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Specific Emitter Identification Based on Amplitude Features

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***Abstract* — This paper describe the Specific Emitter Identification (SEI) technique applied to Electronic Support Measure (ESM) systems. The main idea is to analyze the radar pulses and characterize those by extracting features that should be different for each radar.**
In the paper, A-UMOP (Amplitude Unintentional Modulation On Pulse) feature extraction algorithms are proposed and used to characterize the radar pulses: a measurement campaign has been conducted to acquire real radar pulses from different radar modes and radar signals, to confirm the applicability of the proposed features extraction techniques with respect to the different radar setup.

***Key-Words* — Specific Emitter Identification, Unwanted Modulation On Pulse, Fingerprinting.**

I. INTRODUCTION

Electronic Support Measure (ESM) sensors [1]-[3] are largely employed for emitter detection, classification and identification purposes.

Classical radar systems perform classification and/or identification functions using target RCS measures or scattering distribution range profile extraction as in High Range Resolution (HRR) radars [4]-[6].

However using of ESM sensors offers great advantages with respect to the employment of traditional radar systems:

- the lower cost of passive ESM sensors with respect to classic radar, due to the receive only architecture;
- the un-detectability of the system, thanks to the passive based detection strategy;
- the higher detection range obtainable by exploiting the one way signal attenuation, i.e. Range Advance Factor (RAF);
- the all time and all weather capabilities, due to the intrinsic higher robustness to the sea-state (sea clutter) and rain (volumetric clutter), with respect to classical radar systems.

Classical ESM systems are able to measure a large set of radar signal parameters: frequency, Pulse Repetition Interval (PRI), Pulse Width (PW), Phase Modulation On Pulse (PMOP) like chirp, barker codes etc. [7]-[9]. The possibility to digitally measure [10] such parameters gives to the ESM systems the opportunity to resolve targets, exploiting data processing techniques such as deinterleaving [11]-[13]; moreover there is also the possibility to identify targets on the basis of the classical waveform parameters, by means of a-priori information, stored in the emitter library [14].

However, in most cases the traditional ESM systems cannot identify, in unique way, different devices of the same type or class. On the other hand this challenging task is addressed by the Specific Emitter Identification (SEI) methodology and techniques [15]-[16]. The basic idea is to collect the waveform from an emitter and then process the pulses to extract unique quantities. These quantities refer to different waveform features and should be different for each radar emitter. Those features typically includes intra-pulse features like Amplitude Unintentional Modulation On Pulse (A-UMOP), Phase Unintentional Modulation On Pulse (P-UMOP) [17] or other signal characteristics that could be specific for a given emitter. For example in [17]-[18] the P-UMOP feature of the received signal is exploited: a second order Power Spectral Density (PSD) function is evaluated (Bi-Spectrum) and further processed for feature extraction, leading to satisfactory results for simulated data. Other features of the real radar systems that can be exploit to identify in a unique way an emitter includes the non-linear distortions of the power amplifier [19]. In [20]-[21] the authors rely on Scaled Conjugate Gradient and M-estimation algorithms to improved the frequency alignment of the pulses. This technique is compared with the maximum likelihood estimation. In papers [22]-[24] is provided an overview of methods of identification emitter sources based on regression analysis: a formal mathematical approach is used in order to extract, select and classify radar signal features. In [25] feature extraction algorithms tested on real radar data, showing that if an emitter changes mode, also the features will change values: the comparison between two similar emitters has to be performed comparing the same radar mode (for example same frequency mode). Techniques like Resemble coefficient extraction and Support Vector Machine have been used in open literature [26] showing the ability to discriminate between emitters with different signal MOP. In this paper real radar signals have been acquired to apply some feature extraction algorithmic procedures on live radar data. The analyses have been conducted on different radar modes and different emitter to verify the robustness of the features extraction algorithm with respect to different case studies. The paper is organized as follows: in Section II is presented the SEI processing scheme, while Section III reports the algorithm used for the features extraction; section IV shows the obtained results on real data. Finally, in Section V some conclusions and future research tracks are given.

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II. SEI PROCESSING

In this paper we focus on the characteristics of the single radar pulse: we assume that a radar emits a pulse train with a certain number of pulses that can be characterized by the classical radar waveform parameters (carrier frequency, PW, PRI, MOP, Amplitude etc.).

Once the waveform has been detected and the classic parameters have been estimated (see Fig. 1), the Emitter Deinterleaving based on Classical Parameters will allow the extraction of the emitter track: the waveform is characterized in terms of carrier frequency, PW, PRI, MOP, and so on. The Un-identified Emitter Track is the input to the Classical Emitter Identification process. In the case of available a-priori knowledge (i.e. data stored into the Classical Emitter Library), the emitter identification process associates the extracted track to a known emitter.

The output of the Classical Emitter Identification functional block is an Identified Emitter Track, which designates the SEI processing.

The SEI Automatic Feature Estimation block (see Fig. 1), is a set of rules that real-time implements the features estimation algorithms. Some of those algorithms are described in the next section.

The extracted features, related to a specific radar waveform, provide further information and details on such emitter. The Identified Emitter track with the Extracted Features is the input of the SEI Identification Algorithms: with the aid of a-priori data stored into the SEI Emitter Library, the SEI processing identify the track in the case the specific emitter is already present into the library

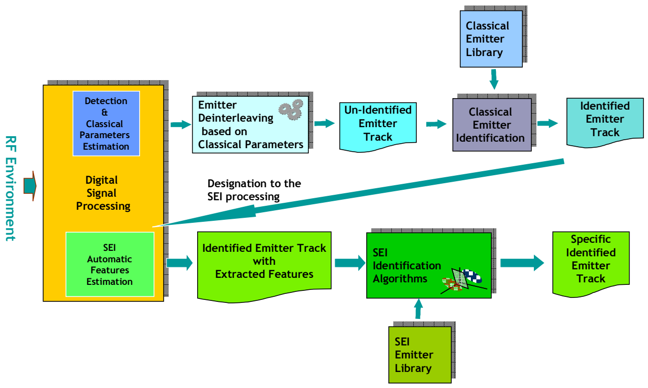

Fig. 1. Block diagram of the classical and SEI processing.

III. ALGORITHM FOR A-UMOP FEATURES EXTRACTION

The SEI Automatic Feature Extraction block implements several algorithms, related to the different signal characteristics. The algorithms include both A-UMOP as well as P-UMOP extraction. In this Section we describe some of the algorithm dedicated to the A-UMOP Features Extraction (Fig. 2). The input is a single radar pulse assumed to be

$$x(t) = [A + \Delta A(t)]e^{j[2\pi f_0 t + \vartheta(t) + \Delta\vartheta(t)]} \quad t \in [t_0, t_0 + PW] \qquad (1)$$

where t_0 represent the pulse start time, A represents the signal amplitude, f_0 the radar carrier frequency, $\vartheta(t)$ the PMOP (for example barker, chirp, poly-phase, etc.), $\Delta A(t)$ and $\Delta\vartheta(t)$ represent respectively the A-UMOP and P-UMOP. The aim is to provide a characterization of $\Delta A(t)$ and $\Delta\vartheta(t)$ by the use of adequate algorithmic procedures. More precisely in this paper we will focus on the characterization of $\Delta A(t)$.

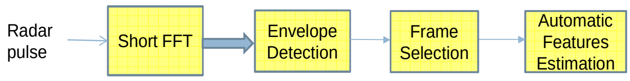

Fig. 2. Block diagram of the Algorithm for A-UMOP Features Extraction.

The first step in the signal processing is to apply a Short Time Discrete Fourier Transform (STDFT), in order to estimate the carrier of the signal, and track its changes over time:

$$STDFT[p,k] = \sum_n x[n]g^*[n-p]e^{-j\frac{2\pi kn}{N}} \qquad (2)$$

where

- n represents the index related to the sampled time instant tn;
- N represents the STDFT length in terms of sample number;
- p represent the index of the output time frame;
- k represents the index of the frequency;
- x[n] represents the signal sampled at the time instant;
- g[n] represents the windowing function;
- represents the complex conjugate operator.

An example of the output of the STDFT is provided in Fig. 3, where a radar pulse with a PW equal to 2.6us and a IF frequency after down-conversion of 710MHz has been considered.

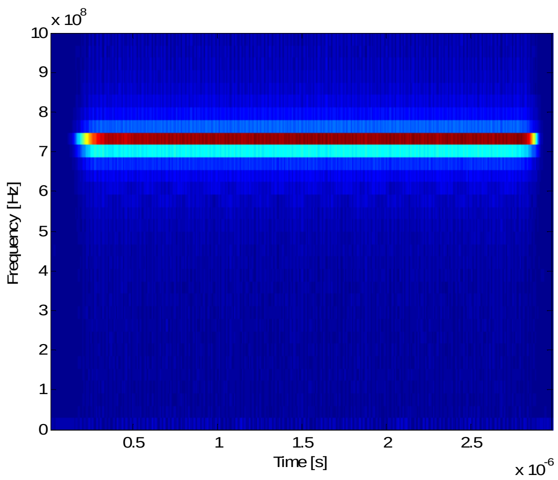

Fig. 3 STDFT of a radar pulse.

The output of the STDFT is then properly analyzed in order to select the time/frequency areas that contain the useful signal components.

In this way is possible to extract and digital down convert the useful signal, that can be represented by the following model

$$y(t_m) = [A + \Delta A(t_m)] \cdot e^{j[2\pi\Delta f\, t_m + \vartheta(t_m) + \Delta\vartheta(t_m)]} \quad (3)$$

where

- y(tm) represents the useful signal sampled at the time instant tm;
- A represents the nominal amplitude;
- ΔA(tm) represents the A-UMOP;
- Δf represents the offset between the pulse IF frequency and the frequency after the digital down conversion.;
- $\vartheta(t_m)$ represents the PMOP (for example barker, chirp, poly-phase, etc.)
- $\Delta\vartheta(t_m)$ represents the P-UMOP.

It can be observed that the terms $\Delta A(t_m)$ and $\Delta\vartheta(t_m)$ contain the information useful for the SEI process, and the rate (tm- tm-1) of the UMOP data (that depends on the adopted digital down-conversion algorithm) has to be consistent with the expected bandwidth of the UMOP information.

Let assume for sake of simplicity that the pulse is un-modulated, i.e. $\vartheta(t_m) = \Delta\theta_0$, that represents the phase offset: it is possible to estimate the linear shape of the phase that is equal to

$$\angle\hat{y}(t_m) = 2\pi\Delta f\, t_m + \Delta\theta_0 \quad (4)$$

After this estimation, proper phase compensation is applied to the signal, obtaining by doing so

$$z(t_m) = y(t_m) \cdot e^{-j\angle\hat{y}(t_m)} \cong [A + \Delta A(t_m)] \cdot e^{j\Delta\vartheta(t_m)} \quad (5)$$

that contains both A-UMOP and P-UMOP.

In the following part of the paper we will focus on the characterization of the A-UMOP.

For example, in Fig. 4 is reported $|z(t_m)|$ for the same pulse of Fig. 3, where is possible to note that the amplitude shape exhibits some differences with respect to the nominal rectangular shape.

In particular is convenient to define four fundamental frames inside the signal duration (Fig. 5), in order to extract A-UMOP related to different characteristics:

- Rise time frame: it refers to the power transition from the noise floor to the maximum amplitude;
- Transitory time frame: is the interval after the rise time frame where the amplitude of the signal is not yet constant around the nominal amplitude value A;
- Constant amplitude time frame: where the amplitude of the signal is almost constant around the nominal value;
- Fall down time frame: it refers to the power transition from the nominal amplitude to the noise floor level.

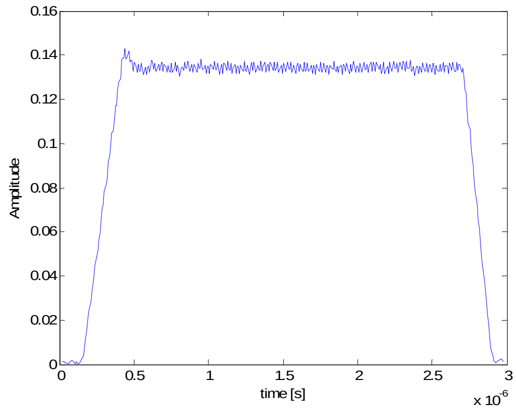

Fig. 4 Envelope of the phase compensated radar pulse.

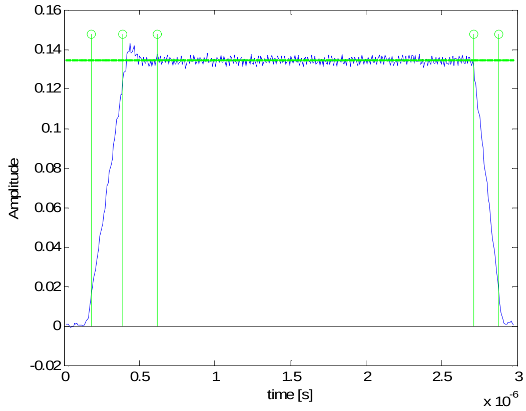

Fig. 5 Frame selection of envelope.

This approach allows extracting a certain number of features for each time frame. In the following of the paper we will focus on typical characteristics already used in open literature [22]-[24], such as

- Rise time duration, denoted as t_{rise}
- Rise time slope, α_{rise}
- Overshoot, denoted as R_{over}
- Fall time duration, denoted as t_{fall}
- Fall time slope, denoted as α_{fall}

Those features will be extracted for each pulse with proper algorithms and will be represented over a 3-D space.

IV. RESULTS ON REAL SIGNAL DATA

To analyze the depicted SEI processing, a measurements campaign has been performed at Elettronica S.p.A. facilities. Two emitters of the same typology and with identical classical parameters have been properly down converted and captured and stored using a 8 bit Analog to Digital Converter with sampling frequency equal to 2GHz. We will refer to the first emitter as Emitter A and the second emitter as Emitter B. Details on the analyzed dataset are reported in Table I for the emitter A and Table II for the Emitter B. It can be noted that for each emitter, three operation modes are possible; more precisely the three radar modes of each emitter, denoted as Mode 1, Mode 2 and Mode 3, mainly differ one each other for the carrier frequency.

TABLE I DATASET EMITTER A

	Mode 1	Mode 2	Mode 3
IF frequency (MHz)	600	674	710
Nominal Peak Power (dBm)		63.63	
Nominal PW (us)		2.6	
Emitter Serial Number		XXXX-XX-XXX-XX74	

TABLE II DATASET EMITTER B

	Mode 1	Mode 2	Mode 3
IF frequency (MHz)	600	674	710
Nominal Peak Power (dBm)		63.63	
Nominal PW (us)		2.6	
Emitter Serial Number		XXXX-XX-XXX-XX65	

For each pulse, the five features previously described are extracted: in such way each pulse can be represented in a multidimensional space trough a five-dimensional vector

$$Pulse_i = [\quad t_{rise}(i), \alpha_{rise}(i), R_{over}(i), t_{fall}(i), \alpha_{fall}(i) \quad] \quad (6)$$

This process is repeated for 10 pulses for each radar mode of each emitter.

However, in order to have a comprehensive representation of the obtained results, the extracted features have been properly grouped and plotted in a 3-D space, according to the following vectors

$$\Delta_i = [\quad t_{rise}(i), \alpha_{rise}(i), R_{over}(i) \quad]$$
and (7)
$$\nabla_i = [\quad t_{fall}(i), \alpha_{fall}(i), R_{over}(i) \quad]$$
with
$$i = 1, \ldots, 10$$

In the next figures we will analyze the ability of the features to characterize the emitter in a unique way. The analysis will be done for all the radar modes to understand if the behaviour is invariant with respect to the radar mode.

In Fig. 6 the A-UMOP features vectors Δ_i and ∇_i are shown for ten pulses of each emitter, with respect to the Mode 1: the two different emitters are plotted in two different colours in order to verify the ability of the extracted features to discriminate the two different radars.

It is possible to observe that the features of Emitter A (blue) and Emitter B (red) are placed in very different position, for both the Δ_i as well as for the ∇_i vectors.

In this case, since the A-UMOP extracted features exhibit different values, a correct discrimination between Emitter A and Emitter B is possible.

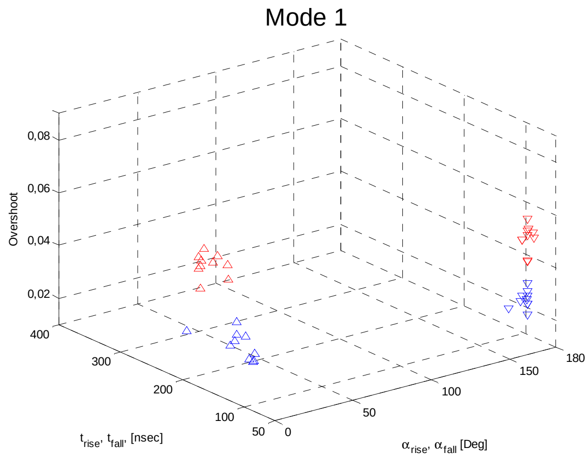

Fig. 6 A-UMOP features for Mode 1, Emitter A (blue) and Emitter B (red).

In Fig. 7 the A-UMOP features vectors Δ_i and ∇_i are shown for ten pulses of each emitter, with respect to the Mode 2. It can be observed that the vectors ∇_i related to the two different emitters are partially overlapped; as to the features of the vectors Δ_i, it can be noted that the values are partially overlapped even if the blue and the red vectors are centred around different values.

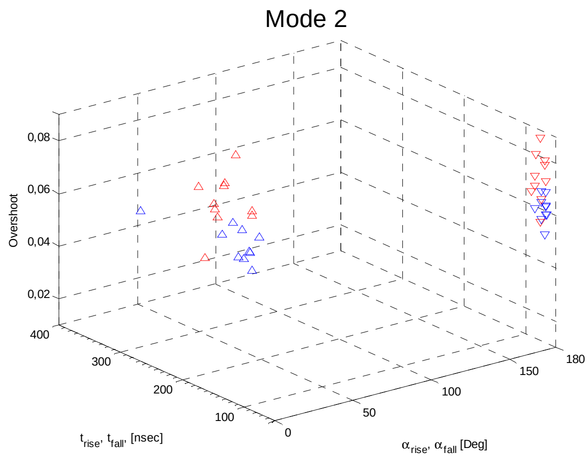

Fig. 7 A-UMOP features for Mode 2, Emitter A (blue) and Emitter B (red).

Finally, in Fig. 8, the same analysis is reported with reference to the Mode 3, showing that the vectors ∇_i related to Emitter A and Emitter B are completely overlapped: a discrimination procedure based only on such features will lead to wrong results. On the other hand, the features associated with the vectors Δ_i are distributed over different areas, especially with reference to the rise time feature. It can be underlined that in this case the majority of the information is concentrated over few features: the SEI discrimination procedure can exploit this behaviour in order to achieve higher performances.

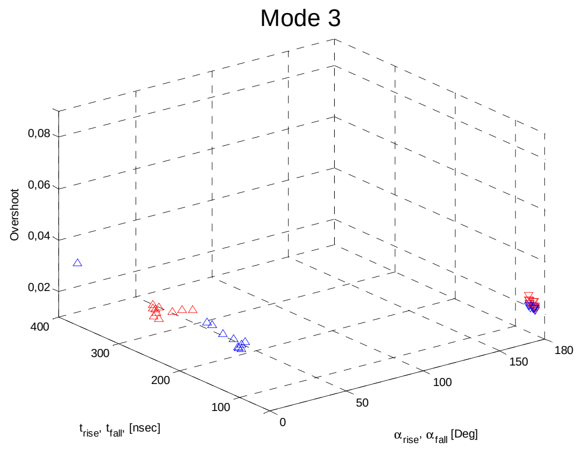

Fig. 8 A-UMOP features for Mode 3, Emitter A (blue) and Emitter B (red).

Is it possible to conclude that is not a-priori predictable if a feature will be useful to the signal discrimination, and the more the available extracted features, the higher the performances of the SEI processing (in accordance to[15], [25]).

V. CONCLUSIONS

In this paper the problem of SEI for radar emitters has been analyzed, also with the aid of real radar signals.

A-UMOP Features extraction algorithm has been described and analyzed on real data, to asses the performance in terms of discrimination feasibility.

The analyses have shown that for the majority of the case at the hand, one or more A-UMOP features allow a robust automatic classification procedure, in order to discriminate emitters that have equal nominal parameters but different serial numbers.

Moreover the analyses have shown that is not a-priori predictable which features are able to provide information in order to maximize the performance of the discrimination algorithms.

REFERENCES

[1] F. Neri, "Introduction to Electronic Defense Systems," 2nd Edition, Scitech Publishing, Inc, 2006.

[2] R. G. Wiley, "Electronic Intelligence: The Analysis of Radar Signals," Artech House, Inc, Norwood 1993.

[3] D. C. Schleher, "Electronic Warfare in the Information Age," Artech House, Inc, Norwood 1999.

[4] A. W. Rihaczek, "Principles of High Resolution Radar," Artech House, Inc, Norwood 1996.

[5] S. P. Jacobs, and J. A. O'Sullivan, "Automatic target recognition using sequences of high resolution radar range-profiles," IEEE Transactions on Aerospace and Electronic Systems, Vol. 36, Issue 2, pp. 364 – 381, April 2000.

[6] D. E. Nelson, J. A. Starzyk, and D. D. Ensley, "Iterated wavelet transformation and signal discrimination for HRR radar target recognition," IEEE Transactions on Systems, Man and Cybernetics, Part A, Vol. 33, Issue 1, pp. 52 – 57, January 2003.

[7] R. G. Wiley, "ELINT: The Interception and Analysis of Radar Signals," Artech House, Inc, Norwood May 2006.

[8] G. Galati, "Advanced Radar Techniques and Systems," Institute of Electrical Engineers (IEE) ISBN 086341172X (0-86341-172-X).

[9] F. Berizzi, A. Binetti, G. Corsini, E. Dalle Mese, A. Garzelli, F. Gini, and M. Greco, "Teoria e Tecnica Radar," Regione Toscana, 2002.

[10] J. Tsui, "Digital Techniques for Wideband Receivers, Second Edition," Artech House, Inc, Norwood 2001.

[11] V. Chandra, and R. C. Bajpai, "ESM data processing parametric deinterleaving approach," IEEE Region 10 International Conference 'Technology Enabling Tomorrow: Computers, Communications and Automation towards the 21st Century.', vol. 1 pp. 26-30, 11-13 Nov 1992.

[12] L. W. Ward, "Investigation of Using the Walsh Transform for Deinterleaving Simulated ESM (Electronic Warfare Support Measures) Receiver Output," Master Thesis, Naval Postgraduate School, Monterey California, Dec. 1983.

[13] D. J. Milojevic, and B. M. Popovic, "Improved algorithm for the deinterleaving of radar pulses," IEE Proceedings F Radar and Signal Processing, vol. 139, issue 1, pp. 98-104, Feb. 1992.

[14] S. Challa, and G. W. Pulford, "Joint target tracking and classification using radar and ESM sensors," IEEE Transactions on Aerospace and Electronic Systems, Vol. 37, Issue 3, pp. 1039 – 1055, July 2001.

[15] K. I. Talbot, P. R. Duley, and M. H. Hyatt, "Specific Emitter Identification and Verification," Technology Review Journal, Vol. 11, Number 1 Spring/Summer 2003, pp. 113 -133.

[16] L. E Langley, "Specific emitter identification (SEI) and classical parameter fusion technology," IEEE WESCON/'93 Conference Record, pp 377 – 381, 28-30 Sep 1993.

[17] Tao-wei Chen, Wei-dong Jin, and Jie Li, "Feature Extraction Using Surrounding-line Integral Bispectrum for Radar Emitter signal," IEEE International Joint Conference on Neural Networks, pp. 294 - 298, 1 - 8 June 2008.

[18] Bingnan Pei, Zheng Bao, and Mengdao Xing, "Logarithm bispectrum-based approach to radar range profile for automatic target recognition," Pattern Recognition, Vol. 35, Issue 11, Pages 2643 - 2651, Nov. 2002.

[19] Ming-Wei Liu, and J. F. Doherty, "Specific Emitter Identification using Nonlinear Device Estimation," IEEE Sarnoff Symposium, pp. 1 – 5, 28 - 30 April 2008.

[20] J. Lunden, and V. Koivunen, "Robust Estimation of Radar Pulse Modulation," IEEE International Symposium on Signal Processing and Information Technology, pp. 271 - 276, Aug. 2006.

[21] J. Lunden, and V. Koivunen, "Scaled Conjugate Gradient Method for Radar Pulse Modulation Estimation," IEEE International Conference on Acoustics, Speech and Signal Processing, Vol. 2, pp. II-297 - II-300, 15 - 20 April 2007.

[22] A. Kawalec, and R. Owczarek, "Specific emitter identification using intrapulse data," IEEE EURAD First European Radar Conference, pp. 249- 252, 2004.

[23] A. Kawalec, and R. Owczarek, "Radar emitter recognition using intrapulse data," IEEE 15th International Conference on Microwaves, Radar and Wireless Communications, Vol. 2, pp. 435 – 438, 17-19 May 2004.

[24] A. Kawalec, T. Rapacki, S. Wnuczek, and R. Owczarek, "Mixed Method Based on Intrapulse Data and Radiated Emission to Emitter Sources Recognition," IEEE International Conference on Microwaves, Radar & Wireless Communications, pp. 487 – 490, 22 - 24 May 2006.

[25] S. D'Agostino, G. Foglia, and D. Pistoia, "Specific Emitter Identification: Analysis on real radar signal data," Radar Conference, EURAD 2009, pp. 242-245, Oct. 2009.

[26] Gexiang Zhang, Laizhao Hu, and Weidong Jin, "A novel approach for radar emitter signal recognition," IEEE Asia-Pacific Conference on Circuits and Systems, Vol. 2, pp. 817 – 820, 6 - 9 Dec. 2004.