

Fast-decision identification algorithm of emission source pattern in database

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Abstract. This article presents Fast-decision Identification Algorithm (FdIA) of Source Emission (SE) in DataBase (DB). The aim of this identification process is to define signal vector (V) in the form of distinctive features of this signal which is received in the process of its measurement. Superheterodyne ELectronic INTeLLigence (ELINT) receiver in the measure procedure was used. The next step in identification process is comparison vector with pattern in DB and calculation of decision function. The aim of decision function is to evaluate similarity degree between vector and pattern. Identification process mentioned above differentiates copies of radar of the same type which is a special test challenge defined as Specific Emitter Identification (SEI). The authors of this method drew up FdIA and three-stage parameterization by the implementation of three different ways of defining the degree of similarity between vector and pattern (called 'Compare procedure'). The algorithm was tested on hundreds of signal vectors coming from over a dozen copies of radars of the same type. Fast-decision Identification Algorithm which was drawn up and implemented makes it possible to create Knowledge Base which is an integral part of Expert DataBase. As a result, the amount of the ambiguity of decisions in the process of Source Emission Identification is minimized.

Key words: Fast-decision Identification Algorithm, Specific Emitter Identification, Emitter Pattern, DataBase, superheterodyne ELINT receiver.

1. Introduction

Source Emission Identification process in DataBase is not a trivial task. Generally, the biggest difficulties result from the lack of a precise and detailed description of a source emission model in DataBase. The other problem is the kind of classification method which is used [1–3]. If the description of emission source is expanded to a precise pattern of a source emission copy of the same type, difficulties connected with identification of this source increase in geometric progress. It is connected with precise decision function description, procedures and algorithm which make it possible to define the degree of cohesion of a pattern copy in DataBase with signal vector [4–5]. Such an attitude towards the process of the recognition process which enables to identify copies of the same type is called Specific Emitter Identification and it is based on the extraction of distinctive features. These features define precisely the copy of emission source [6–9]. Methods which are well known and described in literature are the methods used to define unwanted radiated emission which is generated by source emission. Additionally, specific fractal features are often used [10–11]. These can be received in the process of signals transformation, which are generated by recognition objects [12–14]. Also, in this research, what is important is creating DataBase which should include as much information describing the source emission as it is possible. The process of designing such a DataBase often requires artificial intelligence tools, knowledge-based techniques and advanced methods of designing for instance, entity-relationship modelling [15–17]. As a result of such an attitude, it is possi-

ble to define distinctive signature of an emitter source which includes all significant information about this source [18–19].

2. Identification procedure

On the basis of measurements which were done, emission sources were described with the use of a collection of distinctive features. Such an attitude should provide explicit distinguishability in the process of identification in DataBase. Explicit identification of an emission source is considered as distinguishing particular radar copies of the same type [8, 13, 19]. In the measure procedure, superheterodyne ELINT (ELectronic INTeLLigence) receiver was used. This receiver makes it possible to define the value of Radio Frequency with measurement accuracy 0.5 MHz (in the band 0.5–18 GHz) and value of Pulse Repetition Interval in scope from 2 μ s to 20 ms, with measurement accuracy 0.05 μ s. Identification process was carried out with the use of a relational DataBase. This DB, designed by the authors of this article, was used with Entity-Relationship Modelling (E-RM). In identification process Fast-decision Identification Algorithm was implemented as well. The scheme of identification process is presented in Fig. 1. The signal vector is a formalized structure of record type. Its fields include particular frequency and time parameters of incoming radar signal. Signal vector of time parameters can be defined as $V^{(PRI)}$, according to Eq. (1), where PRI – is Pulse Repetition Interval, PRI_{min} – is minimum value of PRI, PRI_{EV} – is expected value of PRI, PRI_{max} – is maximum value of PRI, $nPRI$ – is number of PRI values, $nPRI_{EV}$ – is number of expected values

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of PRI, PW – is Pulse Width, PW_{\min} – is minimum value of PW, PW_{EV} – is expected value of PW and PW_{\max} – is maximum value of PW

$$\mathbf{V}^{(PRI)} = [PRI_{\min}, PRI_{EV}, PRI_{\max}, nPRI, nPRI_{EV}, PW_{\min}, PW_{EV}, PW_{\max}] \quad (1)$$

Signal vector of frequency parameters can be defined as $\mathbf{V}^{(RF)}$, according to Eq. (2), where RF – is Radio Frequency, RF_{\min} – is minimum value of RF, RF_{EV} – is expected value of RF, RF_{\max} – is maximum value of RF, nRF – is number of RF values and nRF_{EV} – is number of expected values of RF

$$\mathbf{V}^{(RF)} = [RF_{\min}, RF_{EV}, RF_{\max}, nRF, nRF_{EV}] \quad (2)$$

The final structure of signal vector can be defined as \mathbf{V} , according to Eq. (3). This structure also includes parameters concerning information about accuracy of Radio Frequency measurement – $sigRF$, Pulse Repetition Interval – $sigPRI$ and Pulse Width – $sigPW$. These parameters are the basis to define the range of changes of acceptable radar signal parameter, i.e. RF, PRI and PW in tested Fast-decision Identification Algorithm.

$$\mathbf{V} = [\mathbf{V}^{(PRI)}, \mathbf{V}^{(RF)}, sigRF, sigPRI, sigPW] \quad (3)$$

The effect of the identification process is the result signal vector, which can be defined as \mathbf{RV} according to Eq. (4)

$$\mathbf{RV} = \left[P_N \Big|_{\text{for } K_{ij} > 0}, nP_N \Big|_{\text{for } K_{ij} = \max}, K_{ij \max}, \mathbf{PV}^{(PRI)} \Big|_{\text{for } K_{ij} = \max}, \mathbf{PV}^{(RF)} \Big|_{\text{for } K_{ij} = \max} \right] \quad (4)$$

This vector consists of the number of patterns P_N combined with the signal vector, for which K_{ij} – is value of decision function, nP_N – is number of pattern copy, $K_{ij \max}$ – is maximum value of decision function, $\mathbf{PV}^{(PRI)}$ – is vector of pattern time parameters and $\mathbf{PV}^{(RF)}$ – is pattern frequency parameters vector. Decision function K_{ij} serves to evaluate similarity degree i -of this signal vector to j -its pattern located in DataBase. Apart from this above, \mathbf{RV} consists of additional information concerning time of signal recognition, time of signal disappearance, date of recognition, radar purpose, kind of platform, national status and type of radar for which decision function is maximum ($K_{ij} = \max$). The features above of \mathbf{RV} have a significant meaning connected with the operational use of received data in order to create DataBase – as an important part of DB for ELINT systems. The descriptive data above is not taken into account in Eq. (4), as it is not a main aim of this identification.

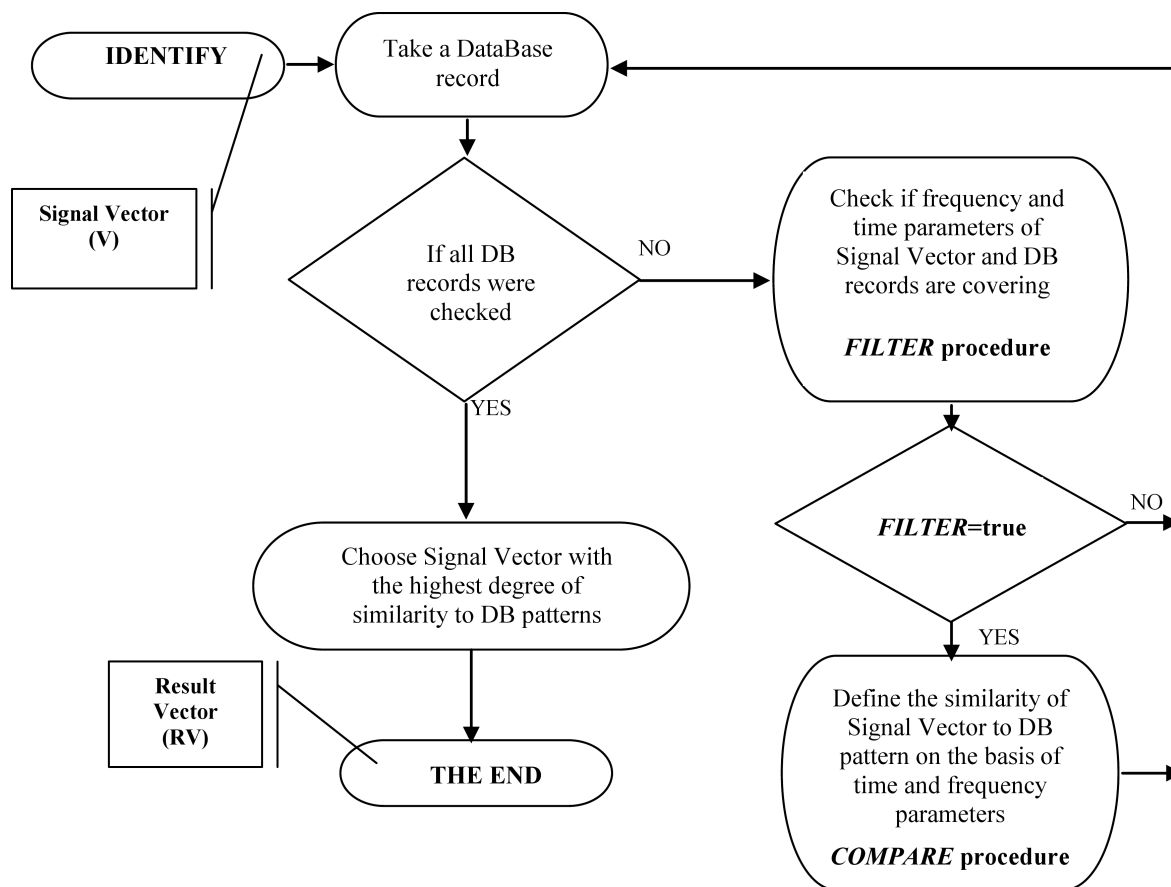


Fig. 1. Algorithm of identification process of Signal Vector in DataBase

3. FILTER procedure

The described and implemented 'Filter procedure' checks the fact of Radio Frequency changes' ranges containing each other and Pulse Repetition Interval radar pattern (in DataBase) with the range of Radio Frequency changes ($RF_{\min} \div RF_{\max}$) and Pulse Repetition Interval ($PRI_{\min} \div PRI_{\max}$) of signal vector. This was presented in Fig. 2. The positive value of these checkings ($FILTER=true$) 'entitles' algorithm to define decision function value K_{ij} , (defining similarity degree signal vector to pattern in DB) and as a result, to define the appropriate **RV** form (after checking all patterns in DB) which is the effect of presented FdIA action.

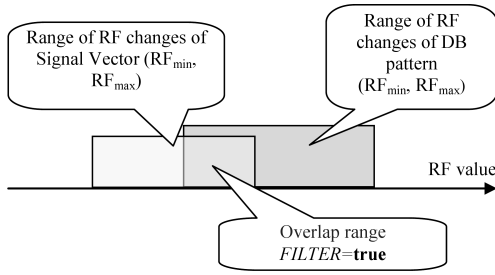


Fig. 2. Comparison of range of RF changes in FILTER procedure

4. COMPARE procedure

The described and implemented 'COMPARE procedure' defines the value of decision function K_{ij} , as evaluation of degree of similarity i -of this signal vector to j -of pattern in DB. Defining the value of decision function is done for each of DB pattern for which the *FILTER* procedure is true ($FILTER = true$). In the tested algorithm the authors drew up three different variants of procedures which realize evaluation of similarity degree of a i -th signal vector to j -th pattern in the DataBase. These procedures are as follows: *COMPARE_1*, *COMPARE_2*, and *COMPARE_3*. These are described in the further part of this article.

4.1. COMPARE_1 procedure. The value of decision function in *COMPARE_1* procedure is defined on the basis of the normalized weighted sum of partial similarity evaluation and acceptable change ranges of parameters of signal vector and parameters of DataBase pattern according to equations (5–6), where K_{kij} is similarity evaluation of k -parameter i -of this signal vector to j -th DB pattern, K_{ij} is evaluation of similarity i -th signal vector to j -th DB pattern – normalized to range of values (0..99), n – is quantity of parameters on the basis of which identification is done, p_{kij} – is compliance of change ranges k -th parameter i -th vector to particular parameter j -th DataBase vector, $w_{k \max}$ – is number which defines possible maximum value of weight k -th parameter

$$K_{ij} = \frac{\sum_{k=1}^n K_{kij}}{\sum_{k=1}^n w_{k \max}} \cdot 99, \quad (5)$$

$$K_{kij} = p_{kij} \cdot w_k. \quad (6)$$

The value of ranges compliance p_{kij} are numbers 0 and 1 according to Eq. (7), where $sigV_k$ is the accuracy of measurement of k parameter

$$p_{kij} = \begin{cases} 0 & \text{for } (V_k + 3sigV_k) < (BD_k - 3sigBD_k) \\ 0 & \text{for } (V_k - 3sigV_k) > (BD_k + 3sigBD_k) \\ 1 & \text{otherwise} \end{cases}. \quad (7)$$

The evaluation of compliance of k -th parameter i -th signal vector with j -th DB pattern depends on compliance p_{kij} and weight w_k . For $w_k = 1$, compliance accepts values (0, 1) (see Fig. 3). The number which defines weight k -of this parameter (w_k) accepts value '1' for all time and frequency parameters. The weight is defined by a constant coefficient which defines the influence k -th parameter on the final decision function value K_{ij} .

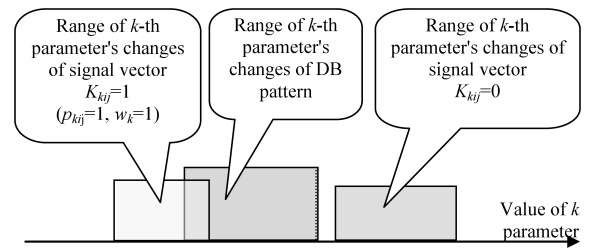


Fig. 3. Graphic representation of K_{kij} evaluation

The w_k value defines the same meaning of all parameters which take part in measurement of decision function value. It is possible to have a change of weights for these parameters, which in some, in more or less degree should influence the evaluation degree of the similarity degree i -th signal vector to the patterns which are in DataBase.

4.2. COMPARE_2 procedure. *COMPARE_2* procedure is modification of *COMPARE_1* procedure which is described above. Modification consists in different calculation of change range compliance k -th parameter i -th vector with j -th DB pattern. However, compliance is not defined binarily ('0' or '1') but on the basis of the degree of containing change ranges with each other k -th parameter i -th vector with a particular parameter j -th DB pattern. The value p_{kij} of this compliance is calculated by Eqs. (8), (9), which take into account the degree of covering of both ranges (see Fig. 4 – left). The defined value p_{kij} accepts values from the bracket (0..1)

$$p_{kij}^1 = \frac{(V_k + 3sigV_k) - (BD_k - 3sigBD_k)}{(V_k + 3sigV_k) - (V_k - 3sigV_k)}, \quad (8)$$

$$p_{kij}^2 = \frac{(BD_k + 3sigBD_k) - (V_k - 3sigV_k)}{(V_k + 3sigV_k) - (V_k - 3sigV_k)}. \quad (9)$$

The number w_k which defines weight k -th parameter accepts value which equals with '2' for all time parameters and value '3' for all frequency parameters. As a result, compliance value k -th parameter i -th signal vector with j -th DB pattern for $w_k = 2$ which accepts values from the bracket (0..2), according to Fig. 4 – right.

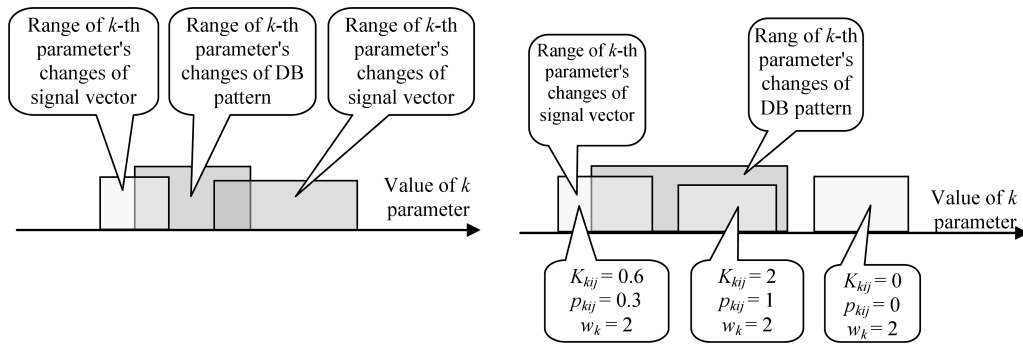


Fig. 4. Defining compliance p_{kij} with the degree of covering of change ranges of signal vector and DB pattern (left) and graphic representation of compliance defining (right)

4.3. COMPARE₃ procedure. *COMPARE₃* procedure is another modification of *COMPARE₁* and *COMPARE₂* procedures. Modification is sophisticated calculation of change ranges' compliance of k -th parameter i -th vector with j -th DB pattern. In this case the agreement is defined with a three-sigma number of change range k -th pattern parameter, in which there is k -th parameter of signal vector. It is treated as a point quantity. Depending on the bracket number and weight w_k, k – this parameter gets a higher compliance evaluation, according to Eq. (10). The method of defining compliance evaluation K_{kij} for $w_k = 2$ is presented in Fig. 5

$$K_{kij} = p_{kij} \cdot w_k = \frac{w_k}{q_{kij}}, \quad \text{where } q_{kij} = p_{kij}^{-1}. \quad (10)$$

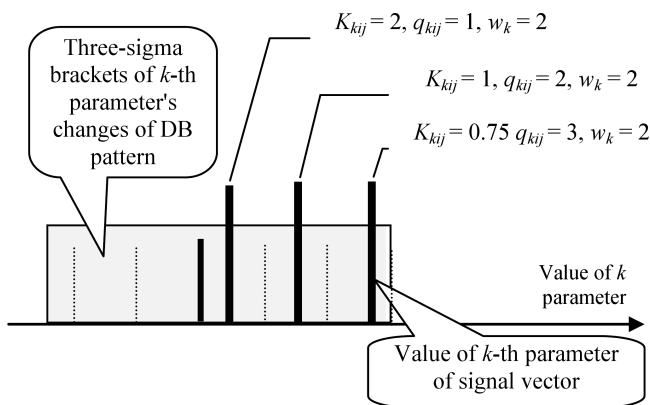


Fig. 5. Graphic representation of compliance defining

5. Results of research

In the process of testing Fast-decision Identification Algorithm evaluation of its working was done on the basis of hundreds of radar signal records which came from several different types of radars. In the set of these records there are also signal vectors coming from a few copies of the same type of radar. DataBase which is implemented for the purpose of this research makes it possible to test quality of FdIA working for three cases of *COMPARE* procedure, (see Fig. 6). Depending on *COMPARE* procedure which is used different decision function values K_{ij} are received. This decision function defines the similarity degree of the signal vector to the pattern in

the DB. The decision function accepts values from the bracket $\langle 0..99 \rangle$, where 'zero' is no similarity of the signal vector in DataBase and 'ninety-nine' is absolute similarity of both vectors.

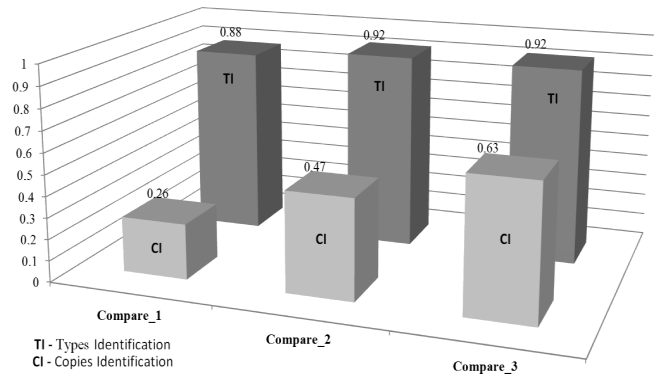


Fig. 6. Results of identification process (TI & CI)

In the case of '*COMPARE₁*' procedure which defines the same importance of all parameters taking part in calculation of decision function values assumed weight is $w_k = 1$ and vector compliance evaluation is received with pattern in DataBase. This value is 88% for identification of radar types (TI) and value is 26% for identification of copies of the same type of radar (CI).

In the case of '*COMPARE₂*' procedure which makes it possible to define the quantity of weights of particular vector parameters and a smooth degree of brackets' covering each other, the degree of covering these ranges with each other is assumed as follows 0.3, 1.0 and 0.0. For all time parameters assumed weight value is 2, and for all frequency parameters assumed weight value is 3. As a result of calculations values of decision function are as follows: 92% for identification of radar types and 47% for identification of radar copies of the same type.

In the case of '*COMPARE₃*' procedure, which makes it possible to define a three-sigma change range k -th pattern parameter which consists of k -th signal vector parameter, the degree of ranges covering is assumed and is as follows 1.0, 2.0 and 3.0. Values of weights for all parameters equal to 2, and values of the agreement evaluation equal to 0.75, 1.0 and 2.0, respectively. In the process of identification, a decision function value for radar types identification is 92%. The value of

decision function for the same radar types identification equals 63%. Also, as a result of use of FdIA-final figures of result signal vectors \mathbf{RV} are calculated. These create new records in DataBase. It is a significant piece of information about radar emission source recognition as it will be also helpful in the further process of Fast-decision Identification Algorithm optimization, because it will make identification process more streamlined and DataBase working more effective.

6. Conclusions

The defined number describing the same weight of each of vector parameters makes it impossible to evaluate the influence of the parameter on identification process. In order to eliminate disfunction of 'COMPARE_1' procedure two following procedures are introduced, i.e. 'COMPARE_2' and 'COMPARE_3' which make it possible to change weights smoothly and to define non binary degree of brackets covering. As concerns the results of radar types identification it can be said, that these are completely satisfactory as values received are at 92% level of correct identification. However, the results concerning in process of identification the copies of the same types of radar are not fully satisfactory, because maximum value of correct identification, which was calculated, is 63%.

The research and measurements which were carried out and the implemented algorithm indicate that what should be done is modernization of this algorithm by using the decision function for time parameters. This function should equal to a weighted sum of partial similarities i.e. expected values of PRI, a sum of values of PRI in a cycle of changes and time of PW of i -th signal vector and j -th pattern in DataBase. Partial similarity of expected values of PRI of the signal vector to compared DB pattern can be estimated on the basis of expected values of PRI and the pattern and the number of values of Pulse Repetition Interval in the cycle of PRI pattern changes in DataBase. It is an area of further research and work on Fast-decision Identification Algorithm.

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