Passive RADAR
Deinterleaving and Clustering unknown RADAR pulses

Manon Mottier, Gilles Chardon, and Frédéric Pascal

Université Paris-Saclay, CNRS, CentraleSupélec, Laboratoire des signaux et systèmes, 91190, Gif-sur-Yvette, France

Abstract. In order to deinterlace a radar signal, a two-step methodology has been developed, tested on simulated data and validated on real data. In a first step our methodology performs a two-dimensional clustering and then using these results, clusters are regrouped using a hierarchical agglomerative clustering combined with optimal transport distances.

Keywords: Electronic warfare, Passive RADAR, Clustering, Optimal transport

1 Introduction

The latest technological advances in recent years have led to the emergence of new innovations in the field of electronic warfare. The complexification and sophistication of electronic equipment has transformed the process of identifying RADAR signals. The identification process is constantly evolving due to artificial intelligence and new methods are constantly proposed for deinterlacing a RADAR signal. These methods must be able to adapt to increasingly complex and voluminous data. The modernisation of identification techniques represents a major challenge in electronic warfare and gives a considerable advantage to those actors capable of mastering them in front of their enemy.

2 Motivation

Historically, deinterleaving was first based on the direction of arrival and frequency to filter the data and then the time of arrival was used to identify patterns of pulse interval [1]. Many improved versions of this algorithm have been proposed, for example by using the sequential difference histogram [2] or the cumulative difference histogram [3]. New methods have been proposed to better account for the nature of the data (missing data and noise) [4]. More and more Deep Learning integrated models have been used to separate the pulses from the signals and identify the transmitters present. The main drawback of most of these methods is that they require a large number of parameters to be configured and are not easily reproducible. Model benchmarks have shown that the use of Deep Learning does not necessarily result in a better performing model than more conventional models such as GMMs[5]. Rencent works have combined a supervised and unsupervised methodology to deinterlace a signal [6]; Studies have shown the interest of applying supervised methods on labelled data and then using a hybrid classification built from several algorithms to obtain a more robust classification [7].

3 Methods

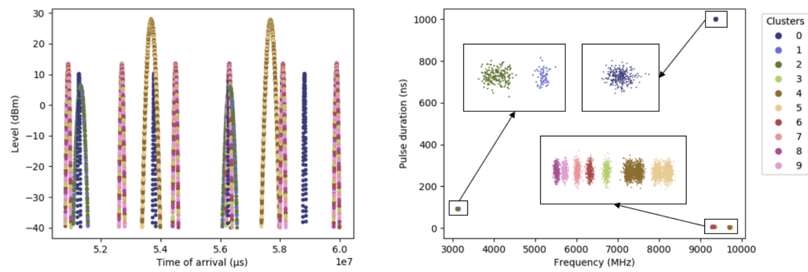
As a continuation of this work we have developed a new approach combining supervised and unsupervised methods. Considering the difficulty of accessing real labelled data, we used a data simulator. This simulator was built by several experts in the field of RADAR intelligence. We spent time on its development and were able to simulate a wide range of signals that could contain pulses from a maximum of 6 transmitters. We challenged several algorithms based on these simulated data which we then applied to real data. Each signal consists of RADAR pulses described by four features : time of arrival, frequency, pulse duration and level. For simulated data, we also have access to pulse labelling.

Clustering is applied in the Pulse Frequency-Pulse duration plane using the HDBSCAN algorithm. The algorithm is set up to overestimate the number of clusters to ensure that obtained clusters only include the pulses of a single RADAR. Underestimating this number would risk creating clusters with pulses from different RADARs. This parameterisation also makes it possible to capture RADARs emitting irregularly and/or having few pulses.

The resulting clusters are merged by using a hierarchical agglomerative clustering integrating the optimal transport distances. The algorithm calculates the distance between each cluster using the optimal transport and then merges the two clusters with the smallest distance. The operation is repeated until a single cluster is obtained. A dendogram is constructed to facilitate the representation and visualization of the results. We have built a decision model using several metrics to determine where to cut the dendogram and merge the clusters.

4 Results

The figure below represents a signal from simulated data. The graph on the left shows that the lobes of the level are overlapping and that some RADARs transmit at the same time. The right graph represents the pulses in the Frequency-Pulse duration plane that was used to perform the clustering. We can see that a single RADAR can be represented by several different clusters; for example a RADAR can transmit on several frequency bands thus creating several clusters during the clustering phase in the Frequency-Pulse duration plane. The colors represents the ten different clusters obtained with HDBSCAN. After applying agglomerative hierarchical clustering with optimal transport distances, we correctly identified the presence of four distinct transmitters.



5 Conclusion

A two-step methodology has been proposed to deinterlace a radar signal using only three parameters. It is capable of classifying the signal pulses into several clusters and then comparing the information from these clusters in order to aggregate them. This methodology provides very good results in most cases but is limited when RADAR have similar characteristics.

References

1. DR Wilkinson and AW Watson. Use of metric techniques in esm data processing. In *IEE Proceedings F (Communications, Radar and Signal Processing)*, pages 229–232. IET, 1985.
2. DJ Milojević and BM Popović. Improved algorithm for the deinterleaving of radar pulses. In *IEE Proceedings F (Radar and Signal Processing)*, pages 98–104. IET, 1992.
3. HK Mardia. New techniques for the deinterleaving of repetitive sequences. In *IEE Proceedings F (Radar and Signal Processing)*, pages 149–154. IET, 1989.
4. Zhiwen Zhou, Gaoming Huang, Haiyang Chen, and Jun Gao. Automatic radar waveform recognition based on deep convolutional denoising auto-encoders. *Circuits, Systems, and Signal Processing*, 37(9):4034–4048, 2018.
5. Xuhua Gong, Huadong Meng, and Xiqin Wang. A gmm-based algorithm for classification of radar emitters. In *2008 9th International Conference on Signal Processing*, pages 2434–2437. IEEE, 2008.
6. Xiaonan Zhang, Pengcheng Luo, and Xinwu Hu. A hybrid method for classification and identification of emitter signals. In *2017 4th International Conference on Systems and Informatics (ICSAI)*, pages 1060–1065. IEEE, 2017.
7. Guillaume Revillon, Ali Mohammad-Djafari, and Cyrille Enderli. Radar emitters classification and clustering with a scale mixture of normal distributions. *IET Radar, Sonar & Navigation*, 13(1):128–138, 2018.