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A new deinterleaving approach based on clustering and PRI type recognition

Kümeleme ve PRI tip tanımaya dayalı yeni bir ayrıştırma yaklaşımı

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A New Deinterleaving Approach Based On Clustering and PRI Type Recognition

Highlights

- *OPTICS clustering for deinterleaving of radar signals in frequency-pulse width plane*
- *Introducing a simulation datasets for PRI type recognition and DTOA-based PRI value(s) finding*
- *Rule-based PRI modulation recognition for detection of fixed, agile, stepped and dwell&switch PRI types*

Graphical Abstract

In this study, a new PRI Type detection method that employs clustering, histogram and rule-based alogirthms is presented.

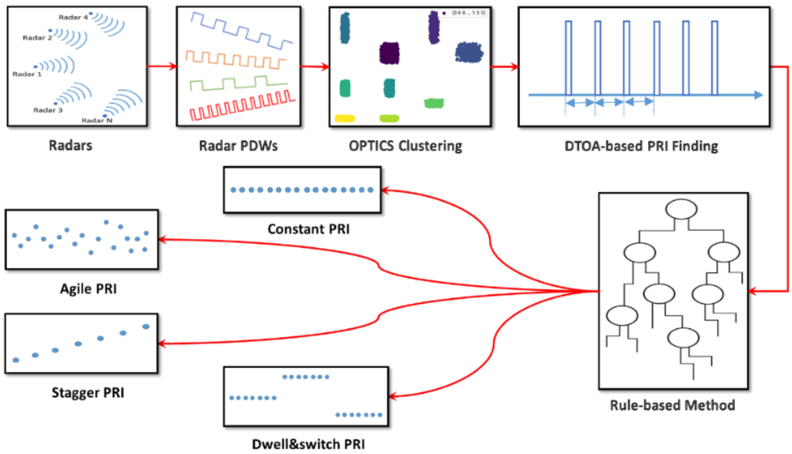

Figure. Graphical summary of the PRI modulation type recognition method

Aim

Deinterleaving of radar signals and PRI modulation type recognition

Design & Methodology

First, the PDWs of the radars are clustered in the frequency-pulse width plane using OPTICS, and then PRI modulation recognition is performed separately for each cluster.

Originality

A new rule-based approach is proposed for recognition of PRI modulation type. For the first time, OPTICS clustering algorithm was used for frequency-pulse width decomposition of radar signals.

Findings

Based on the experiments, the proposed method achieves the accuracy of 98% in agile, 97% in constant, and 89% in stagger, and dwell&switch PRI types.

Conclusion

The proposed method is able to deinterleave multiple radar signals in the environment according to their frequency, pulse width parameters, and recognize the PRI modulation of each of the clustered radars.

Etik Standartların Beyanı (*Declaration of Ethical Standards*)

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

A New Deinterleaving Approach Based On Clustering and PRI Type Recognition

Araştırma Makalesi / Research Article

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ABSTRACT

In an electronic warfare environment, numerous radars operate, each designed with distinct signal waveforms tailored to fulfill specific missions. The deinterleaving of radars is a fundamental function of an electronic warfare system. Following deinterleaving, identifying the Pulse Repetition Interval (PRI) modulation type becomes essential for enhanced radar recognition and understanding of its function. In this study, a new clustering and rule-based method is proposed to deinterleave radar pulses and recognize the PRI modulations. Ordering Points to Identify Clustering Structure (OPTICS) method is employed to cluster the radar signals. Difference of Time of Arrival (DTOA)-based method is employed to find the PRIs in the clustered data. A rule-based method is used to determine the PRI type from the obtained PRI values. In the experiments, the clustering and PRI type recognition phases were analyzed separately. The performance of K-means and OPTICS were tested under different conditions: (i) high cluster counts, (ii) close proximity of clusters, (iii) different cluster densities and forms. The PRI type detection performance was also tested on a simulation dataset consisting of 4 different PRI types (constant, agile, stagger and dwell&switch). The results indicate that the new method is effective in determining the PRI modulations.

Keywords: Deinterleaving, clustering, OPTICS, pulse repetition interval modulation, electronic warfare.

Kümeleme ve PRI Tip Tanımaya Dayalı Yeni Bir Ayrıştırma Yaklaşımı

ÖZ

Bir elektronik savaş ortamında, her biri belirli görevleri yerine getirmek için özel olarak tasarlanmış farklı sinyal dalga formlarına sahip çok sayıda radar çalışır. Radarların ayrıştırılması bir elektronik harp sisteminin temel ve önemli bir işlevidir. Ayrıştırma işleminin ardından Darbe Tekrarlama Aralığı (DTA) modülasyon tipinin belirlenmesi, radarın tanınması ve işlevinin anlaşılması için çok önemlidir. Bu çalışmada, radar darbelerini ayrıştırmak ve DTA modülasyonunu tanımak için yeni bir kümeleme ve kural tabanlı yöntem önerilmiştir. Radar sinyalini kümelemek için Kümeleme Yapısını Tanımlamak için Noktaları Sıralama (OPTICS) yöntemi uygulanmıştır. Kümelenmiş verilerdeki DTA'yı bulmak için darbelerin geliş zamanı farkı kullanılmıştır. Geliş zamanı farkı temelli yöntem sonucunda elde edilen DTA değerlerinden DTA tipini belirlemek için kural tabanlı bir yöntem kullanılmıştır. Deneylerde, kümeleme ve DTA tipi tanıma aşamaları ayrı ayrı analiz edilmiştir. K-means ve OPTICS'in performansları (i) yüksek küme sayıları, (ii) kümelerin yakınlığı, (iii) farklı küme yoğunlukları ve formları gibi farklı koşullar altında test edilmiştir. DTA tipi bulma performansı da 4 farklı DTA türünden (sabit, çevik, kademeli ve bekle&değiştir) oluşan bir simülasyon veri kümesi üzerinde test edilmiştir. Sonuçlar, yeni yöntemin bir radar sinyalinin PRI türlerini belirlemede etkili olduğunu göstermektedir.

Anahtar Kelimeler: Ayrıştırma, kümeleme, OPTICS, darbe tekrarlama aralığı modülasyonu, elektronik harp.

1. INTRODUCTION

Electronic Warfare (EW) systems primarily detect the existence and functioning of all radar systems in the environment and are named as Electronic Support (ES). There are many radars and each of them may have different and specific functions. The radar functions can be early warning, search, acquisition, track, and missile guidance [1]. EW systems detect radars and their functions that may pose a threat to them. After detecting the presence and function of the radar systems, EW systems may apply electronic attack using some parameters of the radars. Electronic attacks are used to protect critical platforms and people. When the EW system in a platform cannot properly apply electronic attack techniques, the platform is more visible to the target radar. So, deinterleaving of the radar systems in the environment has become a critical issue.

There are many imperfections to affect the received radar pulses such as missing pulses, clutter effects, and measurement errors. Additionally, the interleaving of many radar signals due to the dense environment increases the difficulty of the deinterleaving process. The input parameters for deinterleaving are Pulse Descriptor Words (PDWs). PDW mainly contains frequency, Pulse Duration/Width (PD/PW), Time Of Arrival (TOA), Pulse Amplitude (PA), and Angle Of Arrival (AOA). Deinterleaving process can be applied using all or some of these parameters. Also, deinterleaving can be applied in one step or more than one step. In some approaches,

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deinterleaving can be applied in two steps such as clustering and Pulse Repetition Interval (PRI) type recognition.

The PRI types basically used in literature are constant, agile, stagger, and dwell&switch. Radars commonly use the constant PRI type for search and track operations [2]. Agile PRI type is used for anti-reconnaissance and anti-jamming. Stagger PRI type is used to determine blind speeds in radars. The dwell&switch PRI type is employed to resolve range and velocity ambiguities. The mainly used frequency types are constant and agile. The agile frequency type is used by radars as protection when an electronic attack is applied to it.

Different methodologies have been carried out in the literature for deinterleaving and PRI type recognition. Kauppi et. al. suggested a set of features to recognize the PRI modulations which are constant, stagger, jittered, sliding, dwell&switch, and periodic [3]. A multi-layer neural network was applied to cluster the PRI modulations, after features are extracted. It is given that for each PRI modulation, over 99% perfect classification is reached. Han et al. applied simultaneously deinterleaving and PRI modulation recognition using multi-task learning with a Convolutional Neural Network (CNN) [4]. The Continuous Wavelet Transform (CWT) is used in the preprocessing stage to find PRI modulations with constant, jitter, sliding up, sliding down, and wobbulated PRI modulations. The method is compared with traditional CWT for different window sizes. It is stated that the method is better in the cases of deinterleaving precision versus spurious pulses rate up to 30% and missing pulses rate up to 30%. Also, the modulation recognition performance of the method for the spurious pulses up to 30%, missing pulses up to 30% is given. Cheng et al. performed deinterleaving of mixed radar signals only using the TOA parameter in four steps [5]. These steps are Correlation Matching Method (CMM), improved PRI transform, the sequence retrieval algorithm, and difference histogram method, sequentially. By applying these operations, constant, stagger, and jitter PRI modulations are estimated. Also, the proposed method is compared with Discrete Fourier Transform (DFT) and improved Sequential Difference (SDIF) histogram approaches. The mean PRI estimation errors according to missing pulse rate up to 15% and jitter bound rate of PRI up to 12% are analyzed. Mottier et al. performed the deinterleaving and clustering of radar signals using pulse amplitude, time of arrival, frequency, and pulse width parameters [6]. Clustering was done with the Hierarchical Density-Based Spatial Clustering (HDBSCAN) method using pulse width and frequency parameters. Then, hierarchical clustering with optimal transport distance applied for agglomerating clusters belonging to a radar system. It is not aimed to find the PRI modulations in used data. Only the results of the synthetic data they created are given. Hasani et al. used two sequential approaches which are PRI finding based on TOA and sequence search (pulse sorting) by using pulse width and frequency [7]. SDIF algorithm used for PRI finding. After the potential PRI values are found, they are categorized as jittered and non-jittered PRI. Two different sequence search techniques applied for these two categories. For the sequence searching part, the two operations classification by using carrier frequency and pulse width and assigning the suitable PRIs within the TOA values of the pulses were used, simultaneously. Constant, stagger, and jitter PRI types found by applying this approach. The performance of accurate pulse separation versus number of emitters up to 16 was given for both the proposed method and an only TOA based method. Kang et al. proposed the hierarchical automaton for pulse group recognition that has a two-layer structure [8]. The bottom layer actualized the recognition of pulse subgroups. At the top layer, the sequential input of pulse subgroups and recognition of pulse groups actualized. The aim of the proposed technique was pulse group signal waveforms of multi-function radars. The used PRI types in pulse groups are constant and stagger. The recognition accuracy was given for different pulse missing rates and interferential pulse rates. Based on the experiments, when missing pulse rate or interferential pulse rate was increasing, the recognition accuracy was also decreasing down to 80%.

Chao et al. applied semantic segmentation with neural networks for deinterleaving [9]. It has some advantages like no need for PRI value and modulation type. However, this method does not distinguish radars having same PRI modulations and radars having similar PRI values. As a continuation of the work, Chao et al. proposed a new method which is named Bidirectional Gated Recurrent Unit (BGRU) as multi parameter-based deinterleaving [10]. Unlike other studies, different types of PRI, RF, PW, and PA could be found by using BGRU. BGRU compared SDIF, PRI transform, and Semantic Segmentation Deinterleaving (SSD) with only PRI parameter methods, and it gave good results. The SSD-Multiparameter method gave better accuracy results under the conditions of pulse loss rate up to 50% and noise to target ratio up to 50%. These results obtained for four different data sets that have measurement errors. Xie et al. suggested a method that is first-order difference curve based on sorted TOA difference sequence (FDC-DTOA) [11]. For this approach, only the TOA parameter was used. It has been stated that this approach has good results for missing pulses cases up to 45% and PRI jitter modulation type that has jitter boud up to 16%. FDC-DTOA compared with classical and enhanced versions of Cumulative Difference of Histogram (CDIF), PRI transform, SDIF methods, and successful results obtained compared to them. Feng et al. applied the domain-adaptive few-shot learning and combined net method for PRI modulation types of constant, jitter, sliding, wobbulated, stagger, and dwell&switch [12]. It gives better results than CNN and Temporal Convolutional Network methods according to missing rate up to 60% and spurious rate up to 60%.

Cheng et al. presented a clustering-based Square Sine Wave Interpolation (SSWI) method and a threshold criterion for deinterleaving stagger and jitter PRI types [13]. SSWI, which used only the TOA parameter, compared with the Correlation Matching Method (CMM) and sequence correlation. As a result of the comparison, SSWI achieved the fastest execution time, gave better results with a loss rate of up to 15%, and jitter rates of up to 12% for different data sets. Mottier et al. proposed two different methods named as normal and improved hierarchical agglomerative clustering merged with optimal transport distances (HACOT-IHACOT) [14]. In HACOT, HDBSCAN is used for clustering by using pulse width and frequency parameters; while in the improved form of the method, HDBSCAN is used for frequency, pulse width and TOA parameters. As a last part of these two approaches, agglomeration is used for the clusters that have similar temporal characteristics, according to optimal transport distances. The aim of the methods was deinterleaving of complex emitters ignoring the PRI modulation. The IHACOT method is checked against with PRI histogram and PRI transform methods; and it is stated that it gives better results in most cases. Nuhoglu et al. produced a method Combined PRI Transform (CPRIT) which is a hybrid method based on the PRI transform technique [15]. Unlike approaches based on sequential processes such as first clustering and then finding PRI, CPRIT advocates performing these two operations simultaneously. It is mentioned that CPRIT gave good results at the point of correct detection rate and false alarm rate according to the SDIF and PRI transform. The CPRIT had also excellent performance for the deinterleaving of constant, stagger, jitter, pulse group constant, and pulse group jitter PRI types. Mao et al. used the Sep-RefineNet semantic segmentation network technique to deinterleave constant, jitter and stagger PRI modulations [16]. It is compared with SDIF, CDIF, and PRI transform. Based on the experiments, the Sep-RefineNet semantic segmentation network technique produces better F1-score results according to benchmarked techniques in the cases of missing pulse and aliasing pulse rates up to 20%.

In this study, a new method is presented based on a combination of clustering and rule-based PRI modulation recognition approaches. In clustering, the Ordering Points to Identify the Clustering Structure (OPTICS) algorithm is used. The DTOA based PRI detection is realized. Additionally, a new rule-based method is proposed to classify PRI types. According to the results of the proposed approach, 4 different PRI types are correctly recognized even if numerous emitters/radars exist at the same time.

The rest of the study is presented as follows. In Section 2, K-means and OPTICS clustering methods are presented as background knowledge. In Section 3, the introduced method with all steps is defined. In Section 4, datasets used in simulation are explained, experimental results and discussions are given. In Section 5, the concluding remarks and future aspects are specified.

2. BACKGROUND

2.1. K-means

K-means is an unsupervised and simple partitioning-based clustering method [17]. It partitions a group of data sets into K different clusters where K is a positive integer number [18]. K-means has a wide range of applications in image processing, pattern recognition, unsupervised learning of neural networks, artificial intelligence, machine vision, classification analysis, and many other fields [19].

K-means clustering allocates data points to one of the K clusters based on their distances from the cluster centers. Initially, it places the centroids of the clusters randomly in the space. Each data point is then mapped to the cluster whose centroid is closest to it. After assigning each point to a cluster, new centroids are calculated. This iterative process continues until a satisfactory set of clusters is found [20]. The clustering is accomplished by reducing the sum of squares of the distances between the data and the relevant cluster center. [20, 21].

The K-means clustering method works as follows:

1. Select K which is the cluster number
2. Select randomly K centroids or points
3. Appoint each data point to their nearest center to form K predefined clusters
4. Compute the variance and set a new center points of each cluster
5. Repeat step three to reappoint each data point to the new nearest centroid of each cluster.
6. If any reappointment occurs, back to step-4. If not, the process ends.

2.2. Ordering Points to Identify Clustering Structure (OPTICS)

OPTICS is a clustering algorithm to determine density-based clusters for spatial data [22]. OPTICS is also an enhanced version of Density-Based Spatial Clustering of Applications with Noise (DBSCAN). The flexible epsilon feature makes the OPTICS algorithm advanced for clusters in data of changing density. Let the point set be $M = \{m_1, m_2, \dots, m_j\}$. Some definitions related with the OPTICS clustering algorithm are defined as follows [23]:

1. **ϵ - domain:** For $m_j \epsilon M$, its ϵ - domain is a subset of M containing points whose distance from m_j is not greater than ϵ. That is, $N_\epsilon(m_j) = \{m_i \epsilon M \mid distance(m_i, m_j) \leq \epsilon\}$ The number of points in $N_\epsilon(m_j)$ is noted as $\mid N_\epsilon(m_j \mid$. Usually, *eps* is used to represent the clustering radius ϵ. If the maximum eps is too small, the algorithm may not correctly cluster all points that belong to the same cluster and it causes multiple small clusters instead of a single large cluster [22]. Conversely, if the maximum eps is too large, the algorithm may join different clusters as one cluster.

2. **Core point:** For any $m_j \in M$, m_j is a core point if $|N_\epsilon(m_j)| \geq min\_samples$, where $min\_samples$ is an integer constant.
3. **Core distance:** the minimum radius that makes a point m a core point is called the core distance of m.
4. **Reachability distance:** The reachability distance of a point p with respect to a core point m denoted as $rd(p, m)$ is the maximum value between the actual distance of m to p and the core distance of m. The reachability distance is not defined if p is not a core point.

The OPTICS algorithm is basically based on building a reachability graph [22]. It ranks the points in the dataset according to their reachability distances, then constructs the reachability graph. The ranking is done by starting from a random point and finding its nearest neighbor. Then, the algorithm determines the reachability distance between two points and adds the point with the highest reachability distance to the ranking list. The procedure is repeated for the next point in the list. The procedure stops when all points are ranked. After the points are sorted, the reachability distance graph is generated.

3. PROPOSED METHOD

The deinterleaving processes that use only the TOA parameter of the pulses have high complexity and they are generally time consuming approaches. To simplify the process and gain more reliable results, the deinterleaving operation is performed in three main steps. These are clustering, PRI finding, and PRI modulation detection.

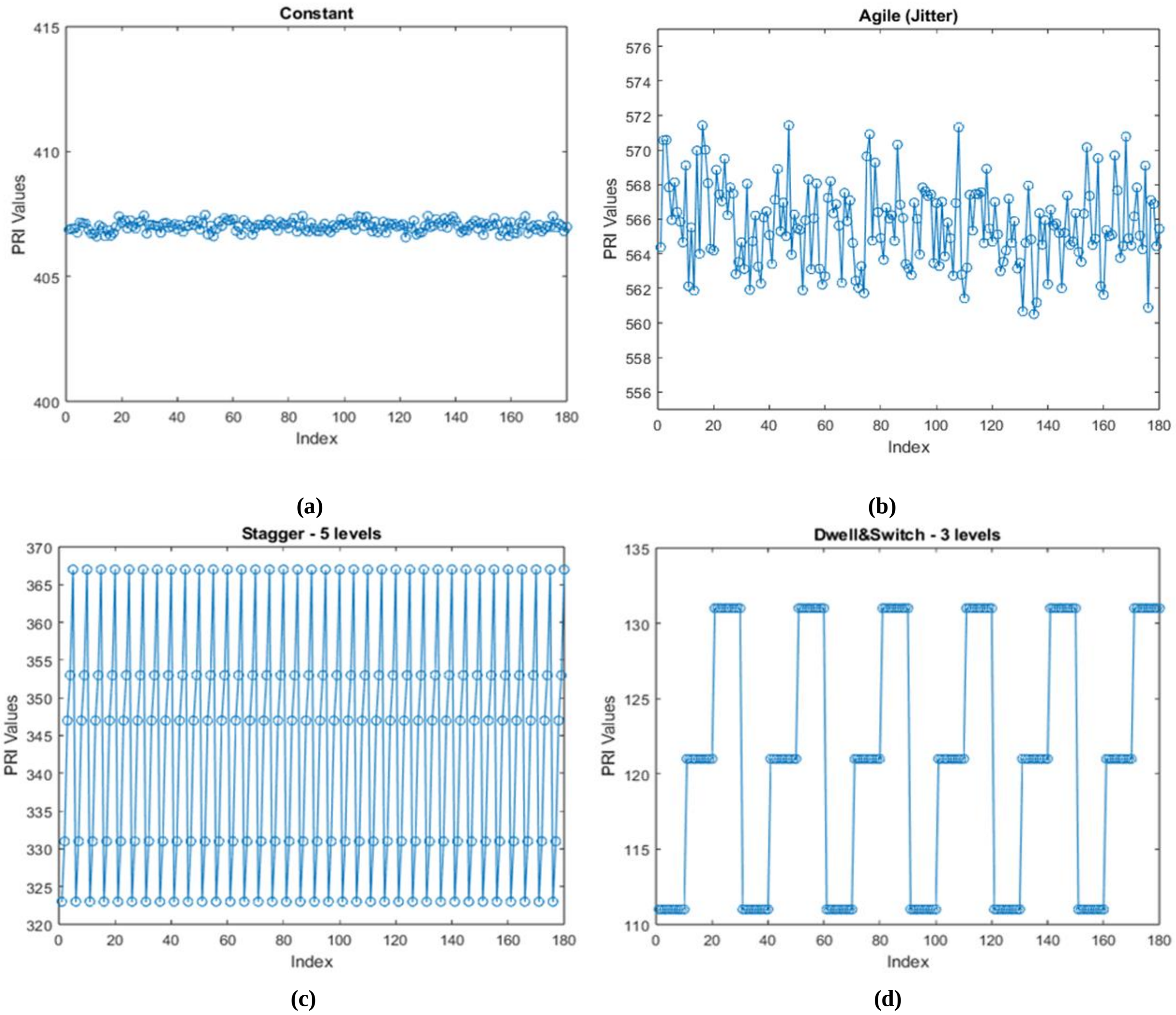

Figure 1. Different PRI types (a) Constant (b) Agile (Jitter) (c) Stagger (d) Dwell&switch

Various data types for deinterleaving process are generated. Firstly, the single emitter PDWs are generated according to parameter types and values. The generated frequency types are fixed and agile; PRI types are fixed, agile (jitter), stagger, and dwell&switch; pulse width types are fixed and agile. For fixed types of all these PDW parameters there is also a small agility. Then, the single emitters are combined and sorted in time. The types of PRI used and produced are visualized in Figure 1. The difference between constant and jitter PRIs is the jitter amount. For constant PRI type, the jitter amount is smaller or nearly zero compared to the jitter PRI type. In Figure 1(a), the constant PRI has the mean value of 407 and the jitter value is +/- 1 µs. In Figure 1(b), the agile (Jitter) PRI has the mean value of 566 and the agility value is +/- 6 µs. Stagger PRI has three properties which are PRI levels, level number, and sequence. Level number is the number of unique PRI values of stagger PRI type. Sequence is the order of the stagger levels, and it is also called Pulse Group Repetition Interval (PGRI). In Figure 1(c), stagger levels are [323(A), 331(B), 347(C), 353(D), 367(E)], level number is 5, and sequence is ABCDE (or 323-331-347-353-367). The dwell&switch PRI type has four properties which are PRI levels, level numbers, sequence, and dwell count (or dwell time). The only difference between stagger and dwell&switch PRIs is dwell count. The dwell count (or dwell time) is the repetition number (or duration) of the one PRI level. In Figure 1(d), PRI levels are [111(A), 121(B), 131(C)], level number is 3, sequence is ABC (or 111-121-131), and dwell count is 10 pulses per level.

Clustering is the grouping of the data points according to similarities. It has therefore been used for pre-processing step in machine learning methods and for grouping data from many different fields such as medicine, materials, environment [24-32]. The criteria for determining the similarities in clustering are smallest distances, graphs, density of data points, or various statistical distributions. A clustering algorithm generates clusters where the similarity of within-cluster is quite high. In the meantime, the similarity between clusters is much less. Cluster analysis has a wide range of applications such as data mining, statistics, image processing, machine learning. [33-36].

OPTICS clustering is a density-based approach that determines clusters based on the density and connectivity of data points [22]. OPTICS clustering does not require a predefined number of clusters as in the K-means method. Clusters can have different densities and any shape including non-spherical. It can also identify noise data as outlier.

In this study, the input variables used in clustering are frequency and pulse width. They have different units and value ranges. The unit of frequency is megahertz (MHz) and its value ranges between 2000-18000 MHz. The unit of pulse width is microseconds (µs) and its value ranges between 0.1-300 µs. For these differences, the min-max normalization method is applied to these variables and the variables are scaled to the range between 0 and 1.

The PRI finding is the second part of the deinterleaving process. After clustering of the two dimensional frequency versus pulse width data, the DTOA-based PRI finding method is employed to find candidate PRIs. The DTOA values are calculated for each cluster by taking differences of the sequential TOA values. Then, the unique values of the DTOAs are found and they are ranked from smallest to largest. After that, the neighbors of the ranked DTOAs are checked according to a rule. The rule merges DTOAs if neighboring DTOAs are closer than 4 us to each other. The value of 4 us comes from the constant PRI acceptance condition. The DTOAs obtained after this check are considered as candidate PRIs. All the candidate PRIs are checked for harmonics and minimum repetition number of candidate PRI values. Candidate PRIs that pass these checks are designated as PRIs. In this study, it is assumed that each cluster has one emitter or in other words each cluster has one type of PRI modulation type.

A rule-based sequence search is performed based on PRIs and their positions in each cluster. There are rules for sequence search to find PRI type. Rules are given below.

A rule-based sequence search is performed based on PRIs and their positions in each cluster. There are rules for sequence search to find PRI type. Rules are given below.

- If there is one PRI in a cluster, jitter value is calculated.
    - If the jitter value is equal or less than ±2 µs, the PRI type is constant.
    - If the jitter value is greater than ±2 µs, the PRI type is agile.
- If there are 2 or more than 2 PRI values in a cluster, the first 100 PRI values in the cluster are used and named as a test array.
- If the PRI number in the cluster is equal to the unique PRI numbers in the test array, PRI type may stagger or dwell&switch.
- After that, the first and second PRI indexes in the text arrays are found and the difference between the first PRI indexes and the second PRI indexes are calculated.
    - If the differences are mainly 1, the PRI type is stagger.
    - If the differences are mainly 5 or more than 5, the PRI type is dwell&switch.
- If PRI numbers in the cluster is greater than the unique PRI numbers in the test array, PRI type is dwell&switch.

The flowchart of the introduced method is given in Figure 2.

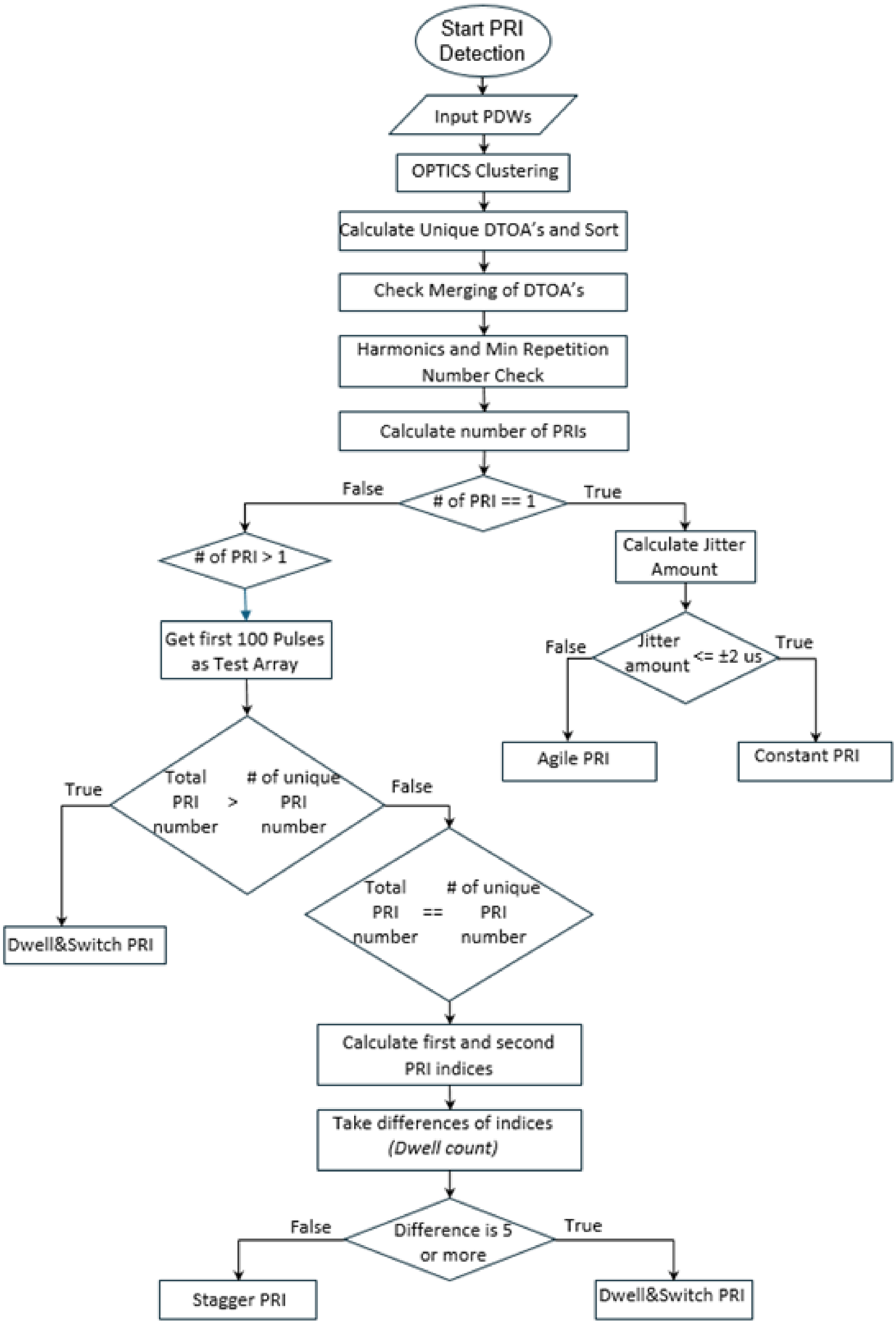

Figure 2. Flowchart of the presented method

4. RESULT AND DISCUSSION

4.1. Data Generation

In this study, three different synthetic data sets are generated to evaluate the performance of the presented method. In generation, some limitations are accepted for the data. The level numbers are between 2 and 16 for the stagger PRIs. The level numbers are between 2 and 10 for dwell&switch PRIs. The minimum value of dwell count is 5 pulses and the maximum value of dwell count is 100 pulses. Each emitter (or radar) in the data sets has a different number of pulses varying between 400 and 2520. The number of emitters in a group is selected differently from 6 to 15. In addition, different unintentional jitter amounts are added to the frequency, pulse width and PRI (or TOA) values for each emitter. The details about the synthetic data sets are given in Table 1.

Table 1. Details of the data sets for clustering

	Emitter No	Frequency Type	Frequency Value (GHz)	Pulse Width (us)	PRI Type	Level Number	PRI Value (us) and Jitter Value
Data Set 1	1	Constant	8(+-2 MHz)	3.5(+-0.1 us)	Dwell&Switch (10-pulse count per dwell)	3	111-121-131 (+-2 us)
	2	Agile	8.035 (+- 20 MHz)	4.3(+-0.6 us)	Stagger	3	277-283-291 (+-2 us)
	3	Constant	8(+-4 MHz)	4.3(+-0.6 us)	Stagger	2	511-531(+-2 us)
	4	Agile	8.035 (+- 30 MHz)	3.5(+-0.1 us)	Stagger	5	323-331-347-353-367 (+-1 us)
	5	Agile	8.015 (+- 15 MHz)	5.1(+-0.1 us)	Agile	1	407(+-12 us)
	6	Agile	8.015 (+- 15 MHz)	6.1(+-0.8 us)	Constant	1	419(+-2 us)
Data Set 2	1	Constant	8(+-6 MHz)	8.1 (+-0.1 us)	Constant	1	300 (+-1.8 us)
	2	Agile	8.035 (+- 20 MHz)	8.3(+-0.6 us)	Stagger	4	115-127-133-141 (+-2 us)
	3	Constant	8(+-10 MHz)	9.5(+-0.6 us)	Agile	1	577 (+-15 us)
	4	Agile	8.045 (+- 30 MHz)	9.5(+-0.1 us)	Dwell&Switch (20-pulse count per dwell)	2	657-667 (+-2 us)
	5	Agile	8.015 (+- 15 MHz)	7.2 (+-0.1 us)	Agile	1	230 (+-11 us)
	6	Agile	8.015 (+- 15 MHz)	11.5(+-0.8 us)	Dwell&Switch (15-pulse count per dwell)	4	521-529-535-543 (+-2 us)
	7	Agile	8.070 (+- 30 MHz)	12(+-1.8 us)	Dwell&Switch (18-pulse count per dwell)	3	135-150-163 (+-2 us)
Data Set 3	1	Agile	4(+-20 MHz)	2(+-0.5 us)	Stagger	11	305-315-325-335-345-355-365-375-385-395-405(+-2 us)
	2	Constant	4(+-9 MHz)	8(+-1.5 us)	Dwell&Switch (12-pulse count per dwell)	7	654-666-680-690-702-714-722(+-1.9 us)
	3	Constant	4(+-8 MHz)	20(+-3 us)	Constant	1	740(+-1.9 us)
	4	Agile	4.1 (+-20 MHz)	2(+-0.5 us)	Agile	1	800 (+-8 us)
	5	Constant	4.1 (+-10 MHz)	8(+-1.7 us)	Stagger	15	433-444-456-467-479-488-499-510-522-530-541-553-565-577-588 (+-1.8 us)
	6	Agile	4.1 (+-20 MHz)	15(+-2 us)	Dwell&Switch (6-pulse count per dwell)	10	124-134-146-156-168-180-194-206-216-230 (+-1.6 us)
	7	Agile	4.2 (+-20 MHz)	5(+-0.8 us)	Constant	1	275 (+-1.5 us)
	8	Constant	4.225 (+-10 MHz)	20(+-2.8 us)	Agile	1	594 (+-6 us)
	9	Agile	4.5 (+-30 MHz)	7.5(+-1 us)	Stagger	7	210-220-230-240-250-260-270(+-3 us)

Table 1. (Cont.) Details of the data sets for clustering

	Emitter No	Frequency Type	Frequency Value (GHz)	Pulse Width (us)	PRI Type	Level Number	PRI Value (us) and Jitter Value
Data Set 3	10	Agile	4.5 (+-35 MHz)	17(+-1.5 us)	Dwell&Switch (8-pulse count per dwell)	5	331-339-347-355-361 (+-2 us)
	11	Agile	4.15 (+- 25 MHz)	22(+-2.4 us)	Agile	1	150 (+-9 us)
	12	Agile	4.03 (+- 25 MHz)	13(+- 1 us)	Stagger	5	750-759-765-771-781 (+-2 us)
	13	Agile	4.2 (+- 32 MHz)	12(+- 1.6 us)	Constant	1	189 (+-1.7 us)
	14	Agile	4.25 (+- 36 MHz)	8(+- 0.9 us)	Agile	1	380 (+-8 us)
	15	Agile	4.28(+-30 MHz)	15(+-2 us)	Agile	1	782(+-7 us)

4.2. Clustering Results

In this section, the clustering results of the method are analyzed in different conditions with the synthetic datasets. K-means and OPTICS clustering results for generated 3 different data sets, whose details are given in Table 1. K-means and OPTICS clustering results for 3 different data groups in the Data Generation section are given in Figure 3. The important point is that the OPTICS gives better results than K-means for different sizes and different densities of clusters. Also, different numbers of emitters and at least 1 each of constant, agile, stagger, and dwell&switch PRI types are used for each data group.

Data set 1 consists of 6 different clusters. In this data set, the condition of the radar signals which are so close in frequency and pulse width is examined. K-means clustering result of data set 1 is given in Figure 3(a). The radar signals in data set 1 are not clustered perfectly. In the figure, clusters 1, 2, 3, and 4 are divided into more than one cluster. The cluster 5 and 6 also included data points belonging to different neighboring clusters 1-2-3 and 2-4, respectively. Because clusters have different densities and they are very close to each other. OPTICS clustering result of data set 1 is given in Figure 3(b). As can be seen from the figure, the radar signals forming the cluster are successfully separated from each other (although they are very close to each other). It was observed that 2 different points (colored red color) located between two neighboring cluster pairs (cluster 1 and 2, cluster 2 and 3) did not belong to any of the relevant clusters and were successfully determined as outliers by the algorithm.

The data set 2 has 7 different clusters. All clusters have different shapes and distributions. K-means clustering results of the algorithm for data set 2 is in Figure 3(c). It divides cluster 1 into 3 different clusters. Cluster 2-3 and 4-5 were merged and they create two cluster. Only, cluster 6 and 7 are clustered correctly in this data set. In data set 1, no cluster was correctly separated, while in data set 2, 2 clusters were correctly clustered. The reason for this improvement is that the distances between the clusters are farther than in data set 1. OPTICS clustering result of the algorithm for data set 2 is in Figure 3(d). For example, cluster number 1 has a big shape and large amount of distribution while cluster number 2 has a small shape and small amount of distribution. The result shows that the algorithm exhibits good performance for the different shapes and different distributions.

In data set 3, there are 15 clusters and they have different properties. The different types (constant and agile) of frequency and pulse width are also created in the clusters. The frequency, pulse width, and PRI parameters have different properties and combinations in all clusters. Also, the clusters have different shapes and densities. K-means clustering results of data set 3 is given in Figure 3(e). Cluster 1 and 2 are divided into two clusters by a false division, as can be seen by eye. Cluster 3 was labelled not as one cluster but as two clusters. Cluster 4 and 5 should be two separate clusters, but they were found as a single cluster. Cluster 6 is almost correctly categorized. Other 9 clusters are detected correctly. OPTICS clustering results of data set 3 is given in Figure 3(f). It was clearly observed that the algorithm achieves good results in the cases of higher number of clusters and different cluster shapes and densities. As can be seen from the analysis of the OPTICS algorithm from different datasets, it achieves good results for different sizes and different densities of clusters.

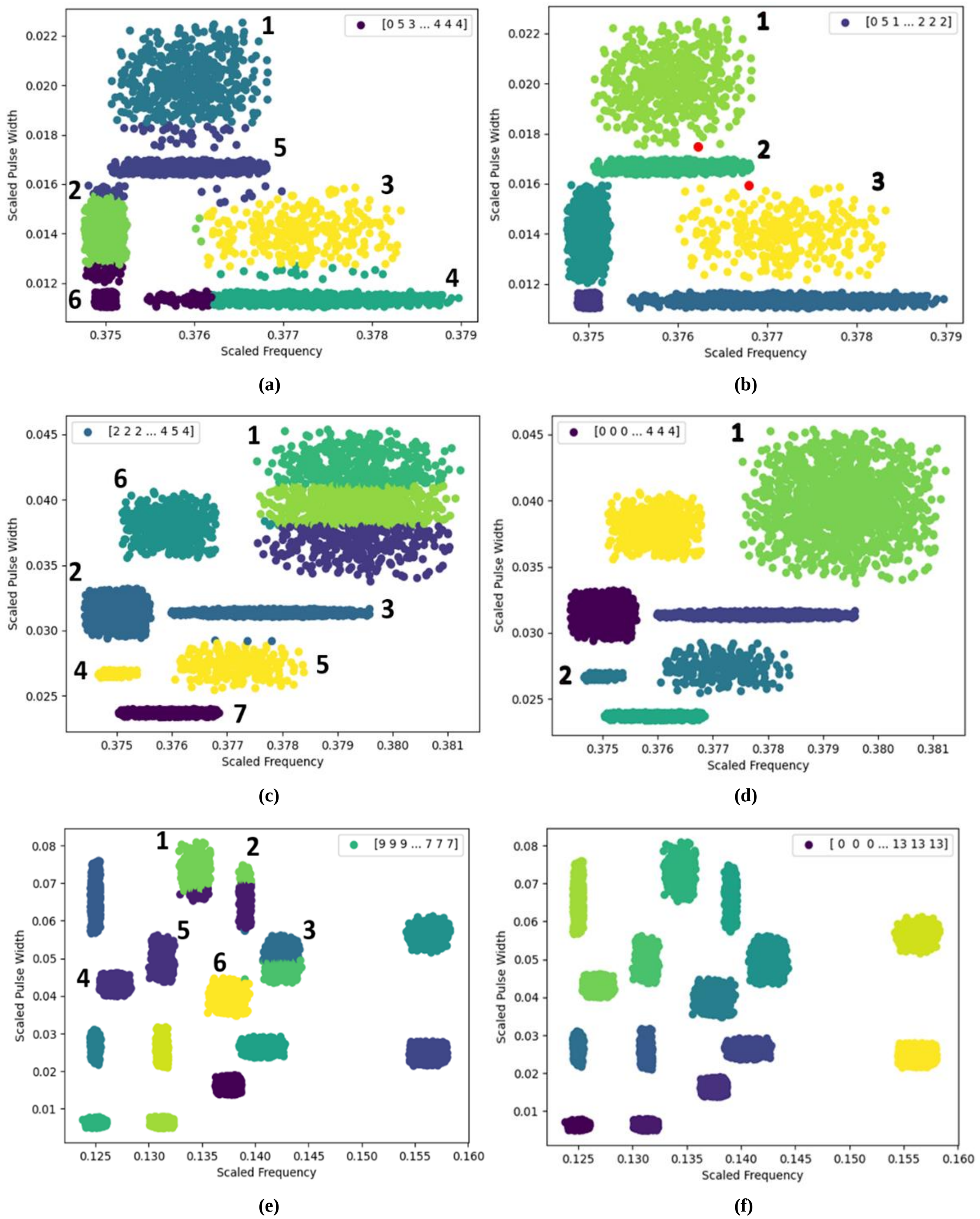

Figure 3. Clustering results: (a) K-means and (b) OPTICS results of Data set 1 (c) K-means and (d) OPTICS results of Data set 2 (e) K-means and (f) OPTICS results of Data set 3

4.2. PRI Modulation Results

After obtaining the satisfactory results from the clustering of the 5 different data sets which simulates the different radar waveform types, the PRI type classification performance of the presented algorithm is analyzed. For this purpose, a new synthetic data set is generated to assess the performance of the presented algorithm. This dataset comprises of a total of 400 different radar signals, including 100 radar data for each of the 4 PRI types. The performance of the presented method is given in the form of a confusion matrix in Figure 4.

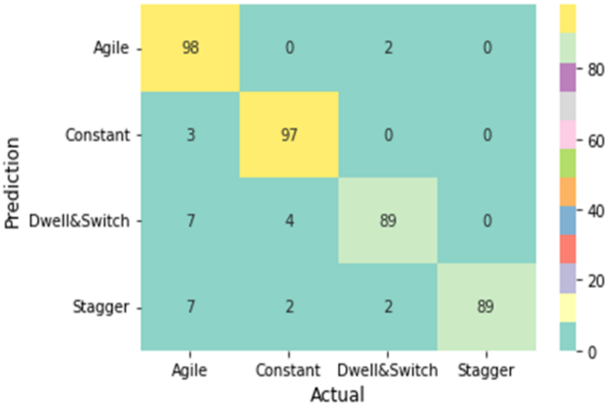

Figure 4. Confusion matrix of the proposed method

As can be observed from Figure 4, the method gives good results in identifying agile and constant PRI types. However, the detection performance of the method decreases for dwell&switch and stagger PRI types. If the difference between the close extreme values of neighboring PRI levels is less than 2 µs for stagger and dwell&switch PRI types, the algorithm gives the PRI type result as agile or constant. Because the algorithm finds these two levels as one level, and then calculates the jitter value for the new one level. According to the jitter value (if jitter value is less than 2 µs result is constant, if jitter value is more than 2 µs result is agile), the algorithm finds the PRI type as constant or agile. If the PDW's number in the data set is not adequate to find the correct PRI type and generated PRI levels that have random distribution are concentrated around certain values, the algorithm can find the result as dwell&switch PRI.

Based on the results of the overall proposed method, if the erroneous result occurs in one of the early steps of the proposed method, it directly affects the last step. Despite this situation, the proposed method produced highly accurate results in different circumstances.

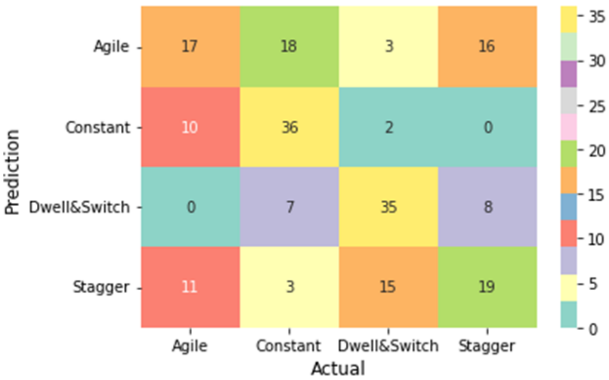

Figure 5. Confusion matrix of the proposed method

In order to validate the performance of the proposed method and evaluate its success, it is compared with the method presented in the paper by Kauppi et al. [3]. The dataset presented in this study was used to evaluate both the proposed and compared methods under the same conditions. Unlike this study, the compared study assumes that the PRI signal is deinterleaved before PRI modulation detection. Hence, the dataset presented in the study was clustered with the OPTICS method. Then, 5 unique features, namely single histogram peak, pulse interval changes, local extrema of pulse intervals, directional pulse interval changes, and stable sum. These are extracted from the clustered data set in accordance with the article. Subsequently, a multilayer perceptron (MLP) network was applied to classify 6 different types of PRI: constant, dwell and switch, stagger, sliding, jitter, and periodic PRI. MLP networks consist of 5 input features extracted from the data set, a hidden layer with 3 neurons and an output with 6 neurons that classifies the data set into 6 PRI types. However, the proposed work aims to recognize 4 different types of PRIs from the dataset, so the number of output neurons was reduced from 6 to 4. According to the article, the dataset is separated into training and test sections with a 50:50 ratio. The MLP network was trained for 20 epochs with randomly shuffled training and test sets. This process is repeated three times and the average of the results specify the performance of the model. In order to repeat this process, the benchmarking algorithm was run 3 times and the confusion matrix of the best performing model is given in Figure 5. According to the results in Figure 5, the compared algorithm recognizes the constant and dwell&switch types better than the agile and stagger types. The constant and stagger PRI types mainly false detected as agile. On the other hands, dwell&switch and agile types are mainly false detected as stagger. However, overall performance of the presented method is better than the benchmarking algorithm for our data set.

Furthermore, performance metrics derived from the confusion matrix are computed for both the proposed model and the benchmark model. In the benchmarked algorithm, the average of 3 consecutive runs of the algorithm is presented. Table 2 shows the evaluation results of both methods in terms of accuracy, macro F1-score, macro-averaged recall and macro-averaged precision performance. The results clearly indicate the superiority of the proposed method over the benchmark method in classifying 4 different PRI Types. According to the experimental results, the proposed methods provide a performance improvement of 73.74% in accuracy, 79.28% in macro F1-score, 71.90% in acro-averaged precision, and 71.48% in macro-averaged recall metrics. In our proposed method, some elimination methods such as harmonic control and repetition count control are applied in the PRI calculation stage. Thanks to these eliminations, the values that do not belong to the real sequence are eliminated and only the values with a high probability of being PRI are used in the type finding process. Therefore, it is thought that these eliminations are effective in giving more accurate results of the proposed method.

Table 2. Performance metrics

Performance metric	This study	[3]
Accuracy	0.9325	0.5367
Macro F1-score	0.9328	0.5203
Macro-averaged precision	0.9377	0.5455
Macro-averaged recall	0.9325	0.5438

6. CONCLUSION

In this study, a new method is proposed to recognize the 4 different PRI types which are constant, agile, stagger and dwell&switch. Proposed method operates in three stages. Initially, clustering is performed with the OPTICS method. OPTICS clusters the radar PDWs by using frequency and pulse width. The method operates well in simulations for a large number of clusters, clusters with different densities and distributions. Then, a DTOA-based PRI detection method is used to find the PRI's in the clustered data. Lastly, a rule-based system is employed to find the PRI types. Based on the experiments, the proposed method achieves the accuracy of 98% in agile, 97% in constant, and 89% in stagger and dwell&switch PRI types.

The combination of clustering, PRI finding and PRI modulation recognition to accomplish the deinterleaving gives good results in this study. In the clustering stage, the OPTICS method distinguished all combinations of fixed and agile types of frequency and pulse width parameters. In the PRI modulation recognition stage, PRI finding and identifying 4 different PRI modulations, even with different characteristics, are performed. As a result, the proposed method is able to deinterleave multiple radar signals in the environment according to their frequency and pulse width parameters and recognize the PRI modulation of each of the clustered radars. Also, the clustering performances of K-means and OPTICS for a given data set are compared. The results show that OPTICS clustering gives better results in the cases of close proximity of clusters and different cluster densities and shapes.

The algorithm proposed in this article is open to improvement in some aspects. One cluster may contain more than one emitter. Additionally, for simulation simplicity, we do not use missing and spurious pulses, but to work in a real environment, one must work with data sets that include these factors.

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in their study do not require approval from an ethics committee and/or any specific legal or private permissions.

AUTHORS' CONTRIBUTIONS

Şefika ÇAĞLAN: Contributed to literature research, software, methodology, writing - original draft.

Ali DEĞİRMENCİ: Contributed to visualization, software, methodology, analyse the results.

İlyas ÇANKAYA: Contributed to conceptualisation, methodology, writing, reviewing and editing, supervision.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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