# MID-TERM REPORT: ARTIFICIAL INTELLIGENCE FOR PASSIVE RADAR


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# 1 Introduction

## 1.1 Contextualisation

The technological evolution of the last few years has allowed many innovations in the electronic field and more particularly in the field of electronic warfare. Electronic equipment is becoming increasingly complex and sophisticated, leading to a transformation of the RADAR signal processing chain (improvement of receivers and emitters, spreading of emissions over the spectrum, waveform modification, autonomous weapon system etc). All these changes represent a continuous challenge to propose new and more accurate techniques to classify and identify emitters in a signal.

Over the next few years, the modernization of identification techniques will represent a major challenge for electronic warfare: they will give a considerable advantage to those actors capable of mastering them, enabling them to gain power and gain an advantage over the enemy. The amount of information to be processed increases exponentially with the input of a growing number of different sensors and by the improvement of their interception sensitivity. Only a complex decision system can highlight the essential information to build a strategic picture of the situation. Data processing in Radar includes all the algorithmic processes developed from the interception of a signal by a listening system. For military platforms, this data is a decisive source of information for battlefield surveillance and related activities (identification and state of engagement of enemy platforms, interpretation of the situation or evaluation of the threat for example).

## 1.2 The thesis

The thesis is financed by the CIFRE system. This is a collaboration between a research laboratory, “the Signals and System Laboratory of CentraleSupélec” in France, a company, AVANTIX (ATOS Group) and a student, myself.

ATOS is an international leader in the field of digital transformation and is established in more than 70 countries. The group offers its customers a wide range of consulting services as well as digital and secure solutions. Among its solutions, Atos attaches great importance to protecting, anticipating and preparing the future. It’ss a leading provider of defense and cyber security solutions. Among its subsidiaries, Avantix is a French company specialized in electronic warfare. Avantix designs critical high-tech systems to provide homeland protection and military forces, particularly in the Radar processing chain.


Avantix is based in the south of France in Aix-en Provence. I work full time at L2S but occasionally I travel within their offices. Weekly meetings are scheduled with my Avantix supervisors to discuss the progress of the work. Although the thesis is officially financed and supervised by a private company, the thesis is also unofficially supervised by the DGA. I organize twice a year meeting between the laboratory, Avantix and the participants working within the DGA in order to present them the progress of my work and my results.

[0]Direction Générale de l’Armement

### 1.3 The subject

Radars are now confronted with increasingly dense and even complex electromagnetic environments, leading to a transformation of the RADAR signal processing chain. RADARs are becoming more and more complex; new and more sophisticated models are appearing making identification very difficult compared to the last years. For example, several RADARs can have very similar characteristics (they can emit on the same frequency bands...) or now have agility characteristics on their primary parameters that make identification more complex (a RADAR can transmit on several different frequency bands). The aim of my works is to use and develop machine learning tools for passive RADAR intelligence specifically to improve RADAR deinterlacing. A passive RADAR is a detection device that does not emit electromagnetic waves, it is only a receiver that can detect, track, and identify another RADAR(s). RADAR signals deinterlacing includes techniques able of separating, characterizing, and identifying all transmitters present in the signal.

Early conventional deinterleaving work mainly used Direction-Of-Arrival, central Frequency and Time-Of-Arrival for deinterleaving[6] [7]. Recent research papers use deep learning methods[10]. All these new methods require the setting of a very large number of parameters and a large volume of data that is not easily available. More recent work has begun to use a mixture of supervised and unsupervised methods for signal identification based on GMM[8]. Comparisons have shown that deep learning models are not necessarily better than more conventional and simpler models.

As an extension of these works, my research present a new method to deinterleave a signal with HDBSCAN algorithm [2] and a hierarchical agglomerative clustering with Optimal Transport distances[3]. It describes an unsupervised methodology to separate the RADAR pulses present in a signal and classify them in order to determine the number of transmitters present. We combined supervised and unsupervised learning to build our method. The algorithms are developed in an unsupervised learning from simulated data. The method is validated on simulated labelled data.

# 2 Proposed Approach

The objective of this thesis is to propose a method for deinterlacing RADAR signals. RADAR signals deinterlacing includes techniques able of separating, characterizing, and identifying all transmitters present in the signal. Specifically, I receive signals containing the data from an unknown number of radars. My goal is to successfully separate and regroup all the data corresponding to each Radar together. Then I have to characterize all these groups from a Radar database to identify the type of the transmitter present or to update this database with the new detected Radars. This is called Radar deinterlacing. A two-step methodology is developed to deinterlace RADAR signals. We mainly worked from a data simulator to obtain a large diversity of signals representing typical RADARs. First, a clustering algorithm is used to separate the pulses in the F-PW (Frequency-Pulse Width) plane, then a phase of cluster agglomeration is performed using the cluster output of the previous step as a feature for a hierarchical agglomerative clustering combined with optimal transport distances.

## 2.1 The Data

Given the impossibility of obtaining real labeled data sets, we used simulated data to obtain a large diversity of signals representing typical RADARs. These simulated data come from a simulator built and certified by experts in the field. It allowed us to acquire a significant volume of labeled signals, a necessary condition to obtain empirical results. This simulator allowed us to have access to a large variety of signals from existing RADARs. They were simulated from a RADAR database containing the characteristics of 60 typical RADAR systems. Our database contains a lot of heterogeneous signals with various sizes (from 50 pulses to more than 10 000 pulses) and that may contain more than 10 transmitters. RADAR(s) emit continuous pulses and have their own characteristics. Among them we will retain four features: Frequency (F), Pulse Width (PW), Level (L) and Time of arrival (TOA). We have chosen only the most reliable features. We know that the Direction of Arrival (DOA) is a significant element in RADAR identification but this variable is not always well recorded or reliable. We have therefore excluded it from our analysis.

## 2.2 Methodology

### 2.2.1 Step 1: Clustering in the F-PW plane

In this section, we present the first step of the clustering process based on the HDBSCAN algorithm [2]. HDBSCAN is a hierarchical version of the so-called DBSCAN algorithm [5]. The main idea is to regroup points that live in a same dense area. HDBSCAN is an unsupervised algorithm that allows us to search for clusters of varying densities. HDBSCAN makes a spatial clustering: It constructs a distance matrix between points based on the density space with the Mutual Reachability Distance (this is a metric defined to compute a distance between points). The data is used to construct a weighted tree. From this tree a hierarchical clustering is built. Then, the clusters from the condensed tree are extracted. We apply clustering algorithm on two features: Frequency and pulse Width. We have deliberately chosen to use only 2 features to do the clustering because frequency and pulse width are 2 very significant features that allow to distinguish the RADARs. Moreover, adding other variables in the clustering creates a very large number of small clusters. The HDBSCAN algorithm has been set up to overestimate the number of clusters found, in fact underestimating the number of clusters could lead to group pulses from different emitters. For example, we could have some emitters with only few pulses or emitting very little over time.

### 2.2.2 Step 2: Cluster fusion

**Development of a hierarchical clustering algorithm using optimal transport distances:** RADAR systems that use several frequencies and/or pulse widths will not be described by a unique cluster in the F-PW plane. A final hierarchical clustering is used to agglomerate clusters belonging to a RADAR system[3]. This step assumes that clusters from a RADAR will be active at the same time periods, i.e. the time intervals where the RADAR is pointed towards the receiver. This is formalized using optimal transport distances, defined between probability measures.

In the case of two discrete probability measures $\nu = \sum_{n=1}^{N} a_n \delta_{x_n}$ and $\mu = \sum_{m=1}^{M} b_n \delta_{y_m}$ defined on a set $X$, with $\mathbf{a} = (a_1, \dots a_N) \in \mathbf{R}_+^N$, $\mathbf{b} = (b_1, \dots b_M) \in \mathbf{R}_+^M$, and $x_n, y_m \in X$, a transport plan from $\nu$ to $\mu$ is described by a $N \times M$ matrix $\mathbf{P}$, with coefficients $P_{nm}$ describing the quantity of mass taken from $x_n$ to $y_m$. Consistency with the weights $\mathbf{a}$ and $\mathbf{b}$ of the measures $\mu$ and $\nu$ is enforced by the linear conditions

$$\mathbf{P}\mathbf{1}_M = \mathbf{a}, \mathbf{P}^T\mathbf{1}_N = \mathbf{b}^T. \tag{1}$$

where $\mathbf{1}_M$ and $\mathbf{1}_N$ are vectors of ones with appropriate dimensions, and $\cdot^T$ denotes transposition. The total cost $C(\mathbf{P})$ of a transport plan is assumed to be linear, i.e.

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

The coefficients $C_{nm} = c(x_n, y_m)$ of the $N \times M$ cost matrix $\mathbf{C}$ model the cost of transporting a unit of mass from $x_n$ to $y_m$, for a given cost function $c(\cdot, \cdot)$. The optimal transport plan $\mathbf{P}^\star$ is the solution of the following linear optimization problem:

$$\mathbf{P}^\star = \underset{\mathbf{P} \in \mathbf{R}_+^{N \times M}}{\operatorname{argmin}} \ \langle \mathbf{C}, \mathbf{P} \rangle \ \text{ such that } \mathbf{P}\mathbf{1}_M = \mathbf{a}, \mathbf{P}^T\mathbf{1}_N = \mathbf{b}^T.$$

Optimal transport distance between two clusters is computed as follows: a probability measure

$$\mu_j = \frac{1}{N_j} \sum_{k \in C_j} \delta_{t_k}$$

is associated to a cluster $C_j$, and the unit transport cost between two times of arrival $\tau_1$ and $\tau_2$ is taken as

$$c(\tau_1, \tau_2) = |\tau_1 - \tau_2|\,.$$

The exact constraints (1) are often too strict when matching clusters. Indeed, it is frequent that all lobes from a particular RADAR pass do not contain the same proportions of pulses from each sub-cluster. In this case, mass has to be transported from a lobe to another, raising the cost of the optimal transport. The optimal transport problem can be relaxed by using approximate fit between the actual weights, and the weights used to compute the transport plan. This relaxation yields the following optimization problem

$$\mathbf{P}^\star = \underset{\mathbf{P} \in R_+^{N \times M}}{\operatorname{argmin}} \ \langle \mathbf{C}, \mathbf{P} \rangle + \lambda_1 D(\mathbf{P}\mathbf{1}_M, \mathbf{a}) + \lambda_2 D(\mathbf{P}\mathbf{1}_N, \mathbf{b})$$

where, as an example, $D$ can be the Kullback-Leibler distance between probability distributions. The parameters $\lambda_1$ and $\lambda_2$ control the fidelity of the transport plan to the actual weights.

Some signals are very large which makes the optimal transport very long and very expensive in memory. Cluster pulses were not used directly in the optimal transport, but histograms were built from the pulses to reduce computation time and make it numerically more stable. The size of the bins has been determined so as not to lose information on the distribution of impulses by clusters from a decision model. Not all clusters are used in the Optimal Transport; some clusters have too few impulses and could distort the groupings. They are therefore excluded from step 2 and added to the outlier class.

Clusters are fused in a hierarchical way, by iteratively agglomerate the clusters with smallest optimal transport distance. After fusion the distance between the fused clusters and the other clusters is updated. The process is halted when all the clusters are merged and there is only one cluster left. From these results the dendrogram is built and allows to visualize the groupings made. We used 3 unsupervised metrics to create a decision model to determine where to cut the dendrogram and specify the final grouping:

- Silhouette score [9]
- Davies-Bouldin score [4]

- Calinski-Harabasz Score [1]

In order to improve the clustering, it's possible in some cases that clusters are excluded from this step because they do not have enough pulses and/or would distort the groupings. In order to reduce the calculation time of some metrics, it was necessary to reduce the size of the data on which they are calculated. Some clusters containing a lot of pulses have been reduced.

When we work on simulated data, it is possible to evaluate the quality of the groupings made because we have access to the ground truth. We will refer to 3 existing criteria:

- Homogeneity: measures if all points from a given cluster belong to the same class.
- Completeness: measures if all points of a given class are grouped in a single cluster.
- Unclassified rate: measures the amount of data that is lost in the process (Clusters pulses classified as outliers in step 1 by HDBSCAN and excluded clusters in step 2 during optimal transport).

# 3 Application case

In this section, we present an application case using a signal from our data simulator. We apply the different steps of the proposed methodology. A signal representing the pulses from 4 different emitters has been selected.

Fig. 1 represents the data of this signal. The size of the signal is more 12300 pulses and have 4 main parameters. The recording of this signal takes more than 3 minutes, which is relatively long so the signal is not represented in its entirety in the figures. Note that a relatively clean and low noise signal was deliberately chosen.

- The first graph on the top left shows the F-TOA plane. The RADAR transmitting around 3GHz is easily identifiable in this plane because it is separated from the others. We note the presence of 3 other RADARs emitting around 9GHz. 2 RADARs emit on an almost identical frequency band.
- The graph at the top right shows the pulses in the PW-TOA plane. 2 RADARs emit continuously and regularly and are easily identifiable, but the 2 other transmitters have very close pulse widths
- The graph at the bottom left shows the pulses in the L-TOA plane. The lobes overlap in several places and that the emitters are not differentiable.
- The graph on the bottom right shows the pulses in the dTOA-TOA plane. The dTOA has been calculated as the TOA $t_n$ and $t_{n-1}$. We know that dTOA is widely used in RADAR identification; it has been calculated on the whole signal, but not used at this stage because it doesn't make sense: the dTOA is calculated between successive observations which don't necessarily belong to the same RADAR, especially when there are several active transmitters at the same time. For example, the L-TOA plane shows several overlapping of the lobes.

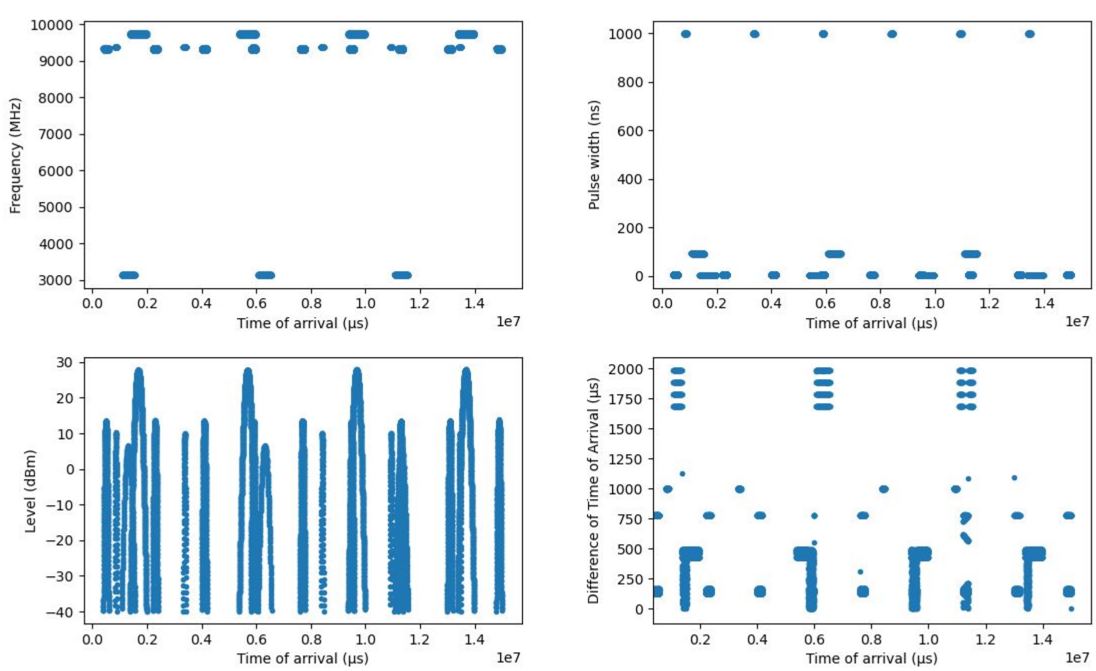


Figure 1: Unlabelled data

[0]Difference of Time of Arrival

## 3.1 Step 1: Clustering

The HDBSCAN algorithm was applied in the F-PW plan. Fig. 3 shows us the results of clustering. HDBSCAN identifies 10 clusters from this signal. Colors represent the 10 different clusters returned by the algorithm (Table 1). Clusters are distributed along the lobes in the L-TOA plane. Clusters have heterogeneous sizes, as some have less than 300 pulses while others have more than 2000 pulses. The clustering results are consistent and show that one transmitter is represented by several clusters. We can see on the plot in the L-TOA plane many overlapping lobes.

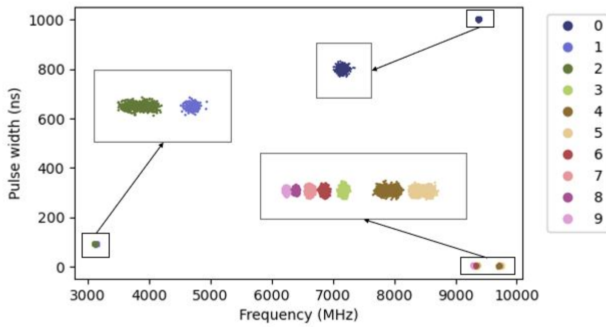


Figure 2: Clustering output zoom

| Cluster | Pulses | % |
|---|---|---|
| -1 | 254 | 2,1 |
| 0 | 623 | 5,1 |
| 1 | 204 | 1,7 |
| 2 | 607 | 4,9 |
| 3 | 1128 | 9,2 |
| 4 | 2612 | 21,2 |
| 5 | 2622 | 21,3 |
| 6 | 1131 | 9,2 |
| 7 | 1115 | 9,1 |
| 8 | 997 | 8,1 |
| 9 | 1012 | 8,2 |

Table 1: Cluster repartition

Fig.2 shows a zoom in the F-PW plane. The pulses are grouped together and form several distinct blocks. An emitter can be represented by several clusters as the pulse packets.

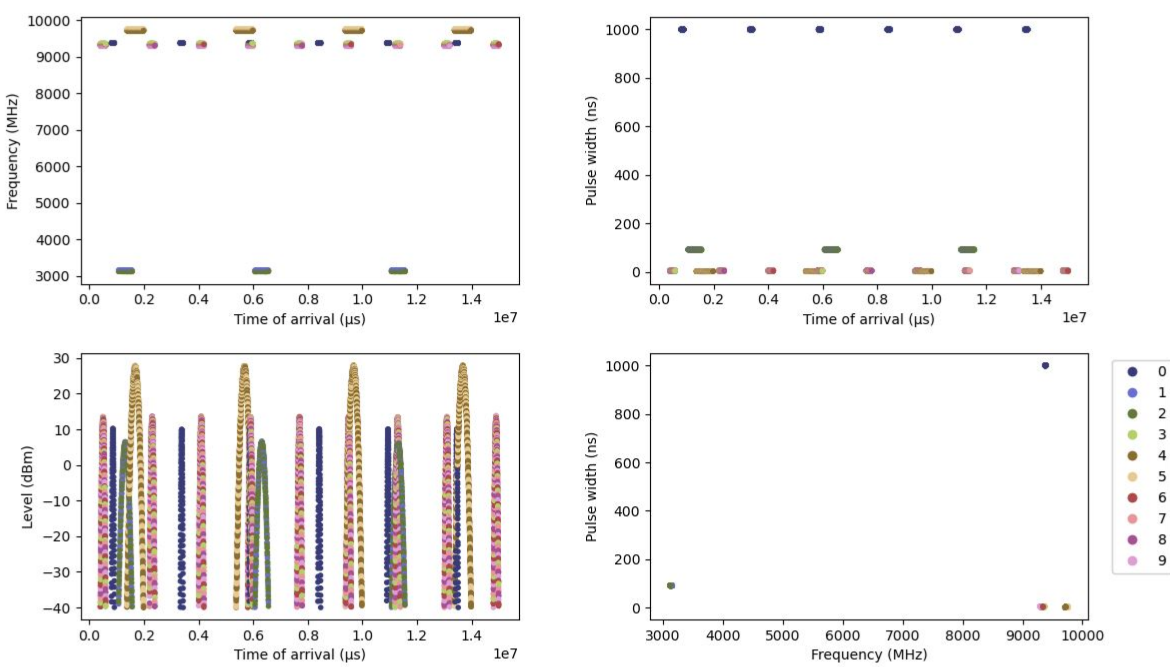


Figure 3: Clustering output

## 3.2 Step 2: Cluster fusion

From the HDBSCAN clusters, a hierarchical ascending clustering was built using the optimal transport distances. At each step, the optimal transport distance between each pair of clusters is computed. The pair of clusters with the smallest distance is merged into a single cluster. This step is repeated until the clusters are fully aggregated.

### 3.2.1 The histograms

Fig. 4 shows the TOA histograms of the previous clusters. The number of bins is determined from a decision model that allows us not to lose information about the data distribution. Here the threshold is set at 602. The cluster 1 and 2 are very similar, the clusters are active at the same time so they will be group together while the cluster 1 and 9 are not active at the same time. In the strategy of aggregation, to quantify this similarity and dissimilarity, we used an optimal transport distance which is defined as the cost to move the points from one place to another. For the clusters 1 and 9, there will be a lot of moving to change the points, so they have a high transport cost. For the clusters 1 and 2, this cost will be defined as the lowest.

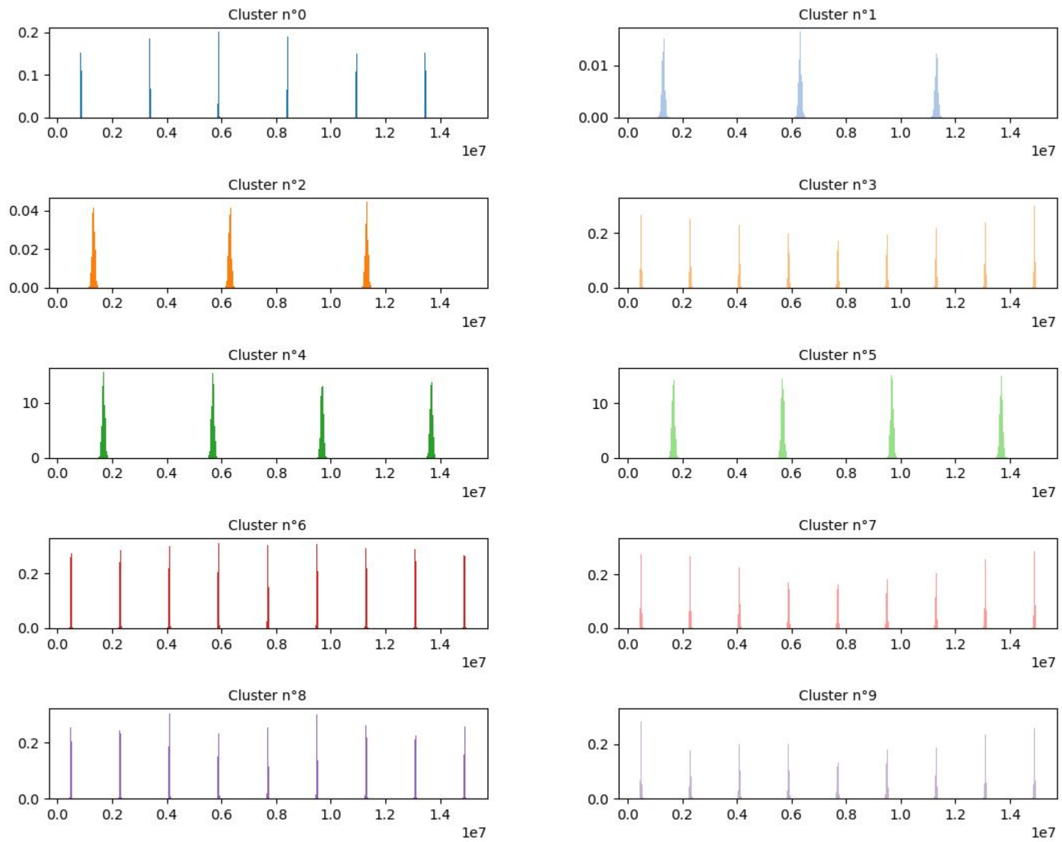


Figure 4: Histograms output

### 3.2.2 The Optimal Transport

In our case, all clusters were kept. The dendrogram presents in a simplified way the aggregations of clusters at each step. The dendrogram was cut using decision rules built from several metrics and from knowledge of the RADAR environment. The decisional system indicates that the dendrogram must be cut so that 4 clusters remain. The red line is used to identify clusters. To reduce the computation time of the metrics in the decision model, only clusters 4 and 5 have been reduced; all other clusters have been preserved.

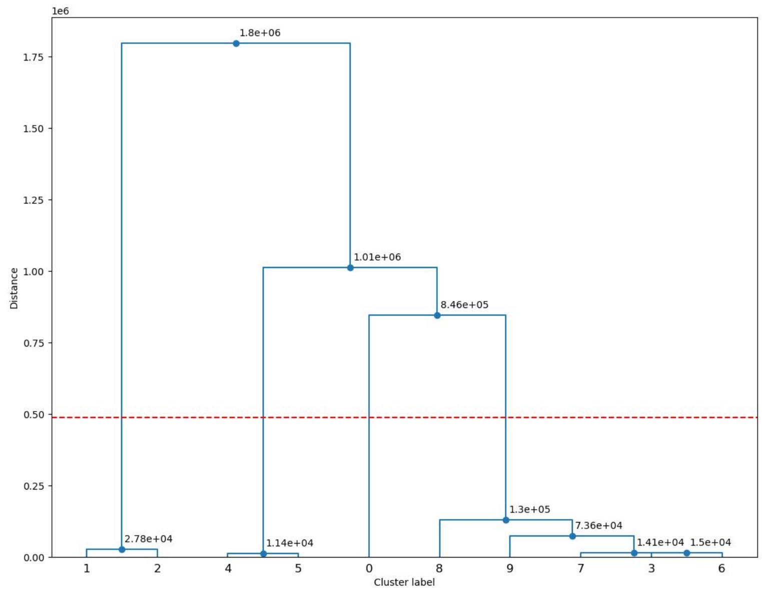


Figure 5: Dendrogram output

### 3.2.3 The final grouping

Finally, Fig. 6 shows the result of cluster agglomeration. Here the clustering has worked perfectly and correctly identifies the 4 transmitters present in the signal. In particular, the overlapping of lobes was perfectly reconstructed and the optimal transport enabled the clusters distributed over these lobes to be grouped together correctly. The graph in the dTOA-TOA plane shows the dTOA reconstructed from the pulses of each RADARs. We can see patterns and now it makes sense. It allows to check the quality of the cluster fusion and can be used as a new feature for classification. The values of homogeneity and completeness are equal to 1 which means that the pulses are correctly distributed in the different clusters and that there is no mixing. The unclassified rate indicates that only 2% of the pulses are lost during the process.

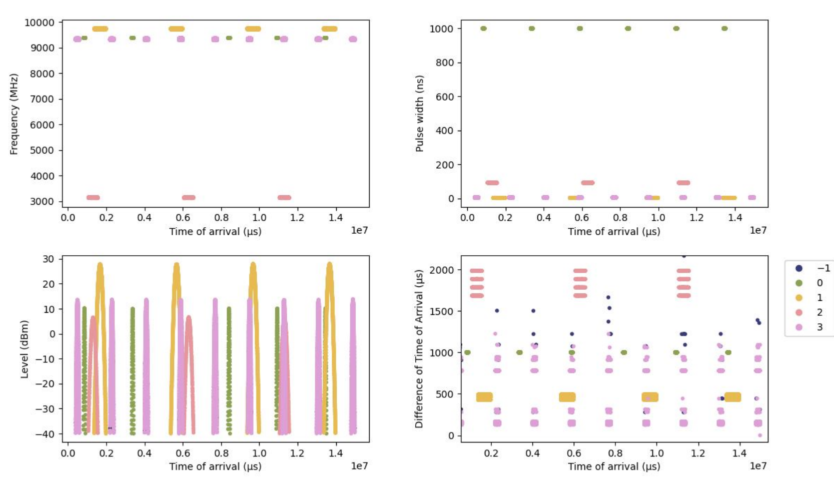


Figure 6: Final grouping

# 4 Conclusions and perspectives

## 4.1 Conclusion

To conclude, we proposed a methodology to deinterleave RADAR signals from its primary parameters. It is able to identify the number of transmitters present in the signal by deinterleaving the pulses. This method gave good results on moderately complex simulated data sets and encouraging results on real data.

This research has been presented at several events and has led to the publication of a Conference paper:

**Publication:**

- M. Mottier, G. Chardon and F. Pascal, "Deinterleaving and Clustering unknown RADAR pulses," 2021 IEEE Radar Conference (RadarConf21), 2021, pp.

**Presentations:**

| Name | Type | Website |
|---|---|---|
| IEEE RadarConf 2021 | International Congress, Atlanta, GA, USA | `https://ewh.ieee.org/conf/radar/2021/` |
| Junior Conference on Data Science and Engineering | Workshop | `https://jdse-paris.github.io/jDSE2021/#page-top` |
| Atos Scientific Community | Atos International Seminar | `https://atos.net/en/about-us/innovation-and-research/scientific-community` |

## 4.2 Perspectives

We have identified several objectives concerning the proposed approach:

- Improvement of the proposed approach:
  - For the moment, we assume that the clusters returned by HDBSCAN contain the observations of only one transmitter, but it's possible that RADARs can have the same characteristics and be confused in frequency and pulse duration. This is the case in harbors or airports where several similar models are used. We are working on improvements in the separation of similar RADAR(s) in Frequency and Pulse Width.
  - We know that some clusters do not contain enough pulses to be properly used in optimal transport. The next objectives are to investigate the use of optimal transport to tackle these challenging problems.
  - The decision model built from several metrics gives correct results on moderately complex signals. We noticed that the dendogram obtained by the optimal transport gave the right results for cluster fusion so we are also developing a new metric to improve our decision model to better cut the dendogram.
- Integration of new tools: We are currently exploring new tools to improve our methodology; for example to transform data or to process long signals using sliding windows.
- Start of the classification phase: We have started the classification phase of the RADAR signals. From the final clusters, the objective is to identify the RADARs present in the signals thanks to a reference database or to enrich the RADAR referential.

These new objectives will allow us to write a second research article to be published in a scientific journal.

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