Classification of micro-Doppler radar hand-gesture signatures by means of Chebychev moments

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***Abstract*—In this paper a method capable of automatically classify radar signals of human hand-gestures exploiting the micro-Doppler signature is designed. In particular, the methodology focuses on the extraction of the Chebychev moments from the cadence velocity diagram (CVD) of each recorded signal. The algorithm benefits from interesting properties of these moments such as the fact that they are defined on a discrete set and hence computed without approximations, as well as the symmetry property that allows to minimize the computational time. The experiments computed on the challenging real-recorded DopNet dataset show interesting results that confirm the effectiveness of the approach.**

***Index Terms*—micro-Doppler, hand-gesture recognition, image moments, millimeter Wave, automatic target recognition**

I. Introduction

GESTURE recognition is without any doubt one of the most challenging issue in the development of modern devices in which the human-machine interaction is made possible without any physical touch by the user. This can be made possible thanks to the intrinsic capabilities of radio-frequency (RF) devices able of operating in weak light condition (e.g., during night) that have lead to the development of millimiter wave (mmW) radars specifically designed to this aim, viz. the Google Soli project [1], the DopNet radar [2], and so on. In this respect, an effective tool to properly perform the gesture sensing and recognition is the well-known micro-Doppler effect [3]. As a matter of fact, micro-Doppler, that can be seen as additional frequency modulations induced by small displacement, rotation or vibration of secondary parts of the object under observation, have been widely exploited for target classification and micro-motion analysis, including hand-gesture, over the last decade [4]–[7].

In such a context, this paper proposes a method capable of automatically classifying radar signals related to human hand-gestures exploiting their intrinsic micro-Doppler signature. In particular, following the line of reasoning of [4], the method extracts the Chebychev moments [8] from the cadence velocity diagram (CVD) obtained from the short time Fourier transform (STFT) of each recorded signal. The choice of using these image moments, already used for hand-gesture classification from optical images [9], is motivated within the radar context for their useful characteristics. In fact, Chebychev moments, differently from Zernike [10], are directly defined on a discrete set, therefore no approximations are needed in their implementation. Additionally, they are characterized by their symmetry property that can be properly exploited to reduce both the computational time as well as the required storage in the database. The analyses are computed on the challenging DopNet dataset [2] showing promising capabilities in terms of hand-gesture recognition also in comparison with other state-of-art methods.

II. Micro-Doppler based Hand-Gesture Recognition Algorithm

This section describes the proposed feature-based algorithm for radar micro-Doppler classification of hand-gesture signatures. Essentially, the methodology is based on the exploitation of the Chebychev moments [8], that thanks to their intrinsic discrete nature are easy to extract. It is also worth to underline that the proposed approach benefits from the symmetry property of these moments thus providing a feature vector of small size hence ensuring a low computational burden. In the next subsections the Chebychev moments are first derived from their homologous polynomials; then the devised feature-based classification algorithm is described in all its aspects.

A. Chebychev Moments

Let consider a non-negative real-defined image, say $f(x,y) \geq 0$. Then, the moments of $f(x,y)$ of order (or degree) $l+h$ are the projection of the function $f(x,y)$ on the monomials $x^l y^h$, through the following integral [11]

$$M_{l,h} = \iint_{\mathbb{R}^2} x^l y^h f(x,y)\, dx\, dy. \quad (1)$$

The moments whose general expression is given in (1) do not share the orthogonality condition due to their dependence on the family of monomials $\{x^l y^h\}$, which in general do not have this property. To overcome this issue, that is the main limitations in using image moments, Chebychev polynomials have been introduced [8]. In particular, Chebychev polynomials of order l are a set of orthogonal functions, with some interesting properties [8], that can be written in the form

$$t_l(x) = (1-L)_l \, {}_3F_2\left(-l, -x, 1+l, ; 1, 1-L; 1\right), \quad (2)$$

where $x = 0, 1, 2, \ldots, L-1$. The term $(a)_l$ is the Pochhammer symbol [12] defined as

$$(a)_l = a(a+1)\cdots(a+l-1) = \frac{\Gamma(a+l)}{\Gamma(a)}, \quad (3)$$

whereas

$${}_3F_2\left(a_1, a_2, a_3; b_1, b_2; z\right) = \sum_{k=0}^{+\infty} \frac{(a_1)_k (a_2)_k (a_3)_k}{(b_1)_k (b_2)_k} \frac{z^k}{k}. \quad (4)$$

It is now worth noticing that (2) can be also rewritten in a more simple form as

$$t_l(x) = l! \sum_{k=0}^{l} (-1)^{l-k} \left(\begin{array}{c} L-1-k \\ l-k \end{array} \right) \left(\begin{array}{c} l+k \\ l \end{array} \right) \left(\begin{array}{c} x \\ k \end{array} \right). \quad (5)$$

An important property of the Chebychev polynomials is that they satisfy the orthogonality condition, that is

$$\sum_{x=0}^{L-1} t_l(x) t_h(x) = \rho(l, L)\delta_{l,h} \quad (6)$$

where $0 \leq l, h \leq L-1$ and $\delta_{l,h}$ is the Kronecker delta function formally defined as

$$\delta_{lh} = \left\{ \begin{array}{lll} 1 & \text{if} & l = h \\ 0 & \text{if} & l \neq h \end{array} \right. .$$

Moreover, the amplitude factor $\rho(l, L)$ is given by

$$\rho(l, L) = (2l)! \binom{L+l}{2l+1}. \quad (7)$$

Now, it is possible to define a scalar version of the Chebychev polynomials, that is

$$\tilde{t}_l(x) = \frac{t_l(x)}{\beta(l, L)} \quad (8)$$

where $\beta(l, L)$ is a scaling factor independent of x that is introduced to ensure the numerical stability during moments calculations. It is defined as

$$\beta(l, L) = L^l. \quad (9)$$

By doing so, the scaled polynomial of order $l = 0$ will be $\tilde{t}_0(x) = 1$, whereas that of order $l = 1$ will be equal to $\tilde{t}_1(x) = (2x + 1 - L)/L$, whose pictorial representation is given in Fig. 1 together with higher order polynomials.

Concluding, the Chebychev moments can be derived projecting the image $f(x, y)$ of size $L \times H$ on the related polynomials given in (8), that is

$$T_{l,h} = \frac{1}{\tilde{\rho}(l, L)\tilde{\rho}(h, H)} \sum_{x=0}^{L-1} \sum_{y=0}^{H-1} \tilde{t}_l(x)\tilde{t}_h(y) f(x, y). \quad (10)$$

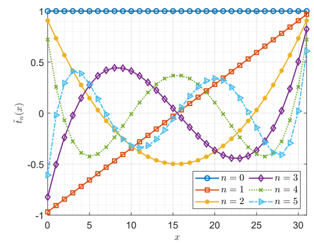


Figure 1. Scaled Chebychev polynomials of order l from 0 to 5 and size $L = 32$.

B. Feature Extraction Algorithm

This section explains the considered micro-Doppler hand-gesture signatures classification procedure, whose main steps are graphically illustrated in the block-scheme of Fig. 2.

This approach uses the same line of reasoning of that proposed in [4], with some modifications as well as with using the Chebychev moments introduced in subsection II-A in place of pseudo-Zernike moments used in [4], [13]. Therefore, the overall procedure starts with the recording of the mmW radar returns associated with one of the gestures of the human hand. The acquired signal, say $s(n)$, is constituted of N samples containing the micro-Doppler components related to the gesture under observation. Then, after some useful signal processing operations that could be used to improve the acquired signal (e.g., filtering operations), its short-time Fourier transform (STFT) is evaluated, that is

$$\text{STFT}(\nu, k) = \sum_{n=0}^{N-1} \tilde{s}(n) w^*(n-k) e^{-j2\pi\nu n/N}, \quad k = 0, \ldots, K-1, \quad (11)$$

with $w(\cdot)$ indicating the so-called smoothing window function used to properly select the signal atoms, $(\cdot)^*$ representing the conjugate operation, and $\nu \in [-1/2, 1/2]$ the normalized frequency.

The subsequent operation in the proposed signal processing pipeline is the evaluation of the CVD, developed in [14], [15] to improve the extraction of micro-Doppler features. This second transformation performs the discrete Fourier transform (DFT) of the STFT for each Doppler frequency. By doing so, it gives a perception of the repetition cycle of each velocity that is indicated as cadence frequency [15]. For completeness its mathematical formulation is herein reported

$$\Delta(\nu, \varepsilon) = \sum_{k=0}^{K-1} \chi(\nu, k) e^{-j2\pi k\varepsilon/K}, \quad (12)$$

where ε indicates the cadence frequency.

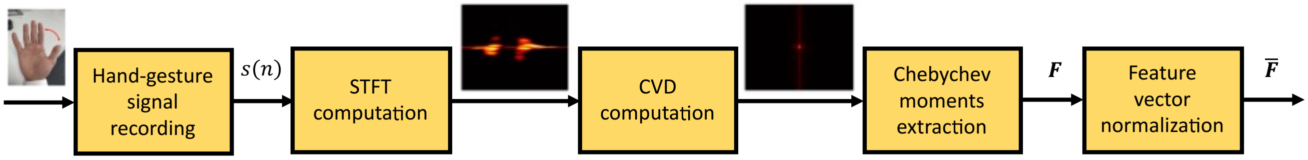


Figure 2. Block scheme of the proposed micro-Doppler hand-gesture signatures classification algorithm.

Before applying the next step of the algorithm, the modulus of the CVD is extracted since it is by definition a complex-valued quantity. Then, the modulus of the CVD is projected onto the orthogonal basis constituted by the Chebychev polynomials. Note that, since the polynomials only depend on the chosen order and on the CVD size (see their expression in (8)), they can be computed off-line improving the real-time usage capabilities of this classification algorithm. Now, applying (10) to $\Delta(\nu, \varepsilon)$, the pseudo-Zernike expansion is obtained as

$$T_{l,h} = \frac{1}{\tilde{\rho}(l,L)\tilde{\rho}(h,H)} \sum_{x=0}^{N_{\mathrm{DFT}}-1} \sum_{y=0}^{N_{\mathrm{CVD}}-1} \tilde{t}_l(x)\tilde{t}_h(y)\Delta(y,x), \tag{13}$$

having indicated with N_{DFT} and N_{CVD} the number of frequency bins used in evaluating the DFT and CVD, respectively. At this point the feature vector is constructed lining-up the quoted moments, namely

$$\boldsymbol{F} = [T_{0,0}, T_{0,1}, \ldots, T_{l,h}] \,. \tag{14}$$

Before populating the classification database, the feature vector $\boldsymbol{F}$ is normalized through a linear scaling operation to avoid bias effects at the classification stage, that is $\bar{\boldsymbol{F}} = (\boldsymbol{F} - \mu_{\boldsymbol{F}}) / \sigma_{\boldsymbol{F}}$, with $\mu_{\boldsymbol{F}}$ and $\sigma_{\boldsymbol{F}}$ the mean and standard deviation of $\boldsymbol{F}$. Therefore, the procedure concludes with the classification step. In what follows, the focus will be on the application of the simple k-Nearest Neighbour (k-NN) classifier in order to easily appreciate the effectiveness of this algorithm with reference to also other feature-based approaches.

III. Performance Assessment

The aim of this section is to demonstrate the effectiveness of the proposed procedure based on the exploitation of the Chebychev moments to recognize different gestures from human hands characterized by different micro-Doppler signatures. To this end, the conducted tests to assess the performance of our classification procedure have been focused on a wide real-recorded dataset of hand-gesture signals acquired by both FMCW and CW radars, referred as DopNet[1] [2]. The short-range radar used in this acquisition campaign was an Ancortek 24 GHz FMCW radar transmitting a chirp. More precisely, the radar has a 12 bits ADC and transmits at a carrier frequency of 24 GHz, with a 750 MHz bandwidth, and a power of $+13$ dBm. The specific dataset comprises 4 separate classes that refer to the following hand-gestures: wave, pinch, swipe, and click. The data provided in this database have been pre-processed and filtered to improve the desired micro-Doppler components and processed to produce the time-Doppler map.

Figure 3 reports, as an example, the modulus of STFT of one instance for each of the four gestures of the DopNet dataset, with the subplots referring to as a) wave, b) pinch, c) click, and d) swipe.

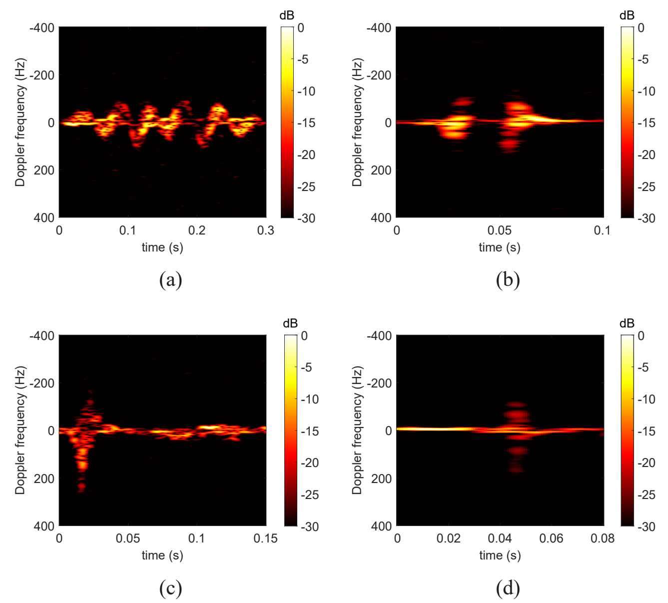


Figure 3. Modulus (expressed in dB) of the STFT of the hand-gestures from the dataset DopNet [2]. Subplots refer to the gesture a) wave, b) pinch, c) swipe, and d) click.

To evaluate the effectiveness of the classification procedure proposed in Section II, the considered figure of merit is the probability of correct classification, say P_{cc}, that is given by the number of correct classified signals divided by the total number of available instances. In particular, the experiments have been realized utilizing the 70% of the available data to train the classifier, and then the other 30% has been used during the test phase to evaluate the P_{cc}. Nevertheless, to avoid biased results due to the specific choice of the training and test set, the above-mentioned P_{cc} has been evaluated as the mean value over 100 independent Monte Carlo runs, referred to as $\bar{P}_{cc}$, namely a random selection of the train and test set has been performed at each trial. By doing so, a complete statistical characterization of the entire classification

[1]Further details about the DopNet dataset and instructions on how to download it are available at https://digital-library.theiet.org/content/journals/10.1049/el.2020.1358

algorithm is obtained. Figure 4 shows the curves of $\bar{P}_{cc}$ for the considered method (indicated as Chebychev) as a function of the moments order also in comparison with the same algorithm using pseudo-Zernike and Krawtchouk moments as well as the method of [16] using Doppler, Time and Range (DTR) based features. As to the classifier, we have set the parameter k equal to 7.

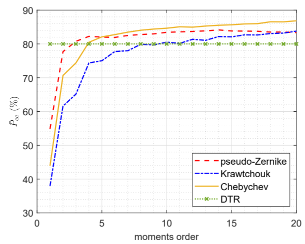


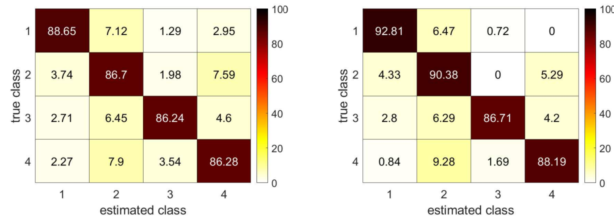
Figure 4. $\bar{P}_{cc}$ versus moments order obtained using a k-NN with $k = 7$.

The curves show that all methods based on moments extraction increase their performances as the order increases. Moreover, Chebychev moments show the best results (it reaches 88.65% for order 20) for this specific application overcoming pseudo-Zernike and Krawtchouk and the DTR method. Furthermore, they offer implementation advantages thanks to the fact that they are directly defined on a discrete set and so easy to compute as well as for the possible exploitation of the symmetry property of the associated polynomials.

To corroborate further the results analyzed in terms of $\bar{P}_{cc}$, in subplot (a) of Figure 5, the average confusion matrix of the devised classification procedure for the four classes of human hand-gestures is shown. Differently form the $\bar{P}_{cc}$ that is a synthetic metric of performance, the confusion matrix allows understanding of the classification accuracy obtained for each specific class and with which of them the algorithm tends mainly to confuse itself. Interestingly, the probability of correct classification is approximately the same for each class, viz. they ranges from the 86.24% of the wave to the 88.65% of the swipe. Additionally, subplots (b) of Figure 5 depicts the confusion matrix of the designed algorithm associated with the maximum P_{cc} obtained over the 100 Monte Carlo tests herein performed. Evidently, there is a performance growth with respect to the average value, with the wave and pinch gestures overcoming the 90% of correct classification. Finally, it is interesting to note that in the latter case, the wave is never classified as click and the pinch is never confused with the swipe.

IV. Conclusion

In this paper, an automatic algorithm for human hand-gestures classification has been developed exploiting the micro-Doppler radar signatures of the measured signals. In particular, the core of the procedure is the extraction of the Chebychev moments from the CVD derived by the STFT of each recorded signal. The quoted choice has been made in order to properly exploit the fact that they are defined on a discrete set and hence implemented without approximation. Moreover, their symmetry property allows to reduce both the computational burden and the required memory to save them. Several tests conducted on the DopNet dataset have demonstrated the effectiveness of the approach in correctly classifying the different gestures.



(a) (b)

Figure 5. Confusion matrix (expressed in percentage) for the four classes of hand-gestures of the DopNet dataset. Subplots refer to the a) average, b) best case.

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References

[1] J. Lien, N. Gillian, M. E. Karagozler, P. Amihood, C. Schwesig, E. Olson, H. Raja, and I. Poupyrev, “Soli: Ubiquitous Gesture Sensing with Millimeter Wave Radar,” *ACM Transactions on Graphics (TOG)*, vol. 35, no. 4, pp. 1–19, 2016.

[2] M. Ritchie, R. Capraru, and F. Fioranelli, “Dop-NET: a Micro-Doppler Radar Data Challenge,” *Electronics Letters*, vol. 56, no. 11, pp. 568–570, 2020.

[3] V. C. Chen, F. Li, S. S. Ho, and H. Wechsler, “Micro-Doppler Effect in Radar: Phenomenon, Model, and Simulation Study,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 42, no. 1, pp. 2–21, January 2006.

[4] C. Clemente, L. Pallotta, A. De Maio, J. J. Soraghan, and A. Farina, “A Novel Algorithm for Radar Classification based on Doppler Characteristics Exploiting Orthogonal pseudo-Zernike Polynomials,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 51, no. 1, pp. 417–430, 2015.

[5] A. Aßmann, A. Izzo, and C. Clemente, “Efficient Micro-Doppler Based Pedestrian Activity Classification for ADAS Systems Using Krawtchouk Moments,” in *11th IMA International Conference on Mathematics in Signal Processing*, 2016.

[6] F. Fioranelli, M. Ritchie, and H. Griffiths, “Multistatic Human Micro-Doppler Classification of Armed/Unarmed Personnel,” *IET Radar, Sonar & Navigation*, vol. 9, no. 7, pp. 857–865, 2015.

[7] L. Pallotta, C. Clemente, A. Raddi, and G. Giunta, “A Feature-Based Approach for Loaded/Unloaded Drones Classification Exploiting micro-Doppler Signatures,” in *2020 IEEE Radar Conference (RadarConf20)*. IEEE, 2020, pp. 1–6.

[8] R. Mukundan, S. H. Ong, and P. A. Lee, “Image Analysis by Tchebichef Moments,” *IEEE Transactions on Image Processing*, vol. 10, no. 9, pp. 1357–1364, 2001.

[9] S. Padam Priyal and Prabin K. Bora, “A Study on Static Hand Gesture Recognition using Moments,” in *2010 International Conference on Signal Processing and Communications (SPCOM)*. IEEE, 2010, pp. 1–5.

[10] A. B. Bhatia and E. Wolf, “On the Circle Polynomials of Zernike and Related Orthogonal Sets,” in *Mathematical Proceedings of the Cambridge Philosophical Society*. Cambridge University Press, 1954, vol. 50, pp. 40–48.

[11] M.-K. Hu, “Visual Pattern Recognition by Moment Invariants,” *IRE transactions on information theory*, vol. 8, no. 2, pp. 179–187, 1962.

[12] R. Diaz and E. Pariguan, "On Hypergeometric Functions and Pochhammer k-Symbol," *arXiv preprint math/0405596*, 2004.

[13] L. Pallotta, C. Clemente, A. De Maio, J. J. Soraghan, and A. Farina, "Pseudo-Zernike Moments based Radar micro-Doppler Classification," in *2014 IEEE Radar Conference*, 2014, pp. 0850–0854.

[14] A. Ghaleb, L. Vignaud, and J. M. Nicolas, "Micro-Doppler Analysis of Wheels and Pedestrians in ISAR Imaging," *IET Signal Processing*, vol. 2, no. 3, pp. 301–311, 2008.

[15] S. Björklund, T. Johansson, and H. Petersson, "Evaluation of a micro-Doppler Classification Method on mm-Wave Data," in *2012 IEEE Radar Conference*. IEEE, 2012, pp. 0934–0939.

[16] M. Ritchie and A. M Jones, "Micro-Doppler Gesture Recognition using Doppler, Time and Range Based Features," in *2019 IEEE Radar Conference (RadarConf)*. IEEE, 2019, pp. 1–6.