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Specific emitter identification based on graphical representation of the distribution of radar signal parameters

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Abstract. The article presents some possibilities of same type radar copies identification with the use of graphical representation. The procedure described by the authors is based on transformation and analysis of basic parameters distribution which are measured by the radar signal especially Pulse Repetition Interval. A radar intercept receiver passively collects incoming pulse samples from a number of unknown emitters. Information such as Pulse Repetition Interval, Angle of Arrival, Pulse Width, Radio Frequency and Doppler shifts are not usable. The most important objectives are to determine the number of emitters present and classify incoming pulses according to emitters. To classify radar emitters and precisely identification the copy of the same type of an emitter source in surrounding environment, we need to explore the detailed structure i.e. intra-pulse information, unintentional radiated electromagnetic emission and fractal features of a radar signal. An emitter has its own signal structure. This part of radar signal analysis is called Specific Emitter Identification. Utilization of some specific properties of electronic devices can cause heightening probability of a correct identification.

Key words: Specific Emitter Identification (SEI), radar recognition, ELINT system, Electronics Warfare System (EWS).

1. Introduction

Recently there has been a rapid development in Electronic Warfare Systems (EWS). There are different methods of electromagnetic environment observation which are used to analyse targets' signatures. These methods increase the quality of algorithms which recognize objects and targets automatically. A difference can be found in the ways of gaining distinctive information. Measurement and Signature Intelligence (MASINT) plays a significant role here [1]. MASINT serves to detect, track, identify and describe the distinctive characteristics of emission sources. Distinctive features of radioelectronic devices in the form of unintentional radiated electromagnetic emission are becoming an important element in the process of recognition and identification [2]. Experts and specialists in recognition and EWS are very interested in the process of creating DataBases (DB). For the time being databases are basic elements of electronic identification and recognition system. In the process of designing a DataBase for Electronic Intelligence (ELINT) system Entity Relational Modelling is used [2, 3]. In order to meet the needs of advanced tactical and technical requirements the recognition system should gain information from the whole scope of electromagnetic spectrum. This system should also use Artificial Intelligence (AI) which should be implemented during such a system design.

Analysis and processing of distinctive information in advanced systems of recognition and identification includes following procedures:

- analysis of signal parameters measures in a thick electromagnetic environment (about thousands or more pulses/s);
- automatic emission sources identification (by comparing signal parameters from a DataBase) in shortest period possible;
- selection procedures and reduction of stream of measured data;
- statistic functions to calculate for instance, average value of parameters, patterns of classes and verification of hypothesis;
- procedures of pulses deinterleaving in case of simultaneous signal from many emitters;
- use of specific knowledge of experts in the process of identification and location of emitters for complicated measurement case or detection of still unknown signals;
- updating procedures and DataBase modification;
- simulation software to generate warfare scenario and examine the procedures of deinterleaving and localization emitter sources.

2. Sampling procedure and structure of basic vector parameters

The radar signal acquisition with the use of ELINT system enables to receive the measurable data structure which is presented in Eq. (1). In the first stage that what is received is Pulse Data Matrix (PDM). This matrix consists of information gained usually from the signal processor card. In the process of measurement there can be other device which specializes in receiving radar signal. This PDM includes following data fields: ordinal number of pulses – L_p, amplitude of pulses – A and value of Radio Frequency – RF. During the process of preliminary signal processing of Pulse Data Matrix – Pulse

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Description Word (PDW) vector is defined. This PDW vector is a formalized structure of record type, where particular fields consist of frequency parameters and time parameters for radar signal according to the following Eq. (1), where $No(k)$ – is number of k-pulse, $T_{OA}(k)$ – is time of incoming k-pulse into [μs], $A(k)$ – is amplitude of k-pulse, $\mathrm{PW}(k)$ – is Pulse Width of k-pulse in [μs], $\mathrm{PRI}(k)$ – is Pulse Repetition Interval of k-pulse into [μs]; $\mathrm{RF}(k)$ – is Radio Frequency of k-pulse in [MHz], $\Delta\mathrm{RF}(k)$ – is Radio Frequency deviation of k-pulse in [MHz], where n – is quantity of pulses in the sample those qualified for analysis and k – is number of pulse in sample

$$\mathrm{PDW} = \begin{bmatrix} No(1) & T_{OA}(1) & A(1) & \mathrm{PW}(1) & \mathrm{PRI}(1) & \mathrm{RF}(1) & \Delta\mathrm{RF}(1) \\ No(2) & T_{OA}(2) & A(2) & \mathrm{PW}(2) & \mathrm{PRI}(2) & \mathrm{RF}(2) & \Delta\mathrm{RF}(2) \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ No(k) & T_{OA}(k) & A(k) & \mathrm{PW}(k) & \mathrm{PRI}(k) & \mathrm{RF}(k) & \Delta\mathrm{RF}(k) \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ No(n) & T_{OA}(n) & A(n) & \mathrm{PW}(n) & \mathrm{PRI}(n) & \mathrm{RF}(n) & \Delta\mathrm{RF}(n) \end{bmatrix}. \tag{1}$$

A process of emitter identification which is not advanced, is based on the use of basic properties of measurable radar signals parameters (PDW vector). In such case it is possible to identify the types of emitter sources, but identification of a copy is almost impossible. The approach to identification presented above has been described many times in literature. If one of the requirements of ELINT system is emitter identification it means that what should be done is the identification of particular copies of these emitter sources. In this case additional methods should be used in order to use advanced DataBases, AI, Neural Networks (NNs) and what is the most important, Specific Emitter Identification (SEI) which are based on intra-pulses analysis, unintentional radiated electromagnetic emission and extraction of fractal features of emitters [4–7].

3. Methods of data clustering in SEI aspect

The method of Specific Emitter Identification is based on extraction of distinctive features and further on the analysis and pattern recognition [8, 9]. In the process of signal acquisition there is too much information. These are often redundant characterized by much too entropy and with no connection with the aim of classification. In such situation what is necessary is the process of features reduction and selection and one more, the use of methods which scale multidimensionally [10, 11]. Also, there are different ways of data clustering in SEI method. These are based on specific data clustering algorithms which can be classified as follows:

- Algorithms searching for global extremum of a function, usually not used as it causes a lot of calculations. Calculations result from the fact that for space V with cardinality of n it is possible to define

$$\frac{1}{L!}\sum_{k=1}^{L}\binom{L}{k}(-1)^{L-k}k^{n} \tag{2}$$

  partitions of L sets;
- As Basic Grouping C-Means Algorithms are based on moving elements they improve criterion function [12]. The disadvantage of this algorithm is great dependence of classification results on initial partition;
- Hierarchical data clustering algorithms (based on top-down and bottom-up procedure);
- Algorithms based on graph theory among which the Nearest Neighbour algorithm (NNa), Mean Minimum Distance algorithm (MMDa), k-Nearest Neighbours' algorithm (kNNa) and Minimum Spanning Tree' algorithm (MSTa) can be differentiated [13];
- Algorithms which use fuzzy sets providing pseudo-disjoint family of fuzzy subsets [12]. Feature Space Mapping models (FSM) combine possibilities of fuzzy logical systems with neural networks algorithms. Both algorithms are dedicated to classification problems. Methods based on histograms and dendrograms are used in order to initiate FSM networks.

4. PRI histogram structure in research procedure

In the procedure of creating a histogram a particular dimension is divided into k intervals (usually presented on X-axis). In each interval the number of vectors is estimated (usually presented on Y-axis). Every interval can be connected with the nearest intervals making in that way a cluster in one dimensional space. If there are several clusters they need to be separated by empty intervals. Assuming that a cluster starts from i- of this interval and covers l intervals, each with s width. As a result position and size of cluster in original space can be presented with following equations (3)–(5)

$$C_x = X_{\min} + s \cdot \left(i + \frac{1}{2}\right), \tag{3}$$

$$\sigma_x = \frac{1}{2} l s, \tag{4}$$

$$s = \frac{|X_{\max} - X_{\min}|}{k}. \tag{5}$$

Each of one-dimensional clusters can be projected onto a lot of disjointed N dimensional clusters. During initialization vectors are analyzed independently in every dimension. In the first dimension a particular vector can belong to C_1^i cluster, and in the second dimension to C_2^j cluster, and finally in N-dimension it can belong to C_N^l cluster. Each N-dimensional cluster can be presented as a chain of clusters $C_1^i \to C_2^j \to \dots \to C_N^l$ with lower size. In that way a decision tree learning appears. In the leaves of the tree there are vectors belonging to N-dimensional cluster which are estimated. If in any dimension the number of clusters is too high then the dimension k is reduced which causes reduction in the number of each dimension. Clusters among which the distance is smaller than it should be are joined into one. In the research procedure next values of Pulse Repetition Interval i.e. $\mathrm{PRI}(1), \mathrm{PRI}(2), ..., \mathrm{PRI}(k), ..., \mathrm{PRI}(n-1)$ are treated as n-dimensional random variable of PRI. By choosing from set of samples distinctive value of PRI_w^l and acceptable interval of variability of PRI (determined by the resolution of ELINT device) – ΔPRI, collection of $\mathrm{PRI}_s^l \in \left\langle \mathrm{PRI}_w^l - \Delta\mathrm{PRI};\ \mathrm{PRI}_w^l + \Delta\mathrm{PRI} \right\rangle$ values was created. As a result of repetition of operation l – times, what was received a state of designated values (in the presented case $l = 7$). According to the description above, expected values received by histogram method are as follows: equation (6), where l is total number of disjoint categories (bins) and s_w is total number of observations that fall into each of disjoint categories resulting from the Holdout Method used [14, 15]

$$\mathrm{PRI}_{s_w}^{l\ \mathrm{MH}} = \mathrm{PRI}_l^{\mathrm{MH}} = \frac{1}{s_{w_l}} \sum_{j=1}^{s_{w_l}} \mathrm{PRI}_j^l. \tag{6}$$

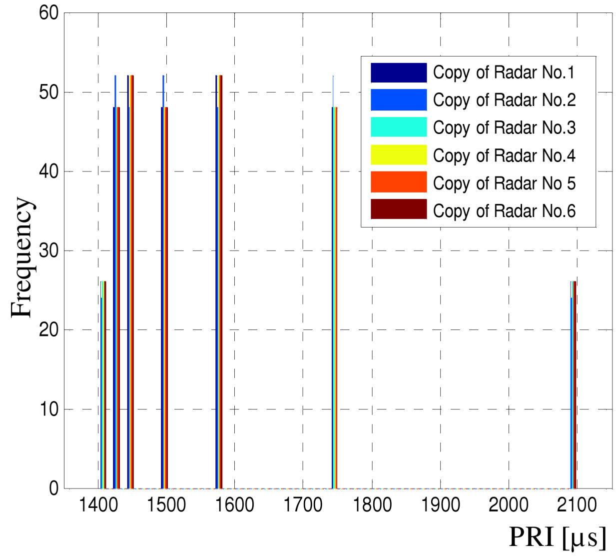

Fig. 1. PRI histogram for six copies of the same type of radars marked by colours

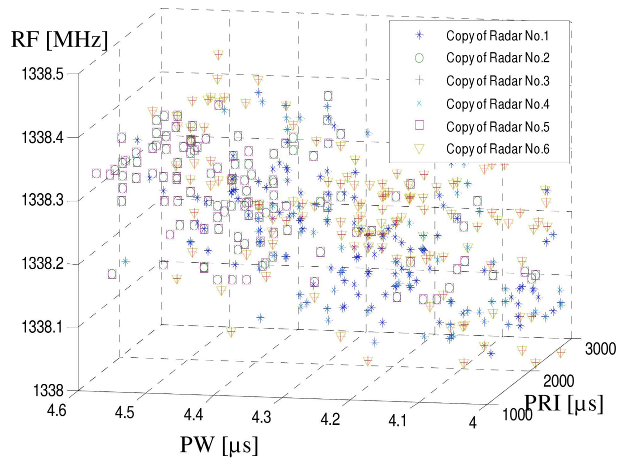

Fig. 2. 3-D graphic depicting of PW, PRI and RF for six copies of the same type of radars

5. Results of received signals analysis – procedure of copies identification

During the research procedure 246 radar emission samples were analyzed. These were from six radar copies of the same type. The sets of samples of PDW were presented in the form of a graph which consisted of basic values of measurable parameters i.e. RF, PW and PRI in Figs. 1, 2. Figure 1 presents PRI histogram of all six examined copies of radars in combined depicting. Figure 2 presents a 3-D graph of RF, PRI and PW parameters of six copies also in combined depicting. A superheterodyne ELINT receiver was used in the measure procedure. This receiver makes it possible to define value of Radio Frequency with measurement accuracy 0.5 MHz and value of Pulse Repetition Interval in the scope from 2 μs to 20 ms, with measurement accuracy 0.05 μs.

The classical ELINT system classifies received samples of PDW (Figs. 1, 2) as the same type. Differentiation of particular radar copies is not accomplished. Data clustering as well as a basic histogram method make it impossible to identify them as there is too much penetration of PW, PRI and RF parameters. In such cases possibility of correct identification of a copy is defined only. What needs to be emphasized is that resolution of RF in Fig. 2 is higher than resolution possibilities of an ELINT receiver which records PDW signal. Thus, in classical ELINT systems in the process of immediate online recognition, the identification of a radar copy is impossible. Also, in the DataBase (supporting recognition process) a single record appears which describes all 6 radar copies in the same way – as emitter sources of the same type. The presented approach is of course correct if the ELINT system has to identify types only. It is an example of classical identification. However, in many cases such approach is not enough. As it is mentioned in the introduction of this article, much more advanced analysis is required from advanced recognition and identification systems. Such analysis should be able to identify copies of the same type.

To identify these emitter sources (which means differentiate each of six copies) SEI methods need to be used. The introductory histogram analysis shows that the examined radar has seven values of PRI, which is presented in Fig. 1. Particular colours show PRI values for each of six radar copies. Figures 3, 5 and 7 present PRI histograms for three randomly chosen copies i.e. copies No. 1, 3 and 5. The difference is only in the quantity of pulses in measured samples. Still the process of distinctive features extraction and copy identification is impossible. To achieve the goal, the analysis of regularity of PRI for chosen radar copies was done. In order to do this, the procedure was implemented in the MatLab environment. Such procedure makes it possible to analyze the regularity of PRI in 3-D space. Graphs are received by the use of 'mesh' function in MatLab. Thus, it is possible to receive a spatial net which presents regularity of PRI period in three dimensions. The results are presented in Figs. 4, 6 and 8. It can be easily noticed that there are deformations in

PRI regularity from copy of radar No. 1. These are marked by a red arrow (Fig. 4). As irregularity exists in PRI sample it is possible that they reveal specific features of a radar. The process of their detection provides explicit identification of a radar copy. What is gained, is a feature which identifies explicitly the copy No. 1 of this radar.

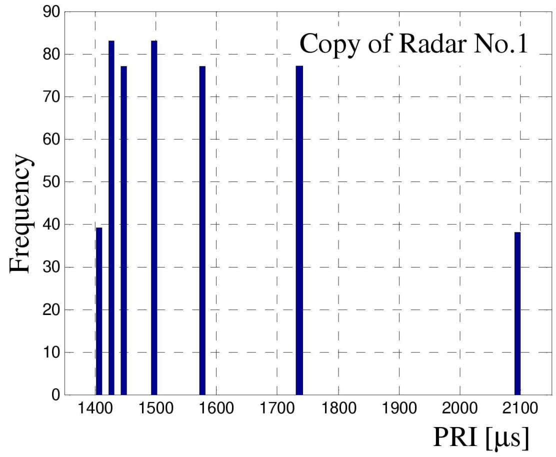

Fig. 3. PRI histogram for selected Copy of Radar No. 1

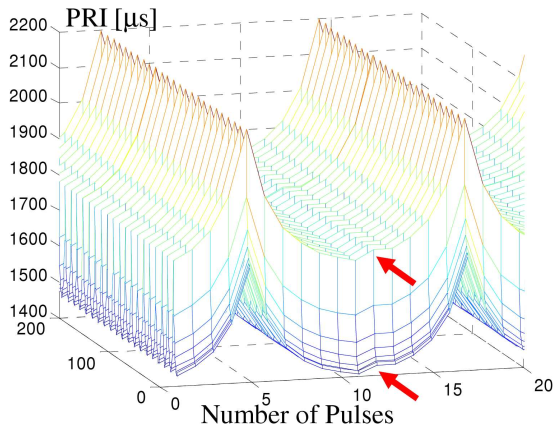

Fig. 4. 3-D graphic depicting of PRI for selected Copy of Radar No. 1 – example of distortion

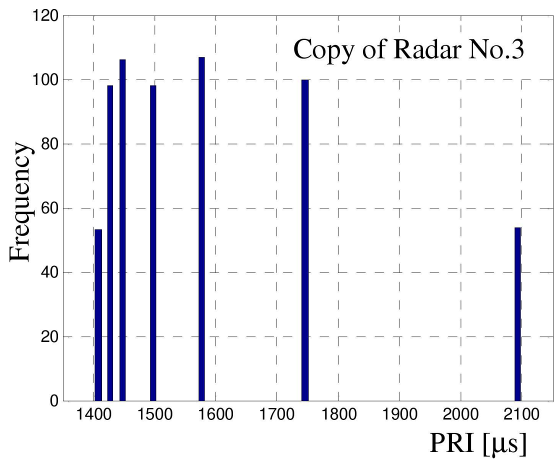

Fig. 5. PRI histogram for selected Copy of Radar No. 3

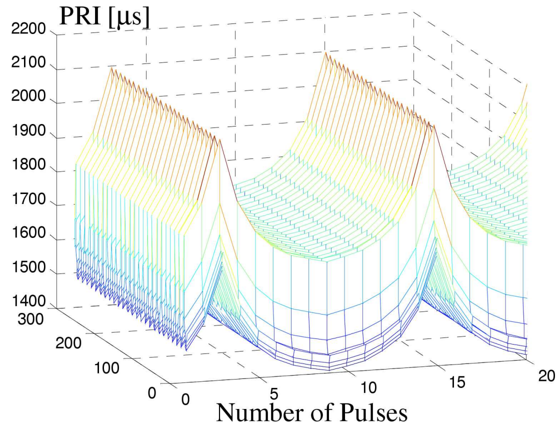

Fig. 6. 3-D graphic depicting of PRI for selected Copy of Radar No. 3

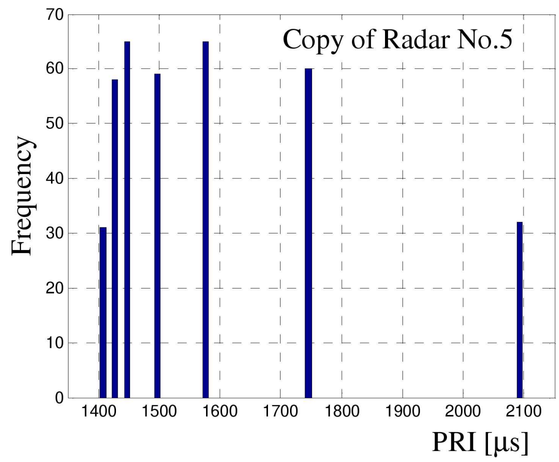

Fig. 7. PRI histogram for selected Copy of Radar No. 5

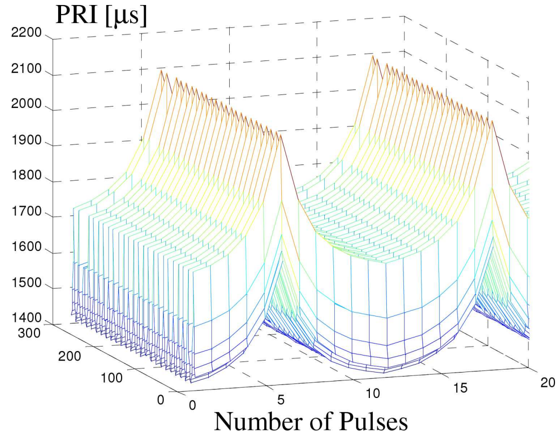

Fig. 8. 3-D graphic depicting of PRI for selected Copy of Radar No. 5

As a result of this analysis PRI deformation can be treated as a distinctive feature of a radar copy. Moreover, a separate record in the database can be created.

In Fig. 9 a graph of PRI in functions of next pulses numbers is depicted. A red arrow presents PRI distortions which are detected. Figure 10 presents the whole series of PRI of analyzed radar signal with a precise definition of time dura-

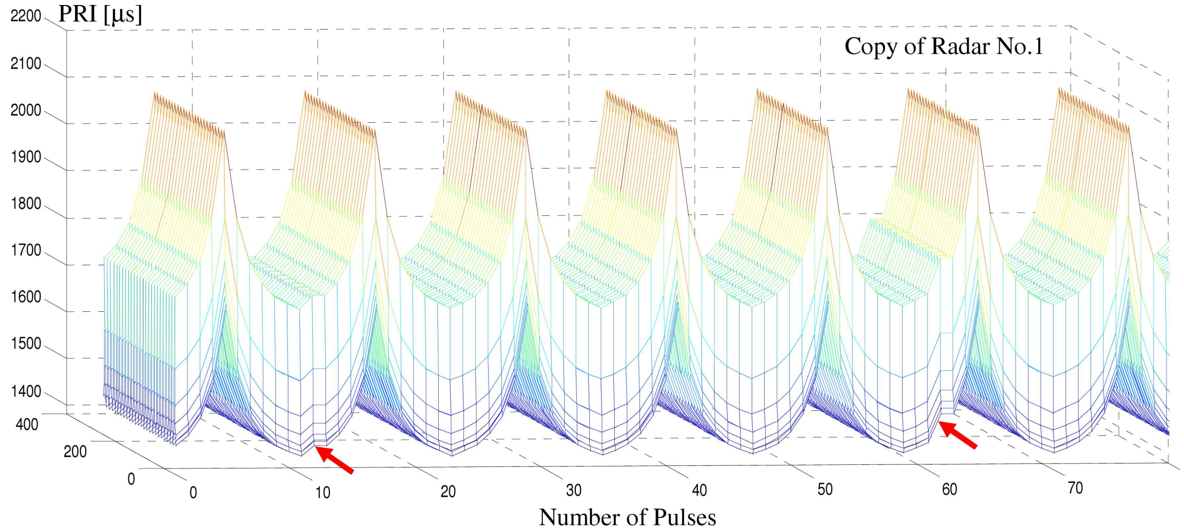

Fig. 9. 3-D graphic depicting of several cycles of PRI for selected Copy of Radar No. 1

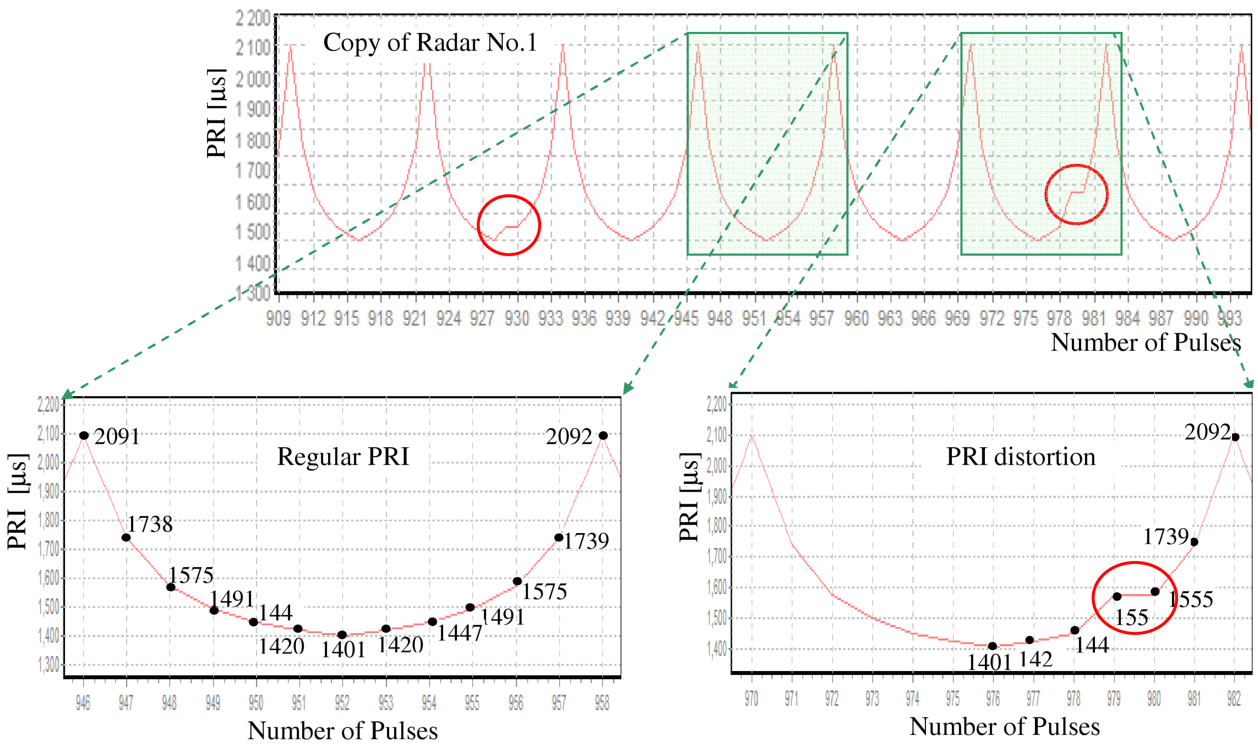

Fig. 10. Depicting of complete series of PRI – an example of PRI distortions

tion of PRI. This figure presents a red circle which shows distortions in PRI sample. Time resolution of Fig. 9 is much higher than the precision of PRI measurement as it is ensured by superheterodyne receiver used in ELINT system.

6. Conclusions

One of the conditions which can assure effectiveness of a radioelectronic identification system is to increase probability of correct identification of an emission source. Identification means recognizing radar copies of the same type. The task is not trivial and requires using expert systems, artificial intelligence, advanced DataBases and above all, SEI methods in the process of radars identification. The authors of this article took on this task in order to identify several copies of the same type of radar, which is much more difficult than type classification. The research was carried out on the basis of hundreds of PDW samples done by ELINT receiver. A graphical representation of the distribution of radar signal parameters and advanced PRI regularity analysis are used in the process of SEI. For the purpose analysis procedures in the MatLab environment and a software are implemented. Thus, graphic depicting and results of this analysis are received. The process of creating measurement vectors, calculation distances between classes, definition of the coefficient of correct identification and the use of classification criteria are not the main problem of this article so their precise description is in works [14–16]. The result of this research are distortions in PRI for a chosen radar copy. Extraction of PRI distortion feature is an offline activity and further efforts of researchers should go toward automatization of feature detection process and online analysis which should be implemented in Electronics Intelligence and Warfare system. In further research the authors of this article intend to create synergy of these SEI analyses worked out so far, because there is a strong premise that through simultaneous use of fractal features of radar signals [17, 18], methods of hierarchical data clustering and graphical representation of distribution it is possible to increase probability to identify correctly radar copies of the same type.

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