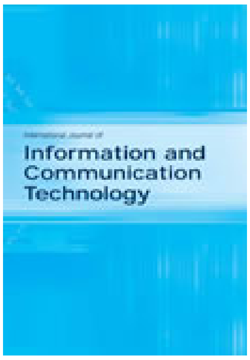

International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

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DOI: 10.1504/IJICT.2022.10044511

Article History:

Received:	02 September 2021
Accepted:	04 December 2021
Published online:	05 December 2023

A PRI estimation and signal deinterleaving method based on density-based clustering

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Abstract: In the existing statistics-based PRI estimation method, it is difficult to improve the PRI estimation accuracy due to the contradiction between the width of the statistical interval and the PRI extraction accuracy. In order to improve the accuracy of PRI estimation, a radar signal PRI estimation and deinterleaving method based on the density-based clustering is proposed in this paper. The dense area of the time of arrival (TOA) difference sequence near the true PRI value is extracted out by density-based clustering. The intra-class mean value is taken as the PRI estimation value and the intra-class point dispersion interval length as the PRI jitter amplitude. Combined with the sequence searching method with dynamic tolerance, the pulse sequence with a large number of pulses and small PRI jitter is preferentially extracted, which can improve the accuracy of signal deinterleaving. The simulation results show that the proposed method can significantly improve the accuracy of PRI estimation and the success rate of signal deinterleaving in the case of PRI jitter and false pulse interference.

Keywords: radar emitters; radar signals; pulse repetition interval; PRI; PRI estimation; signal deinterleaving; density-based clustering; DBSCAN; time of arrival; TOA; PRI jitter.

Reference to this paper should be made as follows: Wang, L., Zhang, Z., Li, T. and Zhang, T. (2024) 'A PRI estimation and signal deinterleaving method based on density-based clustering', *Int. J. Information and Communication Technology*, Vol. 24, No. 1, pp.72–85.

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1 Introduction

Radar signal deinterleaving is a key technology of electronic support measure (ESM) on the modern battlefield. The deinterleaving results affect the subsequent identifications of targets, precise positioning, threat determinations and countermeasures directly. The technology mainly based on two types of parameters deinterleaving algorithms. One of them is non-time parameter such as pulse width (PW), radio frequency (RF), angle of arrival (AOA), pulse amplitude (PA) and so on (Jiang and Fu, 2020; Jiang et al., 2020; Revillon et al., 2019). The other is the time of arrival (TOA), which is commonly used for the pulse repetition interval (PRI) estimation (Rong and Cong, 2020; Tian et al., 2019). Modern electromagnetic environment is very complexed, there might be a large number of radar emitters, same time and same space. The PW, RF and other parameters of the same emitter will experience jitter or even jump modulation, which will overlap seriously in parameter space (Bing et al., 2020; Zhang et al., 2020). The deinterleaving algorithms based on these parameters are difficult to adapt to the modern battlefield environment. However, due to the corresponding relationship with the radar range and working modes, and the stable law under the same working mode, the PRI is still one of the main parameters in radar signal deinterleaving. Anti-sorting design for PRI has also emerged in recent years. Nan et al. (2019) significantly improved the difficulty of signal deinterleaving through disturbing the TOA of radar pulse train with interference pulse and (Zhang et al., 2019) adding PRI jitter and stagger in the process of radar emitter modelling.

The common PRI deinterleaving algorithms often used mainly include dynamic expansion method, cumulative difference histogram (CDIF), sequential difference histogram (SDIF), PRI transform and plane transformation. Among them, the dynamic expansion method is mainly applicable to database situations for specific targets, but it is not applicable to PRI jitters, staggers, agility and other situations. The CDIF is mainly used for analysing the multistage differences of TOA according to the periodicity of pulse signals from the same radar. It is efficient in the PRI's value extraction, but the performance declines rapidly when PRI jitter exists. Since the multistage difference calculation of TOA was removed and the best detection threshold was added in SDIF, the efficiency compared with CDIF has been improved to a certain extent. Other scholars have also improved the histogram method in PRI estimation accuracy with variable statistical interval methods subsequently. Nishiguchi and Kobayashi (2000) proposed the PRI transformation to direct against the harmonic interferences firstly. The algorithm added phase factors to calculate the autocorrelation functions of pulse sequences, which could reduce harmonic interferences significantly. Then two improvements were proposed for the algorithm, one is sliding distance windows with variable start points of PRI boxes and the other is adjusting PRI boxes automatically. The modified algorithm improves the deinterleaving effects in the condition of PRI with jitter. Renjian et al. (1998) proposed the plane transformation algorithm, which could obtain PRI information of each pulses by analysing and processing the image features in the transform domain.

In order to adapt to the increasingly complex environment of radar signal modulation and electromagnetism, some new PRI estimation and deinterleaving methods have appeared in recent years. Xin and Xicai (2008) proposed matrix matching method on the basis of plane transformation, which improved the sorting accuracy by detecting similarity sequence. Zheng et al. (2018) proposed a signal deinterleaving algorithm based on data statistical clustering and correlation processing for PRI stagger pulse signals, which effectively solved the problem of the recognition and analysis about PRI stagger pattern. Yixiao et al. (2019) put forward to combining PRI transform with data field clustering, clustering and sorting the radar signals after PRI transform, which improved the response ability to pulse jitter to a certain extent. Tao et al. (2020) proposed a correlation matching algorithm to estimate the PRI value, which improved the adaptability to pulse loss and jitter, reducing the amount of calculations at the same time. In recent years, neural network has made rapid development in the field of pattern recognitions, and a series of PRI deinterleaving methods based on artificial neural network have been proposed. An attention based recognition framework based on RNN is introduced for pulse flow classification in complex PRI modulation and pulse flow classification in Li et al. (2020), which has robustness to noise but requires large amount of calculations.

PRI estimation accuracy is generally difficult to be improved for the existing PRI deinterleaving methods, and the accuracy of PRI value estimation affects the accuracy of signal deinterleaving directly. A large number of pulses will be deinterleaved by mistake when the PRI estimation error is big. So this paper proposed a method for PRI estimation and signal deinterleaving based on density-based clustering. The multi-stage TOA differences of the pulse train are obtained firstly, and the points of the multi-stage differences will gather in the real PRI and the harmonic will disperse in other regions. Therefore, we can use density-based clustering algorithm to extract PRI value with high precision, and get PRI jitter information according to the dispersion characteristics in the aggregative areas. Due to the PRI center value and jitter amplitude information, the deinterleaving accuracy was improved naturally.

The organisation of this paper was presented as follows: in Section 1, the paper introduced the importance and problems of radar signal deinterleaving, and several classical and new PRI deinterleaving algorithms were analysed and compared. In

Section 2, the PRI value estimating algorithm based on density-based clustering was proposed. In Section 3, on the basis of the second part the paper introduced the basic concept and detailed steps about deinterleaving based on PRI. In Section 4, for different PRI jitter cases, the proposed method was compared with the typical CDIF and PRI transform algorithm in simulation experiments.

2 PRI estimation based on density-based clustering

The algorithm mainly includes two parts: PRI value estimation and pulses deinterleaving. PRI center value and PRI jitter information estimation are mainly based on the aggregation distribution characteristics of TOA differences at the real PRI with density-based clustering algorithm.

2.1 Density-based clustering

The core idea of density-based clustering is to find high density regions separated by low density regions, and treat each independent dense regions as independent clusters. Compared with other clustering algorithms such as k-means, the density-based clustering does not need the prior information of cluster number, and can filter the noise interference. According to different definitions of density, typical algorithms include DBSCAN, OPTICS, DENCLULDE and so on (Bhattacharjee and Mitra, 2021). The DBSCAN is the most classic and mature among them.

There are three input parameters needed in DBSCAN: data set $\mathbf{D}$, neighbourhood radius ε and density threshold MinPts. Set up $x \in \mathbf{D}$

$$N_{\varepsilon}(x) = \{y \in \mathbf{D} : \text{dist}(x, y) < \varepsilon\} \tag{1}$$

where $N_{\varepsilon}(x)$ is the ε neighbourhood of x, dist is the Euclidean distance function. Define the density of x as

$$\rho(x) = |N_{\varepsilon}(x)| \tag{2}$$

If the density of the point x_i, $\rho(x_i) >$ MinPts, then the point x_i is called the core object, otherwise the non-core object or noise. There are three definitions of DBSCAN. Directly density reachable: set $\mathbf{D}_c$ as the set of all core objects, if $x \in \mathbf{D}_c$, $y \in N_{\varepsilon}(x)$, then x and y are directly density reachable. Density reachable: set $P_1, P_2, \ldots, P_m \in \mathbf{D}$, $2 < m$, P_1 and P_m are density reachable if each P_{i+1} is directly density reachable from P_i, where $i = 1, 2, \ldots, m - 1$. Density connected: set $P_1, P_2, P_3 \in \mathbf{D}$, P_1 and P_2 are density reachable from P_3 separately, then it can be said that P_1 is density connected with P_1.

The basic steps of density-based clustering algorithm are as follows: take an unlabelled point from the data set $\mathbf{D}$. If the point is a core object, then find out all the points which are density reachable from that core object to form a cluster. Otherwise, after the point is labelled as noise, the above operation is continued for other unlabelled points until all points in $\mathbf{D}$ are traversed (Wang et al., 2019).

2.2 Adaptive parameter determination

It is obvious that the setting of the neighbourhood radius ε and the density threshold MinPts are very important for the performance of DBSCAN algorithm. When the neighbourhood radius ε is too small or the value of MinPts is too large, the class with less data points will be abandoned, and one class will be split into two or more classes. On the contrary, a large number of noises will be classified into many classes, and originally separated classes will also be classified into one class (Chen et al., 2019). Therefore, the setting of the two parameters will affect the clustering effects directly. For the same type of data clustering, it is feasible to adjust a set of fixed parameters according to the effect.

However, in the application of PRI value extraction, the PRI value of different radars may have different jitter amplitude, which makes it difficult for the density clustering algorithm to obtain the optimal result of clustering. Therefore, it is necessary to adjust the neighbourhood radius ε and density threshold MinPts adaptively according to the characteristics of the data.

The adaptive neighbourhood radius ε: firstly, the distance distribution matrix **DIST** is generated according to the data set **D**

$$\mathbf{DIST} = \{\mathrm{dist}(\mathrm{p},\mathrm{q}) \mid \forall \mathrm{p},\mathrm{q} \in \mathbf{D}\} \tag{3}$$

where dist is the Euclidean distance function. By rearranging the distance values of each row in **DIST** from small to large, the k^{th} distance value of each row conforms to Poisson distribution statistically, so the expected value λ of the k^{th} distance value can be obtained as

$$\lambda = \frac{1}{n}\sum_{i=1}^{n}\mathbf{DIST}(i,k) \tag{4}$$

where n is the element number of **D**. then the optimal solution of k is explored with the actual data. Referring to the experience of literature (Lai et al., 2019), the selected data sets are five different forms of TOA difference sequences of radar mixed signals. Firstly, the MinPts is set to 4, and then the different values of ε are obtained with the k from 2 to N. The clustering results show that when k is greater than or equal to 4, the number of noise and clustering tends to be stable. Therefore, the expected value of the fourth distance of each row is selected as the most appropriate value of the ε. That is

$$\varepsilon = \lambda_4 = \frac{1}{n}\sum_{i=1}^{n}\mathbf{DIST}(i,4) \tag{5}$$

Density threshold MinPts: if the data set **D** contains targets, there must be high-density clustering areas and low-density noise areas in **DIST**, and the density of clustering areas must be higher than the average density. Therefore, the MinPts can be set as the twice average density in the ε neighbourhood of all points in **DIST**.

2.3 Extraction of PRI information

In the conventional PRI estimation methods, only PRI value can be extracted without PRI jitter information, or just qualitative discrimination of PRI jitter. As a result, the tolerance of pulse extraction can only be set according to the maximum jitter amplitude existing in the pulse sequence, which is likely to prone to mis-deinterleaving.

The multi-stage difference calculation was carried out for TOA data of mixed overlapping pulse trains and the corresponding difference points are shown in Figure 1. The original radar pulse is a group of radar pulse signals with PRI 855 μs and 2% jitter, mixed with 50% false pulses. It can be seen from the figure that the difference points show aggregation near the real PRI and the harmonic, the tightness of the aggregation are related to the PRI jitter. In other places, the distribution of the difference points is relatively sparse, corresponding to the low-density region in the density-based clustering.

Figure 1 Distribution of original TOA difference points

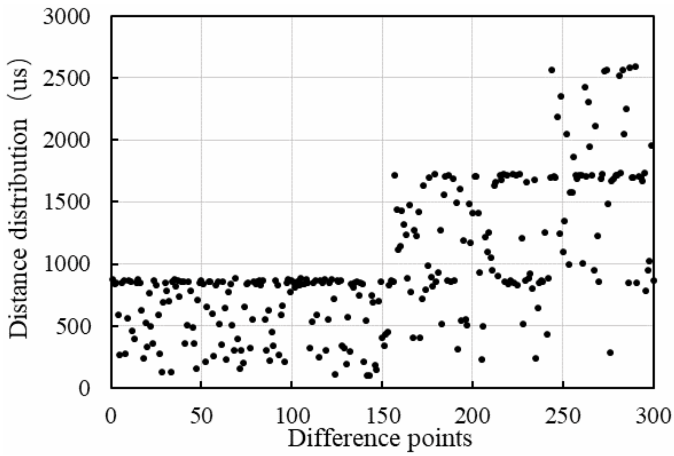
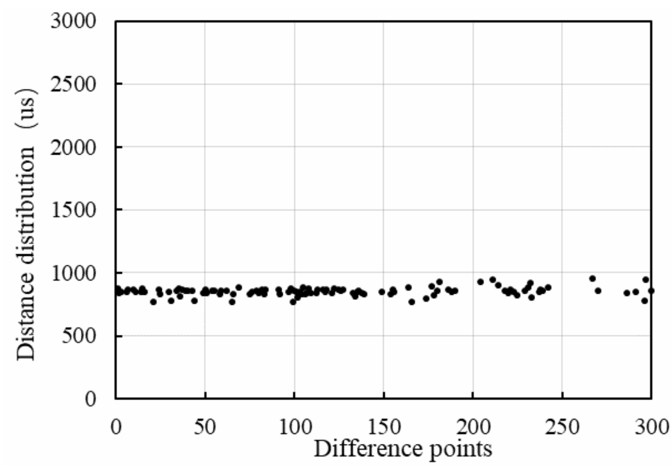


Figure 2 Distribution of TOA difference points after density-based clustering



The difference points of TOA are clustered by density-based clustering, and the class with most points is shown in Figure 2. It can be seen that the sparse difference points are basically eliminated as noise after density-based clustering. Consequently, according to the distribution of the points in the cluster obtained by density-based clustering, the jitter amplitude of the corresponding radar PRI can be obtained.

When multiple clusters are obtained after DBSCAN, PRI extraction priority is calculated for each cluster. The purpose is to ensure that pulse trains with large number of pulses, small PRI value and relatively stable can be extracted first. PRI extraction priority is defined as follows

$$\text{Priority}(i) = Cn(i) \big/ \left[Cc(i) \times Cj(i) \right] \tag{6}$$

where Proprity(i) is the PRI extraction priority of the i^{th} cluster, $i = 1, 2, \ldots, m$, m is the number of clusters. $Cn(i)$, $Cc(i)$ and $Cj(i)$ are the number of points, the means of points and the interval length of points distribution in the i^{th} cluster respectively. Select the class with the highest priority to extract PRI information, assuming that the k^{th} cluster has the highest priority, then the PRI_cen and jitter can be obtained as

$$\text{PRI\_cen} = Cc(k) \tag{7}$$

$$\text{jitter} = Cj(k)/(2 \times \text{PRI\_cen}) \tag{8}$$

3 Deinterleaving based on PRI information

According to the PRI information extracted above, combined with the sequence searching method, the mixed pulses are deinterleaved. The algorithm flow is shown in Figure 3.

1 The TOA sequence of the mixed pulses is imported from the radar reconnaissance data.

2 Judge whether the number of elements in the TOA sequence is greater than 20 or whether the pulse mean density is greater than 0.1/ms. If the conditions are met, go to the next step. Otherwise, there are no radar targets and end deinterleaving. The judgment standard can be flexibly adjusted according to the actual application scene and object.

3 Calculate the multi-stage difference sequence **D** for the TOA sequence, and the stage number depends on the specific application scenario.

4 For each point in the difference sequence **D**, calculate the Euclidean distance between each other to form the distance distribution matrix **DIST**.

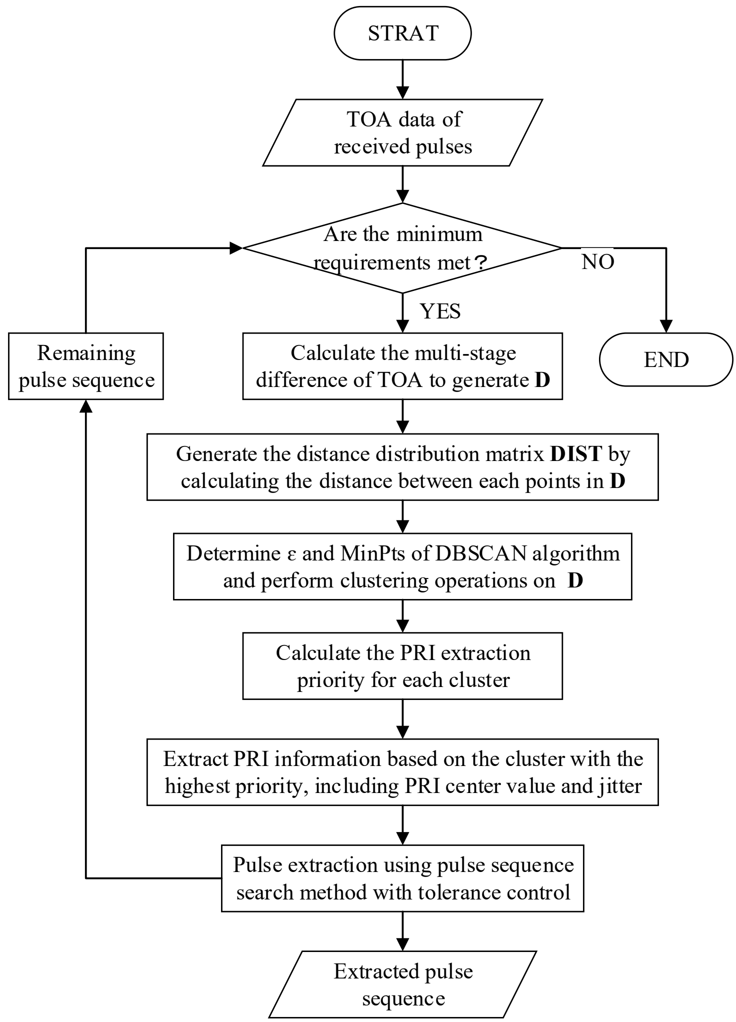
5 According to the distance distribution matrix **DIST**, the parameters neighbourhood radius ε and density threshold MinPts are decided, and then multiple clusters are obtained from **D** by DBSCAN algorithm.

6 Calculate priority for each cluster according to the equation (6), and select the cluster with the largest priority to extract the PRI information according to the equations (7) and (8).

7 According to the extracted PRI information, combined with the pulse sequence searching method with dynamic tolerance, the pulses from the same radar are extracted out from pulse sequence.

8 For the remaining radar pulse sequence, return to step 2 and repeat until the remaining pulse trains do not meet the minimum requirements for deinterleaving. Then the deinterleaving is completed.

Figure 3 Algorithm flowchart proposed in this paper



4 Simulation experiments and discussions

In order to verify the effectiveness of the proposed method, the simulation experiments are carried out to compare the proposed algorithm with the typical difference histogram method and PRI transform in the presence of PRI jitter with different degrees. The comparison and analysis were carried out from two aspects of PRI estimation accuracy and signal deinterleaving success rate.

4.1 Comparison of PRI value extraction accuracy

Only one radar was set in this simulation and the PRI was set to 175.4 μs. PRI jitter was set to 1%, 2%, 5% and 10% respectively. In order to approach the complex battlefield environment, add false pulses of 200% of the total, and the simulation time was set to 20ms. The proposed method was compared with CDIF and PRI transform, which were commonly used in signal deinterleaving based on PRI. The width of the CDIF statistical interval and the width of the sliding window of the PRI transform were both set to 5 μs. The TOA tolerance of the pulse sequence searching method was set to 5%. Monte Carlo simulation was conducted for each group of experiments for 100 times, and the results are shown in Tables 1–4.

Table 1 Comparison of PRI value extraction results with 1% PRI jitter

Algorithms	*PRI means (μs)*	*Std (μs)*	*Estimation error rate*	*Deinterleaving success rate*
CDIF	175.22	1.37	0.78%	97.1%
PRI transform	175.32	1.03	0.59%	98.3%
Proposed method	175.43	0.44	0.25%	100%

Table 2 Comparison of PRI value extraction results with 2% PRI jitter

Algorithms	*PRI means (μs)*	*Std (μs)*	*Estimation error rate*	*Deinterleaving success rate*
CDIF	175.88	2.11	1.20%	90.1%
PRI transform	175.10	1.35	0.75%	95.6%
Proposed method	175.55	0.47	0.26%	100%

Table 3 Comparison of PRI value extraction results with 5% PRI jitter

Algorithms	*PRI means (μs)*	*Std (μs)*	*Estimation error rate*	*Deinterleaving success rate*
CDIF	175.58	4.63	2.64%	83.4%
PRI transform	175.30	2.23	1.27%	89.1%
Proposed method	175.34	0.89	0.51%	99.2%

Table 4 Comparison of PRI value extraction results with 10% PRI jitter

Algorithms	*PRI means (μs)*	*Std (μs)*	*Estimation error rate*	*Deinterleaving success rate*
CDIF	173.96	8.28	4.72%	62.6%
PRI transform	176.62	6.53	3.72%	78.1%
Proposed method	175.38	1.71	0.97%	94.5%

The PRI estimation error rate and the deinterleaving success rate of each method under different PRI jitter are shown in Figure 4 and Figure 5 respectively. It can be seen that with the increase of PRI jitter, the PRI estimation error rates of the three methods are increasing, and the deinterleaving success rates are decreasing. However, the proposed method performs better than the other two methods in both aspects all the time. Especially when the PRI jitter is greater than 2%, the performances of CDIF and PRI transform drop sharply, but the proposed method can still maintain a low estimation error rate and a high success rate.

Figure 4 Comparison of PRI estimation error rate (see online version for colours)

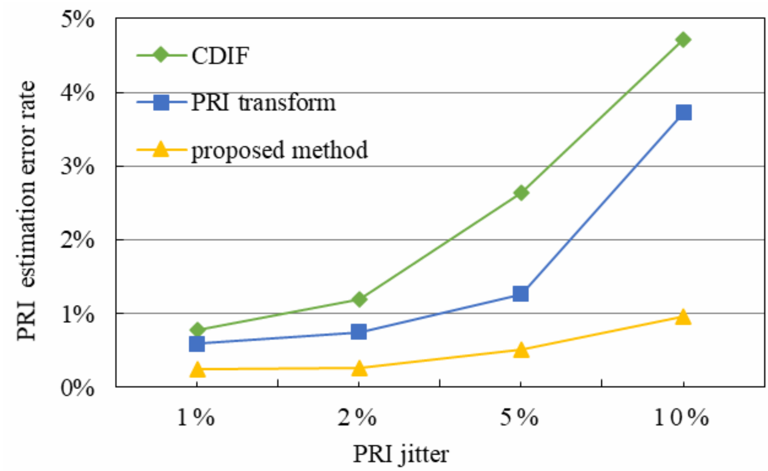
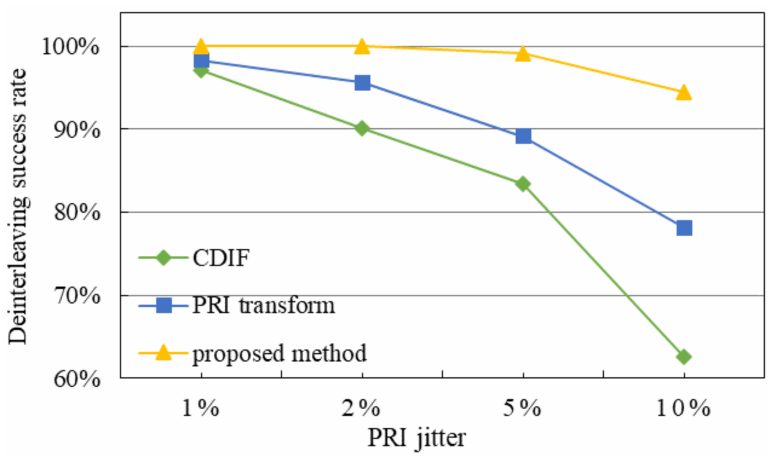


Figure 5 Comparison of deinterleaving success rate (see online version for colours)



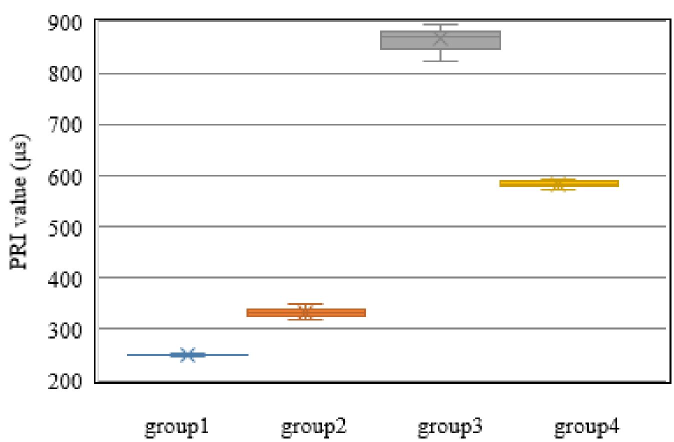
The main reasons for the above results are as follows. In terms of maintaining PRI extraction accuracy, CDIF algorithm was limited by the width of histogram statistical interval. When the interval width was set too narrow, the peak value was too low to exceed the threshold, which may lead to no PRI value being extracted. When the interval width was set too wide, multiple peaks would exceed the threshold, resulting in large fluctuation of the extracted PRI value. Especially when the PRI jitter was large, a wider statistical interval must be used to include the scattered TOA difference points. But this not only reduced the PRI estimation accuracy, but also lead to greater estimation fluctuation. That is, the corresponding PRI estimation standard deviation increases with the increase of PRI jitter, and is always the largest one in the three algorithms as shown in Figure 3. As for PRI transform method, there is also a contradiction between the setting of sliding window width and the estimation accuracy of PRI value, but it performs slightly better than CDIF method.

However, there is no statistical interval or sliding window width setting in the proposed method, relies on the density-based clustering completely and clusters the dense areas of TOA difference points adaptively according to the distribution characteristics of the points. Then, the proposed method determined the PRI center value and PRI jitter according to the mean value and distribution of intra class points. Therefore, the accuracy and stability of PRI valuation can be improved to a certain extent. Since the proposed method can extract the corresponding jitter amplitude for each PRI value, the TOA tolerance can be flexibly set according to the jitter during pulse sequence search, which minimised the possibility of incorrect deinterleaving. Therefore, the proposed method can always perform better than the other two methods in terms of the deinterleaving success rate under different jitter conditions.

4.2 Comparison of multiple deinterleaving ability

Four groups of radar signals were set in this simulation to verify the multi-objective deinterleaving ability of the proposed method. The PRI of the first group was set to 250 µs with 1% jitter, the second group was set to 333 µs with 5% jitter, the third group was set to 855 µs with 5% jitter, and the fourth group was set to 583 µs with 2% jitter. The simulation time was set to 40ms, and add false pulses to 20% of the total.

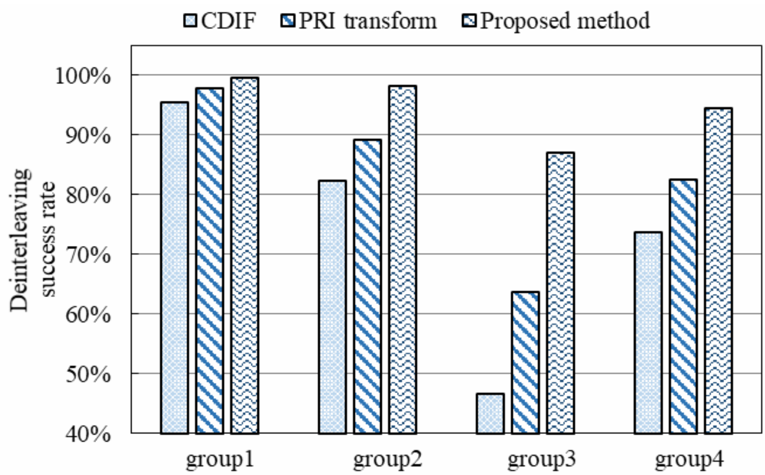
Figure 6 PRI extraction results by the proposed method (see online version for colours)



The multi-stage TOA differences points corresponding to the four groups of different radar signals after density-based clustering are shown in Figure 6. The PRI value extracted by the proposed method was basically consistent with the PRI value and PRI jitter information. The PRI extraction order of the proposed method depends on the PRI value, PRI jitter, and the number of pulses.

Owing to its small PRI value and PRI jitter, the TOA difference points distribution of the first group was the densest, so the signals of the first group were extracted out first. Due to the small PRI jitter and the large number of pulses, the deinterleaving of the first group was not prone to errors, and the dilution effect on the original pulse sequence was the most significant. The second and fourth group had similar scatter density of TOA difference points, but the PRI of the second group was smaller than the fourth group which means there were more pulses in the second group. Therefore, the PRI information and pulses of the second group were extracted before the fourth group. As the maximum PRI value and PRI jitter, and the TOA difference points distribution of which was relatively scattered, the signals of the third group were the last to be extracted. Only the pulses of other groups are extracted out, the dense area of the third group can be noticed.

Figure 7 The deinterleaving success rate of three methods (see online version for colours)



For the above pulses, the proposed method, CDIF and PRI transform are used respectively. The width of the CDIF statistical interval and the sliding window of the PRI transform were both set to 5 μs. The TOA tolerance of the pulse sequence searching method was set to 5%. 100 Monte Carlo simulations were carried out for each group of experiments, and the comparison of experimental results is shown in Figure 7. The comparison shows that for the same radar signals, as the PRI information extracted by the proposed method is relatively high precised and contains the information of PRI jitter, so that the success rate of deinterleaving is higher than the other two methods. For different radar signals, this proposed method can set the TOA tolerance according to the different PRI jitter of different radars. The radar with a large number of pulses and small PRI jitter can be extracted first to ensure a higher extraction success rate and to reduce the difficulty of subsequent deinterleaving. However, the other two methods can only be set according to maximum tolerance. Therefore, it is difficult to improve the success rate of deinterleaving, and will also increase the interference of pulse loss and false pulse in subsequent deinterleaving.

The simulation results show that the PRI estimation accuracy is higher than the usual deinterleaving methods in the case of PRI jitter and false pulse interference. Combined with the information of PRI jitter, the deinterleaving success rate of overlapping pulses trains has been improved accordingly. However, there are also some problems about this proposed algorithm in the experiment. When there were similar PRI values and accompanied by jitter, the distribution of TOA multi-stage difference may overlap partially. Due to the connecting dense area, it will be classified into one class after the density-based clustering, resulting in only one false PRI value between the two real PRIs can be extracted.

5 Conclusions

In order to improve the probability of success about the radar emitter signal deinterleaving in complex environment, an algorithm about PRI estimation and signal deinterleaving based on density-based clustering was proposed in this paper. In addition to improving the PRI estimation accuracy, the PRI jitter information was further increased, and the signal deinterleaving was completed by combining the sequence searching methods with dynamic TOA tolerance. Compared with CDIF and PRI transform algorithms which are the most commonly used, the method proposed in this paper has improved the deinterleaving success rate of overlapping pulses in the presence of PRI jitter. It provides a technical reference for the signal deinterleaving of the electronic investigation system in the actual complex electromagnetic environment, and is very potential to be applicated in the field of military reconnaissance.

However, the method proposed in this paper is limited to dealing with PRI jitter, and can not deal with more complex situations such as PRI stagger, slip, jump and so on. And for the two sets of pulse signals with very close PRI values, the TOA difference points may be connected as one gathering area. At this time, the method in this paper has the risk of PRI extraction error. The deinterleaving method based on PRI only uses the TOA information of pulse trains. Although there might be large fluctuations in conventional parameters such as PW and RF, it still has certain utilisation value if combined with PRI, and can further improve the robustness and accuracy of the deinterleaving algorithm.

There are three main directions for future development of this research. The first is to further optimise the algorithm flow to improve the application ability of the algorithm in engineering; the second is to combine the characteristics of PW, RF, AOA and even intro-pulse modulation to improve the algorithm's multi-target deinterleaving ability in complex environment. The third is to improve the algorithm proposed in this paper for complex PRI modulation forms such as PRI agility and diversity.

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