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Research Article

A Window-Based Approach for PRI Type Recognition in Streaming Data

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Abstract
Pulse Repetition Interval (PRI) type detection is a fundamental step in radar identification. Therefore, many methods have been proposed for PRI type identification. In this study, a new online sliding window-based PRI type detection method is proposed. Initially, the method takes the hyperparameters of window size and window shifting amount from the operator. The method then waits for data to be collected until the number of incoming data samples reaches 1.5 times the window size. The window is shifted over the Difference of Time of Arrival parameter of the incoming Pulse Descriptor Word data and the PRI type is determined according to the change characteristics within the window. The experiments are performed on 13 different datasets containing possible scenarios of PRI types. The results of the experiments show that proposed method can distinguish between constant, dwell&switch, sliding-up, and sliding-down PRI types.

Key Words
Pulse repetition interval (PRI), Streaming data, Constant PRI, Dwell&switch PRI, Sliding window, Electronic warfare

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1. Introduction

In electronic warfare, it is necessary to know the threats in the environment. The identification of radar signals necessitates the extraction and analysis of its parameters. The primary parameters characterizing radar pulses are frequency, pulse width, and Pulse Repetition Interval (PRI). PRI is calculated by taking the differences of the consecutive Time-of-Arrival parameter (TOA) parameters in the Pulse Descriptor Words (PDWs). It is also one of the most important radar data and it has a pattern which is named as modulation. Also, the PRI modulation of the radar provides information about the operating mode of the radar. There are different types of modulation depending on the number and arrangement of PRIs used by the radar. The fundamental PRI modulation types are constant, dwell&switch, sliding-up, and sliding-down. Numerous methodologies have been advanced to ascertain the modulation type of PRI sequences. These can be mainly grouped into clustering-based and TOA-based methods. The clustering-based methods called multiparameter-based methods use more than one parameter (Chao et al., 2022; Cheng et al., 2021). In clustering-based methods, the received signals are first divided into clusters using some parameters, and then PRI modulation recognition is applied. In TOA-based methods, only the TOA parameter is used for PRI type recognition (Cheng et al., 2023; Xie et al., 2023). These types of methods generally use features and histogram-based approaches to detect the PRI type (Ahmadi and Mohamedpour, 2012; Bagheri and Sedaaghi, 2017; Kauppi, and Martikainen, 2007; Kumar et al., 2014; Ryoo et al., 2007; Sridharan et al., 2015).

In the literature, many approaches based on feature extraction have been proposed to distinguish PRI modulation types. The first step in such approaches is feature extraction. Throughout this process, various features are extracted from the signal, and those demonstrating the greatest discriminative capability are selected for utilization. Ahmed et al. (2018) proposed a hierarchical method using a set of wavelet-based features along with some intuitive features to recognize five PRI modulation types. Liu et al. (2017) created a 3-dimensional feature set, then a multi-layer neural network is used to find wobulated, jitter, dwell&switch, and sliding PRI types. Ghani et al. (2017) found out decimated Walsh–Hadamard transform method. Constant, jitter, and stagger PRI types are recognized by using this approach. Shi et al. (2016) created a 3-dimensonal feature set by applying auto-correlation and normalization on 4 PRI modulations. These features are density of peak value, intention of monotone and energy of sequence. Gencol et al. (2016) introduced a new feature set based on wavelet transform. It was stated that the most important property of the proposed method is robustness. The method distinguished stagger, dwell&switch, jitter, sinusoidal, and sliding PRI types. Keshavarzi et al. (2012) recommended four specifications to detect dwell&switch, sliding, wobulated, and jitter PRI modulations. Hu and Liu (2010) provided features based on the characteristics of the PRI sequence in both time and frequency domain for each type of PRI modulations. Zeros-crossing density, harmonic amplitude ratio, and sign properties of difference of the PRI sequence are the features of the method. Ryoo et al. and Ahmadi et al. used autocorrelation features to find PRI modulation types (Ahmadi and Mohamedpour, 2012; Ryoo et al., 2007). Kauppi et al. (2007) employed five features to recognize the six PRI types. Mostly, more than one feature is used to classify one PRI type.

Histogram-based methods have also been widely used in literature. In such methods, the determination of a suitable threshold value is often the most critical point. In addition, the number of pulses must be sufficiently large to produce a smooth histogram and correct results. Furthermore, these methods are directly affected by missing and spurious impacts. Ata'a and Abdullah (2007) used the combination of TOA folding histogram, DTOA histogram and periodogram to find certain PRI. Sridharan et al. (2015) utilized Sequential Difference (SDIF) histogram method to obtain the PRI values. Bagheri and Sedaaghi (2017) introduced new two-stage thresholds for detecting jittered and staggered PRI from histogram-based methods. Ge et al. (2019) suggested an improved pulse correlation-based multi-level time difference histogram method. The method did not search the pulses, it obtained pulse pairs. It was mentioned that stagger, fixed, jitter, slippery, and sine modulated PRI modulation types are recognized correctly.

There are also some new methods in the literature that use a sliding window mechanism to study multifunctional radar signal structure and as a step in the recognition of some PRI modulations. Fang et al. (2019) suggested an algorithm for Multi-function Phased Array Radar (MPAR) behavior recognition. MPAR applies iterative detection based on a fixed length sliding window. The received pulse sequence was divided by a sliding window, and then the conditional probability is computed step by step. The probability output was compared with the previous probability to determine whether there is a change. Although the MAPR gave good results in experiments, it was noted that complex signals that may occur in a real combat environment may affect this method. Zhu et al. (2021) presented a model-based radar time series clustering to cluster multifunction radars work modes. There were 3 different methods and the third one uses window size and slide amount. The method was compared with other clustering methods K-means, Gaussian Mixture Model (GMM), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and spectral. It was stated that the method gives successful experimental results. Qiao et al. (2022) provided a new method based on short time modified pulse repetition interval transform to recognize and estimate its parameters. It consists of a modified Short-Time Modified PRI Transform (STMPT) method to achieve the time-varying characteristics of different PRI modulation types. A one-dimensional array was obtained by the modified PRI transform method. Then, the array was organized as a two-dimensional matrix by adding a short time window in each short time window and shifting it by an overlap. It was reported that the algorithm gives good results for the identification and parameter estimation of fixed (constant), stagger, fast PRI change, and elaborate PRI change types. Tang et al. (2023) presented a window-sliding approach to detect the change points of multi-functional radar work mode. The mode detection was made by computing the discrepancy between two adjacent windows sliding along the MFR sequence and locating the peak in the inconsistency curve when two windows cover different segments.

In addition to these methods, machine learning based deinterleaving methods are also widely used. Liu (2021) proposed a method based on hierarchical deep neural networks, Li et al. (2020) put forward a learning-based neural network method named as autoencoders, and Liu and Philip (2018) employed recurrent neural networks. Han et al. (2021) presented a method based on multi-task learning with a CNN for deinterleaving and PRI modulation recognition. Feng et al. (2022) applied the domain-adaptive few-shot learning and combined net method for PRI modulation types of constant, jitter, sliding, wobbulated, stagger, and dwell&switch. Chao et al. (2022) applied semantic segmentation with neural networks for deinterleaving. It has some advantages like no need for PRI value and modulation type. However, this method did not distinguish radars having same PRI modulations and radars having similar PRI values. Zhang et al. (2023) performed a TOA-based method named as bi-directional long short-term memory (BiLSTM) networks and the temporal correlation algorithm for PRI modulation recognition and sequence search. It was stated that unilinear, bilinear, sawtooth and sinusoidal PRI modulations can be identified. It was also given that the best detection performance of the algorithm was unilinear PRI modulation.

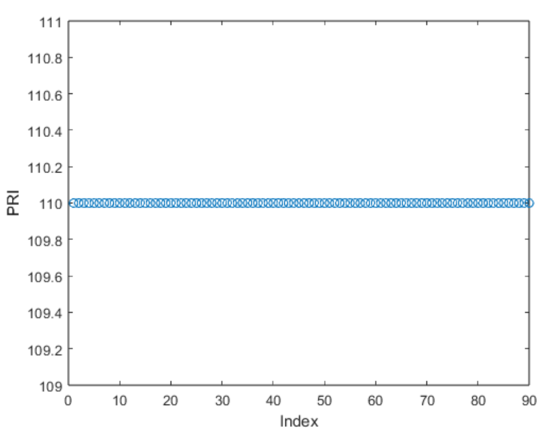
The studies in the literature have mainly grouped as feature extraction-based, histogram-based and neural network-based approaches to find PRIs in radar data. These approaches are generally complex and have high computational time. The sliding window-based studies are mostly proposed as a solution to the problem of multifunctional radar signal structures. The sliding window-based approach presented in this study provides a solution to the identification of classical PRI types of constant, dwell&switch, sliding-up, and sliding-down. The application of this approach on streaming data provides an online and uncomplicated solution to detection of PRI modulation types. Additionally, to the best of our knowledge, sliding window-based approaches are not directly used in PRI type detection in streaming data. For this purpose, a new sliding window-based method for finding PRIs is proposed in this study. This approach uses only the TOA of the radar signal for PRI type detection. The method slides a window on the Difference of TOA (DTOA) values, and then determines the type of PRI by a newly designed rule-based mechanism within the sliding window. The performance of the method is analyzed with synthetically generated simulation data. The experimental results show that the method is effective in detecting 4 different PRI types in radar signals.

The structure of the paper is defined as follows. In Section 2, the types of PRIs are presented, and the proposed methodology is described. In Section 3, properties of the simulation data sets are given and the performance results are discussed. Section 4 provides conclusions and possible future directions.

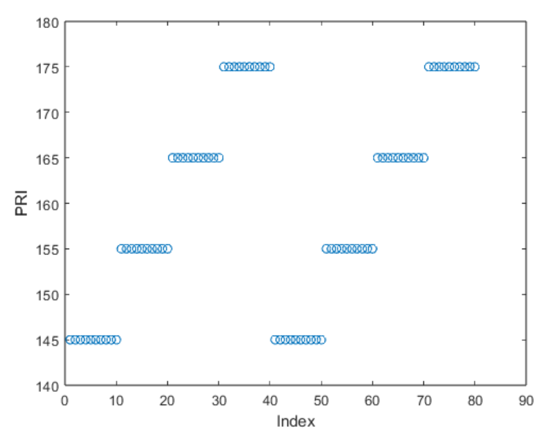
2. Methods

2.1. PRI Types

Four PRI types are used in this study. These are constant, dwell&switch, sliding-up, and sliding-down. For the constant PRI type, the difference between sequential pulses is fixed. So, there is only one PRI value for constant PRI as shown in Figure 1(a). The dwell&switch PRI type is presented in Figure 1(b) and has more than one PRI value. In this type of PRI, the difference between consecutive pulses is the same for a period of time or a certain pulse amount. Then, the difference is changed to another value and the new value remains the same for a period of time or pulse amount. Like the dwell&switch PRI type, the sliding-up PRI type has more than one PRI value and is shown in Figure 1(c). In this PRI type, the difference between consecutive pulses increases and the increase continues until the largest (maximum) value. Then it starts again from the smallest value and continues the same increase until it reaches the largest (maximum) value. The sliding-down PRI type is shown in Figure 1(d) and the pattern of the PRI value changing is the inverse of the sliding-up PRI type.



(a)



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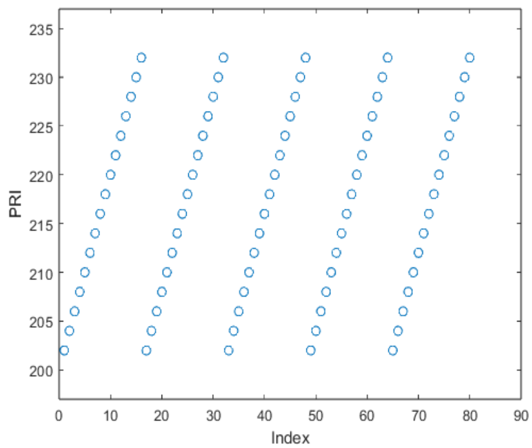
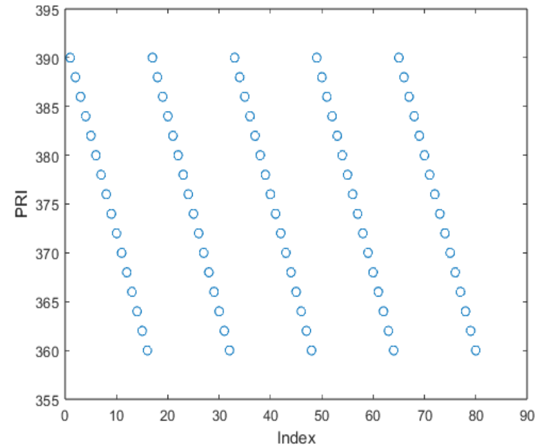


(c)



(d)

Figure 1. PRI Types **(a)** Constant; **(b)** Dwell&switch; **(c)** Sliding-up; **(d)** Sliding-down.

2.2. The Proposed Method

The characteristics of PRIs are changed according to the type of PRI. In the constant type, the PRI value is constant throughout the pulse train. In dwell&switch type, the PRI values change, but this change is not rapid, it occurs at certain intervals (after a certain time or a certain number of pulses). In sliding-up and sliding-down types, PRI values change from pulse to pulse in a continuously increasing and decreasing pattern, respectively. In these two PRI types, the change is on a pulse-by-pulse basis, while in the dwell&switch PRI type, the change is on the basis of a certain number of pulse groups. Therefore, the PRI value change of sliding-up and sliding-down PRI types is faster than the dwell&switch PRI type. Also, in the dwell&switch type, unlike the sliding-up and sliding-down types, the PRI value change need not be in a continuously increasing or decreasing pattern.

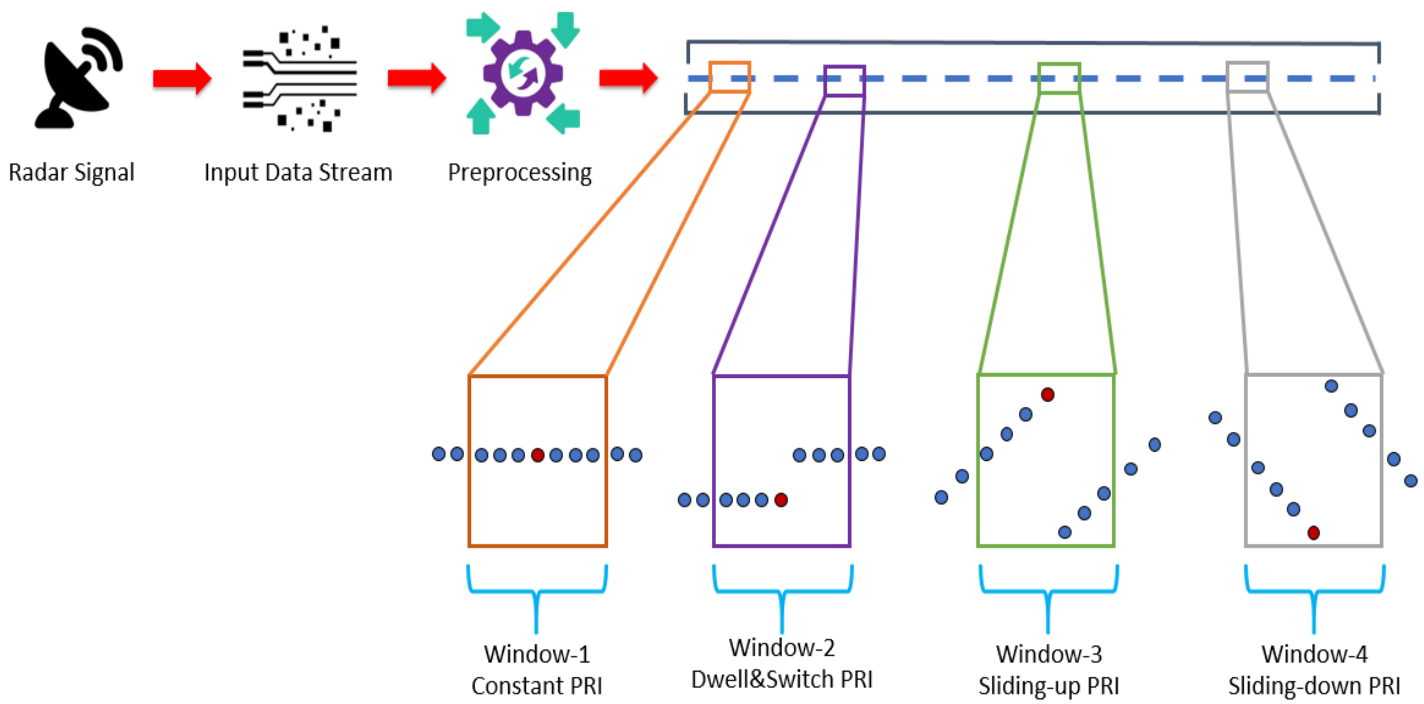


Figure 2. Structure of the Window Based Method.

The characteristic differences of PRI types can be used to discriminate them from each other. Therefore, a new sliding window-based method is proposed that exploits the characteristic differences of PRI types. The overview of the proposed method is briefly described in Figure 2. As can be seen in the Figure 2, the radar signal is received and PDWs of the radar are detected as input data streams. After that, TOA values are taken in the PDWs and the PRI is computed by taking the sequential TOA value differences in the preprocessing step. PRI calculation from the TOA value differences can be defined as

$$PRI(i) = TOA(i) - TOA(i-1) \tag{1}$$

where *i* equals to the sequential pulse index. Therefore, for a sequence of pulses, there is one less PRI value than the number of pulses in the sequence.

An example window of size 7 in Figure 2 is then scrolled over the stream data. All the changes in the window samples are checked.

As can be seen in Figure 2, if there is no change in the all-window samples in, this PRI is called constant PRI. If there is a change in only one window sample and there is no change in all the other window samples, this PRI is called dwell&switch PRI. If there is a decreasing change in only one window sample and all the others are changing in increasing order, this PRI is called sliding-up PRI. If only one window sample has an increasing change and all the others have decreasing changes, this PRI is called sliding-down PRI. Using these characteristic differences, the type of PRI can be determined. Therefore, the proposed method aims to find these features and determine the type of PRI in streaming data using a sliding window-based approach. The algorithm slides the window over the incoming sequential DTOA data. The window size and the amount of sliding must be determined by the operator and the sliding amount should not exceed half the window size. To avoid false detection of PRIs, the minimum window size must be larger than 5 and process at least the next two samples in the streaming data. In this way, the distinction between the PRI types constant and dwell&switch can be classified without reducing the detection rate. Also, if the dwell&switch PRI has a large number of pulses in a dwell, the algorithm can find it as a constant PRI until it detects the change. The proposed online PRI detection method is given in Algorithm 1.

Algorithm 1: Sliding window-based PRI type detection

Input: Read Pulse Descriptor Words (PDWs)
window size, WS, default set to 5
slide amount, SA, default set to 1
Output: Type of PRI
(constant, dwell&switch, sliding-up, and sliding-down)

```
Start the method after data samples ≥ 1.5 × window size
Compute the difference of TOAs (to find PRI)
Compute the differences of consecutive samples (PRI values) in the window
if differences in first window == 0 for all window elements
    Slide the window and compute new window results
    if only one difference ≠ 0 and all the others == 0
        PRI type ← Dwell&Switch
    if all differences in window == 0
        PRI type ← Constant
if differences in first window == 0 for all window elements
        except one element
    PRI type ← Dwell&Switch
if differences in first window ≠ 0 for all window elements then
// check the difference is positive or negative
    if differences in first window > 0 for all window elements
        Slide the window and compute new window results
        if only one change < 0 and all the others > 0
            PRI type ← Sliding-Up
    if differences in first window > 0 for all window elements
            except one element
        PRI type ← Sliding-up
    if differences in first window < 0 for all window elements
        Slide the window and compute new window results
        if only center difference > 0 and all the others < 0
            PRI type ← Sliding-down
        if differences in window < 0 for all window elements
            except one element
            PRI type ← Sliding-down
```

3. Results and Discussion

3.1. Data Set

13 different data sets are generated synthetically to give the performance of the proposed method. The datasets are constructed to contain different variations of the unique features of each PRI type. In this way, more detailed information about the performance of the method can be obtained. The details of the datasets are given in Table 1. The dataset contains different numbers of PRI levels for dwell&switch, sliding-up, and sliding-down PRI types. Also, a different number of dwell pulse numbers is generated for the dwell&switch PRI type. In order to increase dataset diversity, properties of the used PRI types were modified.

Table 1. Dataset Details

Data Sets	PRI Type	Number of PRIs	PRI Values	Dwell count
1	Constant	1	120	-
2	Dwell&switch	2	235-240	16
3	Dwell&switch	4	225-230-235-240	20
4	Dwell&switch	6	262-258-254-250-246-242	14
5	Dwell&switch	8	273-283-293-285-275-269-279-289	12
6	Dwell&switch	12	315-310-305-300-295-290-285-280-275-270-265-260	10
7	Dwell&switch	16	204-210-216-222-228-234-240-246-243-237-231-225-219-213-207-201	8
8	Sliding-Up	10	420-424-428-432-436-440-444-448-452-456	-
9	Sliding-Up	15	431-434-437-440-443-446-449-452-455-458-461-464-467-470-473	-
10	Sliding-Up	20	444-446-448-450-452-454-456-458-460-462-464-466-468-470-472-474-476-478-480-482	-
11	Sliding-Down	10	493-489-485-481-477-473-469-465-461-457	-
12	Sliding-Down	15	462-459-456-453-450-447-444-441-438-435-432-429-426-423-420	-
13	Sliding-Down	20	430-428-426-424-422-420-418-416-414-412-410-408-406-404-402-400-398-396-394-392	-

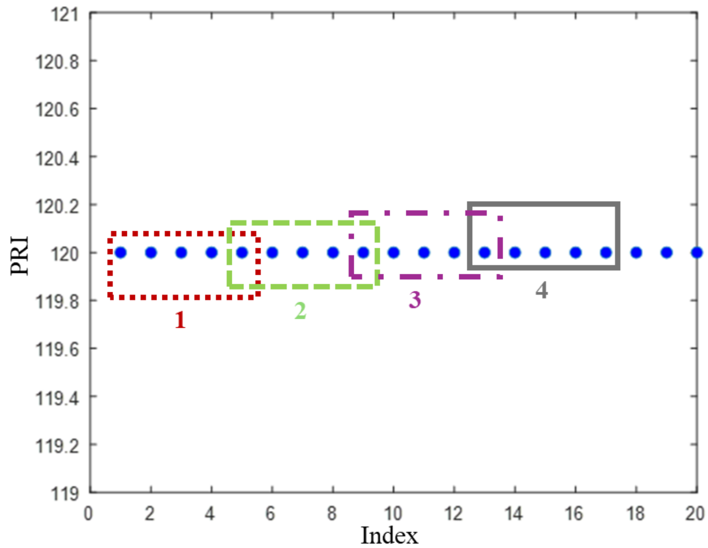
3.2. Experimental Results

The different parameter combinations of PRI modulation types are used to show the performance of the proposed sliding window-based method. The method also gives successive results under the conditions of different window sizes and amounts of slide. Due to page limitations and the similarity of the analyses for the PRI types, a sample data set for each PRI type was selected from the simulation data sets and visualized in Figure 2.

In Figure 2 (a), the performance of the method on the data set 1 is presented. The PRI type of data set 1 is constant and it is successfully detected by the proposed method. In this experiment, window size is selected as 5 and slide amount is 4. It can be observed that window size and slide amount do not have a major influence on the detection of the constant PRI type.

In Figure 2 (b), the result of the data set 2 is presented. The hyperparameters of the method were set to window size 8 and slide size 2. Data set 2 is a PRI type of dwell&switch and is correctly classified according to the result of the method. In the dwell&switch PRI, window size, slide amount and the number of repeated pulses in a dwell directly affect the recognition type and recognition time. For example, if the number of repeated pulses in a dwell is 5 times larger than the window size and the sliding amount is low, it will take longer to decide on the correct PRI type. In such a case, the PRI type is founded as a constant PRI at first. After a sufficient amount of data has been received, the PRI type is detected as a dwell&switch PRI. Therefore, in cases where the dwell count value is too high, the window size and scrolling amount are low (not enough), it takes longer time to find the dwell&switch PRI type.

In Figure 2 (c), the identification of data set 9 is shown. Data set 9 is a sliding-up PRI type and it is identified precisely. For this data, a window size of 6 and a shift amount of 3 are chosen. PRI type detection result of the method on data set 13 is given in Figure 2 (d). The chosen window size is 7 and the slide amount is 4 for this data set. The sliding-down PRI type is determined by the method. Moreover, the sliding-up and sliding-down PRI types can be easily detected by the presented method compared to other PRI types regardless of window size and slide amount.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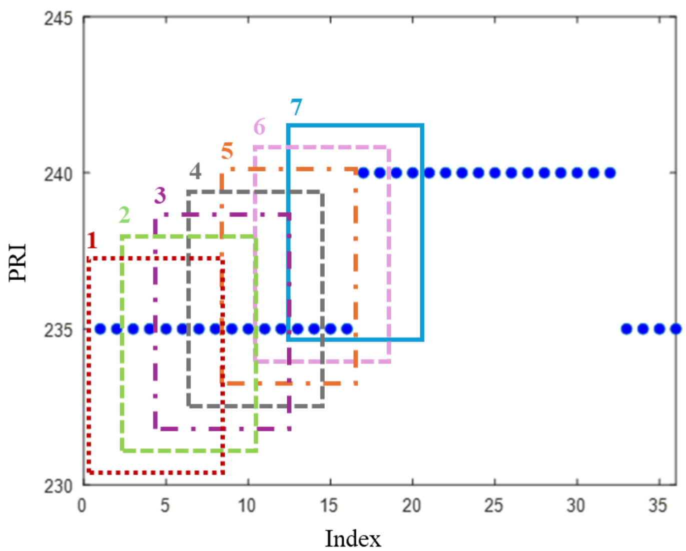
(a)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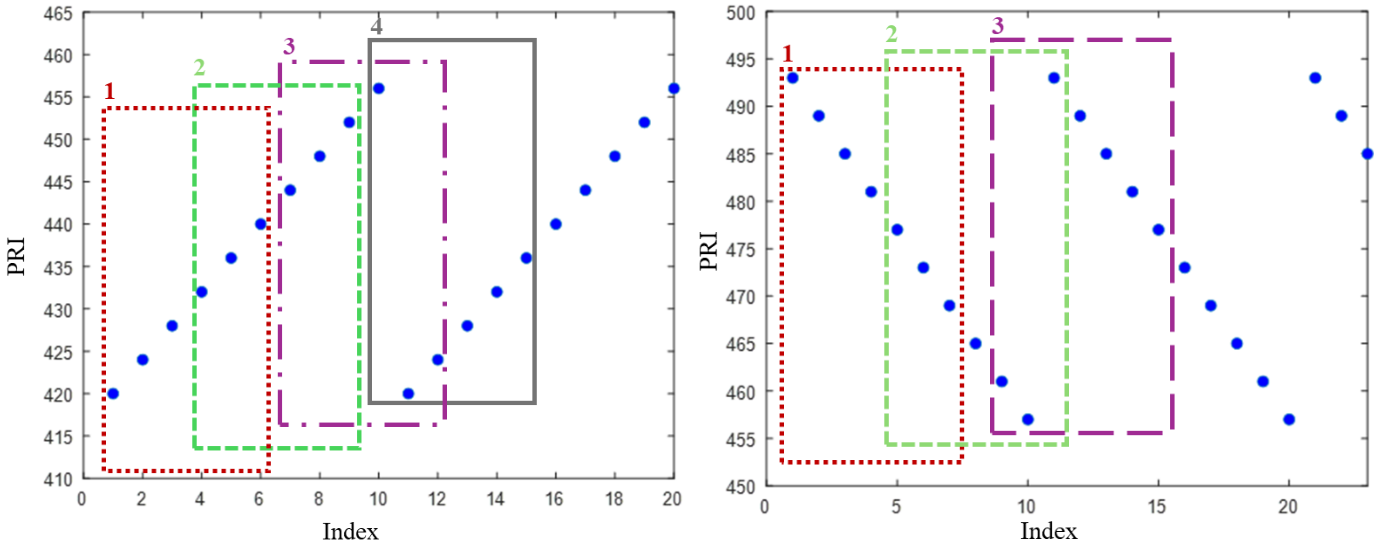
(b)



(c) (d)

Figure 2. Method results of dataset signals for different window size and sliding amounts **(a)** Signal-1 for window size 5, sliding amount 4; **(b)** Signal-2 for window size 8, sliding amount 2; **(c)** Signal-9 for window size 6, sliding amount 3; **(d)** Signal-13 for window size 7, sliding amount 4

4. Conclusion

In this work, a new method is presented to recognize the PRI modulation types in streaming data. These PRI modulation types are constant, dwell&switch, sliding-up, and sliding-down. The proposed method is sliding window-based PRI type recognition. The window size and slide amount of the window is getting from the user. Then, the PDWs of the active radar are read and differences of the sequential TOA parameters of the PDWs are calculated to find PRI values. Next, the window is sliding the PRI values of the streaming data. According to the characteristic differences of the signals in the windows, the PRI type is recognized. Based on the experiments in 13 different data sets, all the PRI types are correctly identified in streaming data. Moreover, based on the experiments, if the waiting time of the dwell&switch PRI type is long, depending on the window size and the amount of sliding, the PRI type of the data can be defined as constant until this time is completed and the switching is detected. There may be ambiguities between constant and dwell&switch PRI types under some conditions and it may take time to resolve the ambiguity. Hence, it can be concluded that sliding-up and sliding-down PRI types can be detected faster than constant and dwell&switch PRI types.

The proposed method is evaluated for different features of PRI types. For dwell&switch PRI type, different dwell counts, and different PRI levels are tested. The different PRI levels and different PRI change values are also examined for sliding-up and sliding-down PRI types. Although the method gives sufficient performance in experiments, it is also open to improvement in the detection of PRI types other than those used.

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