technology for automotive radar sensors in the 77 GHz frequency band,” IEEE Trans. Microw. Theory Techn., vol. 60, no. 3, pp. 845–860, Mar. 2012.

[14] H. P. Forstner et al., “A 77GHz 4-channel automotive radar transceiver in SiGe,” in Proc. IEEE Radio Freq. Integr. Circuits Symp., Jun. 2008, pp. 233–236.

[15] D. A. Ausherman, A. Kozma, J. L. Walker, H. M. Jones, and E. C. Poggio, “Developments in radar imaging,” IEEE Trans. Aerosp. Electron. Syst., vol. AES-20, no. 4, pp. 363–400, Jul. 1984.

[16] F. Berizzi, E. D. Mese, M. Diani, and M. Martorella, “Highresolution ISAR imaging of maneuvering targets by means of the range instantaneous Doppler technique: Modeling and performance analysis,” IEEE Trans. Image Process., vol. 10, no. 12, pp. 1880–1890, Dec. 2001.

[17] Zenaldin, M.; Narayanan, R.M. Radar micro-Doppler based human activity classification for indoor and outdoor environments. In Proceedings of the SPIE Conference on Radar Sensor Technology XX, Baltimore, MD, USA, 18–21 April 2016.

[18] Smith, K.; Csech, C.; Murdoch, D.; Shaker, G. Gesture Recognition Using mm-Wave Sensor for Human-Car Interface. IEEE Sens. Lett. 2018, 2, 1–4. doi:10.1109/LSENS.2018.2810093.

[19] Zhang, Z.; Tian, Z.; Zhou, M. Latern: Dynamic Continuous Hand Gesture Recognition Using FMCW Radar Sensor. IEEE Sens. J. 2018, 18, 3278–3289.

[20] Kim, Y.; Ling, H. Human Activity Classification Based on Micro-Doppler Signatures Using a Support Vector Machine. IEEE Trans. Geosci. Remote Sens. 2009, 47, 1328–1337.

[21] Zhou, Z.; Cao, Z.; Pi, Y. Dynamic Gesture Recognition with a Terahertz Radar Based on Range Profile Sequences and Doppler Signatures. Sensors 2017, 18, 10. doi:10.3390/s18010010.

[22] Deng, L.; Yu, D. Deep learning: Methods and applications. Found. Trends Signal Process. 2014, 7, 197–387.

[23] Lecun, Y.; Bengio, Y.; Hinton, G. Deep learning. Nature 2015, 521, 436.

[24] Szegedy, C.; Ioffe, S.; Vanhoucke, V.; Alemi, A.A. Inception-v4, inception-resnet and the impact of residual connections on learning. In Proceedings of the National Conference on Artificial Intelligence, Phoenix, AZ, USA, 12–17 February 2016; pp. 4278–4284.

[25] He, K.; Zhang, X.; Ren, S.; Sun, J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.

[26] A Ouaknine, A Newson, J Rebut, F Tupin, P Pérez, “CARRADA Dataset: Camera and Automotive Radar with Range-Angle-Doppler Annotations”, arXiv preprint arXiv:2005.01456

[27] C. Gilmore, A. Zakaria, P. Mojabi, M. Ostadrahimi, S. Pistorius and J. Lo Vetri, "The University of Manitoba Microwave Imaging Repository: A Two-Dimensional Microwave Scattering Database for Testing Inversion and Calibration Algorithms [Measurements Corner]," in IEEE Antennas and Propagation Magazine, vol. 53, no. 5, pp. 126-133, Oct. 2011

[28] Gregory L. Charvat, Small and Short-Range Radar Systems, CRC Press, 2017.

[29] W.G. Carrara, R.S. Goodman, and R.M. Majewski, Spotlight Synthetic Aperture Radar Signal Processing Algorithms, Artech House, Boston, MA, 1995.