RADAR Emitter Classification with Optimal Transport Distances

Manon MOTTIER
Université Paris-Saclay, CNRS, CentraleSupélec
Laboratoire des signaux et systèmes
91190, Gif-sur-Yvette, France
manon.mottier@centralesupelec.fr

Gilles CHARDON
Université Paris-Saclay, CNRS, CentraleSupélec
Laboratoire des signaux et systèmes
91190, Gif-sur-Yvette, France
gilles.chardon@centralesupelec.fr

Frédéric PASCAL
Université Paris-Saclay, CNRS, CentraleSupélec
Laboratoire des signaux et systèmes
91190, Gif-sur-Yvette, France
frederic.pascal@centralesupelec.fr

RADAR emitter classification aims at identifying the RADAR emitters present in a measured signal to gain electronic intelligence in a given environment. Recent advances in RADAR technologies make this task more difficult, as RADAR emitters exhibit more complex behaviors: agility in frequency and pulse repetition intervals, complex scanning patterns, etc. In this work, we assume that RADAR pulses have been deinterleaved, that is, the analyzed pulses are assumed to be emitted from a single emitter. Several methods exist to solve this problem, based on the analysis of the pulse repetition intervals [1], [2], deep learning [3], or hierarchical clustering with optimal transport distances [4]. Several supervised classification methods have been proposed to deal with more complex cases. Most of the methods are based on Deep Learning models and consider a small number of RADAR classes [5]–[9]. Algorithms and methodologies are often developed using small datasets or simulated data. Most of the previous methods are based on simulated data, and their result performance strongly relies on the simulator's accuracy. Technological developments have modified the recognition process. The profiles of transmitters have become more and more complex, enhancing the existing panorama of transmitters of new types with more varied patterns. New methods have been developed in order to compare the group characteristics to a known database, also allowing to detect new transmitters [10], [11].

METHODOLOGY

We introduce a classification method based on an optimal transport distance between collected RADAR pulses and RADAR emitter models from a reference database containing more than 60 classes.

A. Data Description

Data are collected by a receiver, listening on a large bandwith. Pulses are then segmented, analyzed, and described by four features: Frequency (f_n), Pulse width (w_n), Level (g_n), Time of Arrival (t_n). Fig. 1 shows a simulated signal gathering the pulses of five different emitters. In the top plot, the pulse level is plotted as a function of time, showing that several RADAR emitters can be active simultaneously. In the bottom plot, pulses are plotted based on their estimated frequency and pulse width. One can clearly see that a given emitter may emit on different frequencies (e.g., six frequencies for emitter 1). Estimated pulse widths are truncated for low-energy pulses, mainly when the receiver is in a side-lobe of the emitter. Real data are challenging to acquire, so that the method will be validated on simulated data. Here, we assume that the RADAR pulses have been correctly separated.

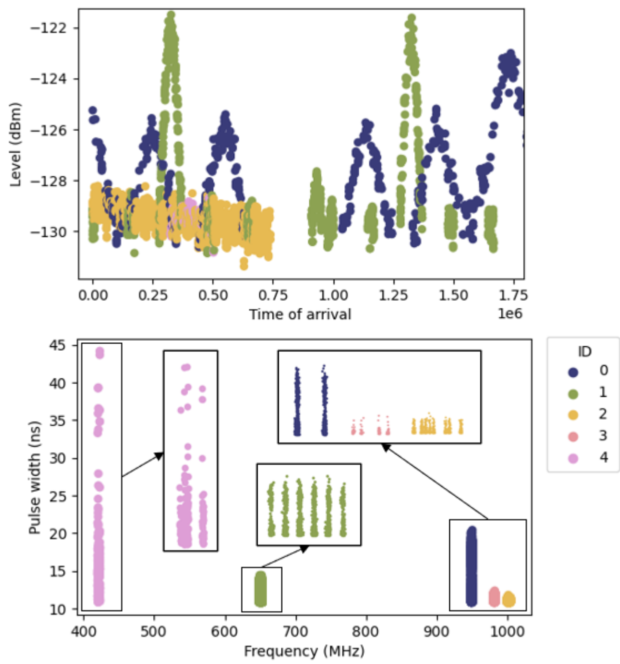

Fig. 1. Set of pulses contained five transmitters. Each color represents an emitter.

B. Algorithm

The proposed methodology is based on the development of a distance between a set of received RADAR pulses and a description of the characteristics of a RADAR emitter from a reference database. Classification is made by identifying the closest (in terms of distribution distance) RADAR emitters to the received data. Optimal transport makes it possible to find a mapping between an original mass distribution and a different target distribution [12], [13]. In this work, we focus on the part of this theory dealing with discrete probability distributions, useful for describing received data and different classes of typical RADARs.

In particular, we consider two discrete probability distributions $\nu = \sum_{n=1}^{N} a_n \delta_{x_n}$ and $\mu = \sum_{m=1}^{M} b_m \delta_{y_m}$, with $\mathbf{a} = (a_1, \dots a_N) \in \mathbf{R}_+^N$, $\sum_{n=1}^{N} a_n = 1$, and $\mathbf{b} = (b_1, \dots b_M) \in \mathbf{R}_+^M$, $\sum_{m=1}^{M} b_m = 1$. A transport plan $\mathbf{P}$ between ν and μ is defined by its coefficients P_{nm}, representing the amount of mass taken from x_n to y_m. With $c(\cdot,\cdot)$ a cost function, and $C_{nm} = c(x_n, y_m)$ the cost of transporting a unit of mass from x_n to y_n, the total cost $C(\mathbf{P})$ of a transport plan is

$$C(\mathbf{P}) = \sum_{n=1}^{N} \sum_{m=1}^{M} C_{nm} P_{nm} \quad (1)$$

The consistency of the transport plan $\mathbf{P}$ with ν and μ is guaranteed by $\mathbf{P}\mathbf{1}_M = \mathbf{a}, \mathbf{P}^T\mathbf{1}_N = \mathbf{b}^T$. The optimal transport plan $\mathbf{P}^\star$ is defined as the minimizer of Eq. (1) under the following constraints:

$$\mathbf{P}^\star = \underset{\mathbf{P}\in\mathbf{R}_+^{N\times M}}{\text{argmin}}\ C(\mathbf{P}) \text{ subject to } \mathbf{P}\mathbf{1}_M = \mathbf{a}, \mathbf{P}^T\mathbf{1}_N = \mathbf{b}^T \quad (2)$$

A set of pulses class is then assigned by identifying the closest RADAR class in the optimal transport distance sense.

C. Results

Fig. 2 shows the result of our classification methodology applied to emitter 1 from Fig. 1. The plot on the left overlays the pulses and the three closest emitter classes. The blue dots fit very well with those on the data. The classifier correctly identifies the emitter present in the data. The plot on the right shows us the transport plan between the distribution of the data and each outputs [14]. Output 2 represents a single-frequency transmitter, so the data points are all sent to the same location. Output 3 represents a RADAR that transmits on six different frequency bands, so the data points are sent on the different Output 1 respecting the proportions of Output 1; this is why pulses around a given frequency are not all sent to the same point.

The results obtained on the simulated data are very encouraging and allow us to identify the class of transmitters confidently. Moreover, the methodology can handle a large number of classes to identify. In order to improve the classification results, several perspectives are of interest: First, one could add a third dimension in the optimal transport theory to better discriminate RADARs. Finally, to propose a complete classification method, this method should be capable of detecting emitters that not present in the database.

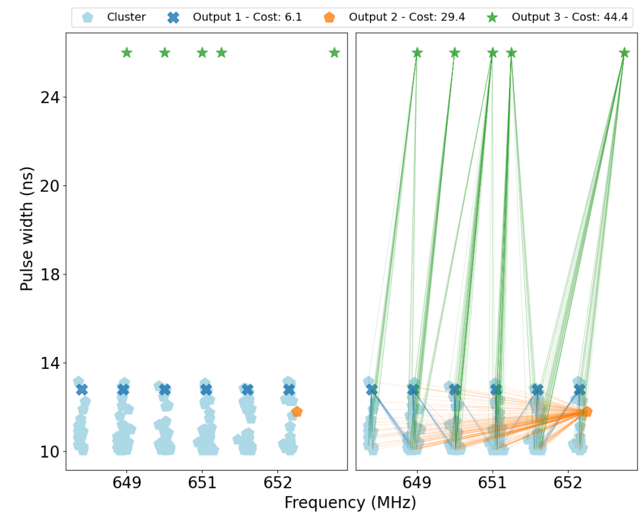

Fig. 2. Classification output for set of pulses 1 in two dimensions. The plot on the left overlap the set of pulses 1 with the first three classes identified by the algorithm. The plot on the right represents the transport plan between the da and those of the algorithm's outputs.

REFERENCES

[1] H. Mardia, "New techniques for the deinterleaving of repetitive sequences," in *IEE Proceedings F (Radar and Signal Processing)*, vol. 136, no. 4. IET, 1989, pp. 149–154.

[2] D. Milojević and B. Popović, "Improved algorithm for the deinterleaving of radar pulses," in *IEE Proceedings F (Radar and Signal Processing)*, vol. 139, no. 1. IET, 1992, pp. 98–104.

[3] X. Li, Z. Liu, and Z. Huang, "Deinterleaving of pulse streams with denoising autoencoders," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 56, no. 6, pp. 4767–4778, 2020.

[4] M. Mottier, G. Chardon, and F. Pascal, "Deinterleaving and clustering unknown radar pulses," in *2021 IEEE Radar Conference (RadarConf21)*. IEEE, 2021, pp. 1–6.

[5] J. Lunden and V. Koivunen, "Automatic radar waveform recognition," *IEEE Journal of Selected Topics in Signal Processing*, vol. 1, no. 1, pp. 124–136, 2007.

[6] Z.-M. Liu and S. Y. Philip, "Classification, denoising, and deinterleaving of pulse streams with recurrent neural networks," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 55, no. 4, pp. 1624–1639, 2018.

[7] Z. Geng, H. Yan, J. Zhang, and D. Zhu, "Deep-learning for radar: A survey," *IEEE Access*, vol. 9, pp. 141 800–141 818, 2021.

[8] L. Ding, S. Wang, F. Wang, and W. Zhang, "Specific emitter identification via convolutional neural networks," *IEEE Communications Letters*, vol. 22, no. 12, pp. 2591–2594, 2018.

[9] M. A. Nuhoglu, Y. K. Alp, and F. C. Akyon, "Deep learning for radar signal detection in electronic warfare systems," in *2020 IEEE Radar Conference (RadarConf20)*. IEEE, 2020, pp. 1–6.

[10] J. Liu, J. P. Lee, L. Li, Z.-Q. Luo, and K. M. Wong, "Online clustering algorithms for radar emitter classification," *IEEE transactions on pattern analysis and machine intelligence*, vol. 27, no. 8, pp. 1185–1196, 2005.

[11] S. Apfeld and A. Charlish, "Recognition of unknown radar emitters with machine learning," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 57, no. 6, pp. 4433–4447, 2021.

[12] C. Villani, *Optimal transport: old and new*. Springer, 2009, vol. 338.

[13] N. Bonneel, M. Van De Panne, S. Paris, and W. Heidrich, "Displacement interpolation using lagrangian mass transport," in *Proceedings of the 2011 SIGGRAPH Asia conference*, 2011, pp. 1–12.

[14] R. Flamary, N. Courty, A. Gramfort, M. Z. Alaya, A. Boisbunon, S. Chambon, L. Chapel, A. Corenflos, K. Fatras, N. Fournier, L. Gautheron, N. T. Gayraud, H. Janati, A. Rakotomamonjy, I. Redko, A. Rolet, A. Schutz, V. Seguy, D. J. Sutherland, R. Tavenard, A. Tong, and T. Vayer, "Pot: Python optimal transport," *Journal of Machine Learning Research*, vol. 22, no. 78, pp. 1–8, 2021. [Online]. Available: http://jmlr.org/papers/v22/20-451.html