

AN IMPROVED DECISION FUSION TECHNIQUE TO INCREASE THE PERFORMANCE LEVEL OF HRR ATR SYSTEMS

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Abstract—According to literature, a significant and up to date research direction to increase the performance level of automatic target recognition (ATR) systems is focused on the use of information coming from an appropriate set of EM sensors and high-quality decision fusion techniques, respectively. Consequently, in this paper a genetic optimized version of Sugeno's fuzzy integral is discussed. In addition, using a real database belonging to the high-resolution radar (HRR) imagery, the superiority of the proposed decision fusion technique related to its standard version and other well-known decision fusion methods is also demonstrated.

1. INTRODUCTION

The *automatic target recognition* (ATR) represents key technological capability of importance for a wide spectrum of military and non-military (civilian) applications. This high-level function enables systems to real-time process a large amount of information acquired by sensors, and allows to readily identify threats that may otherwise be missed for example, by a human operator, respectively. In addition, ATR has become increasingly significant in modern defense strategy because it permits precision strikes against certain tactical targets with reduced risk and increased efficiency, while minimizing collateral damage to other objects [1].

Generally, there are several types of sensors (and their associated imageries) which are usually implemented in an ATR system, such as: visual (video), IR (thermal), laser, radar (SAR, polarimetric

Received 11 March 2013, Accepted 15 April 2013, Scheduled 18 April 2013

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SAR/PSAR, ISAR, GPR) etc. However, due to their all weather, day or night, long stand-off capability, technological advances in this domain, etc., the radar sensors are preferred to be used in the modern ATR system [2]. Consequently, the basic architecture for an integrated system for radar-based situation assessment is synthetically illustrated in Fig. 1.

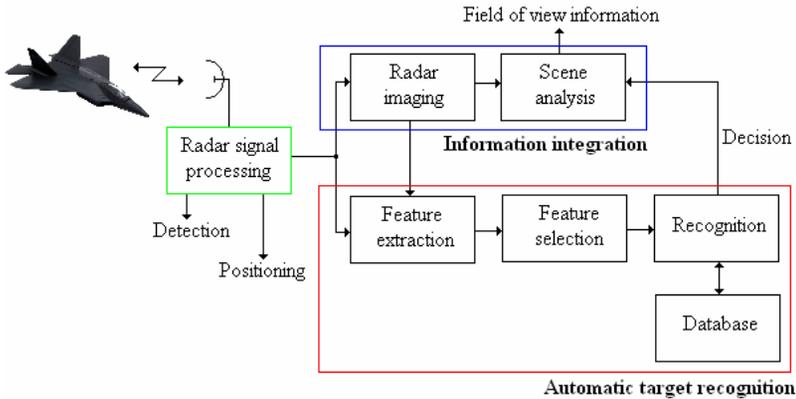


Figure 1. Integrated system for radar-based situation assessment.

The standard approach for radar automatic target recognition is to extract some appropriate features, quantify these features from the targets or target classes to be recognized at every viewing angle anticipated, and finally use these features to train a proper classifier [3]. The recognition performance level is determined by the quality of the extracted target features. In addition, the more precisely they represent the characteristics of the targets, the better classification results are [4]. Consequently, in *high-resolution radar* (HRR) theory, a lot of methods to accurately describe the target characteristics are reported [5, 6], but HR range profiles are often used [7–9].

To improve the performance level of an (radar) ATR system, another very interesting research direction is focused on the use of information coming from a proper set of EM sensors and advanced data (decision) fusion techniques, respectively [10]. The quality assigned to a pattern recognition process also increases in the same time with the quantity of the available (multispectral) information. In addition, by reasons belonging to the electronic warfare theory [11], a fusion technique makes classification systems to become more efficient and powerful at the actions of some noisy factors (e.g., electronic jamming etc.) because each sensor from available data flows provides a different (spectral) robustness.

Generally, the high-level data fusion techniques (also known as hard decision fusion) combine the decisions provided by some experts (e.g., neural classifiers etc.). By extension, it can discuss about decision fusion even though the experts assure only a trust parameter and not a decision (i.e., a soft decision fusion). The experts (classifiers) may be of the same or different types, and may also accept similar or different input feature sets [12]. In addition, although a lot of (standard or advanced) classifiers are described in the theory, a single classifier use may not be satisfactory for a concrete classification task. Consequently, an appropriate set of classifiers could be used and their outputs to be next mixed by different fusion techniques in order to assure the best pattern recognition performances, respectively.

To design a powerful decision fusion process, a lot of interesting methods are indicated in the theory [13–15]. However, the major challenge of all these fusion procedures is to develop optimal (as classification results) algorithms which are able to combine in a proper manner the answers provided by different types of classifiers. For this reason, in the last period of time, other techniques much more efficient based on Dempster-Schafer, possibility or fuzzy logic theories [14–16], and on some hybrid (e.g., fuzzy-genetic etc.) decision fusion algorithms [17–19] respectively, are discussed in data fusion literature.

This paper presents as novelty, a genetic optimized version of Sugeno's fuzzy integral in order to increase the performance level assigned to a HRR ATR system. Consequently, in the first part of the paper, a comprehensive overview of the standard fuzzy integral is presented. Next, using an appropriate genetic algorithm, an optimized version of fuzzy integral is described. In the last part of the paper, using a real database belonging to HRR imagery, some experimental results confirming the significant potential of the proposed decision fusion algorithm related to other well-known data fusion techniques are indicated. Finally, the most important conclusions are also discussed.

2. SUGENO'S FUZZY INTEGRAL

Based on the fuzzy measure concept, Sugeno defines for the first time the fuzzy integral notion that is in fact, a nonlinear functional similar to Lebesgue's integral [18].

If Q is a finite set and $h : Q \rightarrow [0, 1]$ a fuzzy subset of this set, then the fuzzy integral of the function h on Q defined in relation to the fuzzy measure g , is given by:

$$\int_Q h(q) \circ g(\cdot) = \max_{A \subseteq Q} \left\{ \min \left[\min_{q \in A} (h(q), g(A)) \right] \right\} = \max_{\alpha \in [0,1]} [\min(\alpha, g(h_\alpha))], \quad (1)$$

where $h_\alpha = \{q | h(q) > \alpha\}$.

Function $h(q)$ represents the decision of classifier q related to the membership of the unknown patterns to a given input class. Generally, this value quantifies the degree whereby the concept h is accomplished by q .

Term $\min_{q \in A} h(q)$ quantifies the degree whereby the concept h is accomplished by all the elements of subset A (i.e., A is a classifier subset of Q). Also, $g(A)$ represents the importance attached to the classifiers from subset A on the final decision or equivalently, the degree whereby this classifier group accomplishes the concept g .

According to [15], the result achieved by the *min* comparison between the previous two values will point out the degree whereby the classifiers from subset A accomplish the above described criteria. Consequently, the fuzzy integral tries to find the maximum level of the matching between the real possibilities and expectations, values measured by the functions h and g , respectively.

Generally, assuming that the values $h(q_i)$ are already sorted in descending order: $h(q_1) \geq h(q_2) \geq \dots \geq h(q_{N_q})$, where N_q represents the total number of the classifiers, the fuzzy integral is given by equation:

$$\chi = \int_Q h(q) \circ g(\cdot) = \max_{i=1, N_q} [\min(h(q_i), g(A_i))], \quad (2)$$

where $A_i = \{q_1, q_2, \dots, q_i\} \in Q$, and the fuzzy densities $g(A_i)$ are

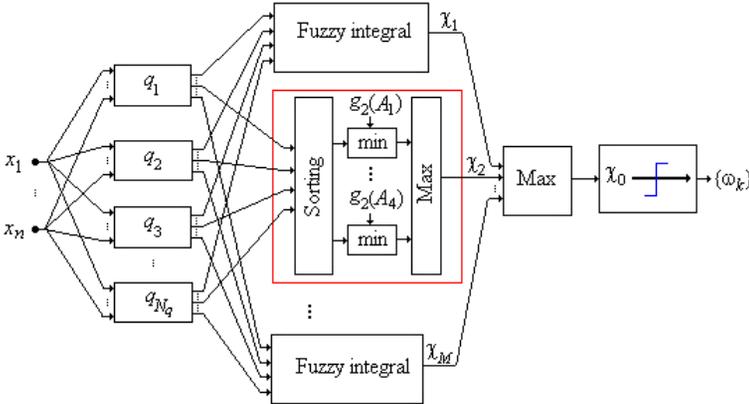


Figure 2. Decision fusion of N_q classifiers through Sugeno's fuzzy integral.

calculated using the recursive equations:

$$\begin{cases} g(A_1) = g(\{q_1\}) = g^1 \\ g(A_i) = g^i + g(A_{i-1}) + \lambda g^i \cdot g(A_{i-1}), \quad i = \overline{2, N_q} \end{cases} \quad (3)$$

Consequently, the algorithm describing the decision fusion of N_q classifiers through Sugeno's fuzzy integral is presented below and synthetically illustrated in Fig. 2.

2.1. Training Stage

1) Using the achieved classification performances, the calculus of the fuzzy density $g_k^i = g_j(\{q_i\})_{i=\overline{1, N_q}, k=\overline{1, M}}$ for each classifier and input class, respectively (in this case, g_k^i represents the classification rate of the classifier q_i for the input class ω_k). Generally, the values of the fuzzy densities can be assigned by an expert (e.g., a proper genetic algorithm etc.) or are fixed as a function by the performances of each individual classifier etc.

2) The calculus of the corresponding value λ_k for each input class $\omega_{k=\overline{1, M}}$ by equation:

$$g(Q) = 1 \Rightarrow \lambda_k + 1 = \prod_{i=1}^{N_q} (1 + \lambda_k \cdot g_k^i), \quad k = \overline{1, M}. \quad (4)$$

2.2. Classification Stage

1) The calculus of the outputs $h_k(q_i)_{k=\overline{1, M}, i=\overline{1, N_q}}$ for each classifier and input class, respectively.

2) The forming of the subsets $Q_k = \{q_1^k, q_2^k, \dots, q_{N_q}^k\}$, and the calculus of the fuzzy integral values for each class, where $g_k(A_i)$ is calculated using (1):

$$\chi_k = \max_{i=\overline{1, N_q}} [\min(h(q_i^i), g_k(A_i))]. \quad (5)$$

3) The membership of the input pattern x is decided using the following rule:

$$\begin{cases} \text{if } \max_{k=\overline{1, M}} \chi_k \geq \chi_0 \quad \text{and} \quad m = \arg \left[\max_{k=\overline{1, M}} \chi_k \right] \Rightarrow x \in \omega_m \\ \text{if } \max_{k=\overline{1, M}} \chi_k < \chi_0 \Rightarrow x \text{ — unknown vector} \end{cases}, \quad (6)$$

where χ_0 represents a trust threshold under which an input pattern is considered as unknown. In addition, this threshold can be set for

example, as the lowest value of the fuzzy integral χ_k obtained during the training stage [16].

More theoretical details about the fuzzy integral and its basic properties can be found in [15].

3. A GENETIC OPTIMIZED VERSION OF SUGENO'S FUZZY INTEGRAL

Having as starting point the above important remark that, the values of the fuzzy densities can be generally provided by an expert, the basic idea is to optimize these values using the solution given by an appropriate genetic algorithm. Consequently, this new approach of Sugeno's fuzzy integral is in fact, a hybrid (i.e., fuzzy-genetic) decision fusion method used to optimize the way to combine the outputs given by many (neural) classifiers. Practically, this algorithm uses the standard fuzzy integral to assure a proper mixing of the answers provided by a set of classifiers based on the importance attached to each by a specific genetic procedure.

Consequently, the chromosomes real encode the fuzzy densities $\{g_k^i\}_{i=1, N_q, k=1, M}$ as a linear concatenated vector $C = (g_1^1, g_2^1, \dots, g_M^1, \dots, g_1^{N_q}, g_2^{N_q}, \dots, g_M^{N_q})$, and its attached fitness was calculated using the following equation:

$$E = \frac{k}{1 + \left[\sum_{A \in Q} |\tilde{g}(A) - g(A)| \right]^{-0.5}} = \frac{k}{1 + \left[\sum_{A \in Q} \left| \tilde{g}(A) - \lambda_k^{-0.5} \cdot \prod_{q_i \in A} (1 + \lambda_k \cdot g_k^i) \right| \right]^{-0.5}}, \quad (7)$$

where the fuzzy measures $\{\tilde{g}(A)\}_A$ were estimated using the solution given by standard fuzzy integral, and k is a constant used for (fitness) calibration.

To implement the parent selection procedure for the next chromosomal generation, the well-known roulette method was used. In addition, the continuous crossover (with two random splitting points and a crossover probability inside [0.6, 0.85]) and uniform mutation were implemented as basic genetic operators. Finally, to stop the genetic algorithm, a specific criterion based on the exceeding of the preset number (with a constant value) of chromosomal generations was also used.

Generally, it is well-known that, the most performant chromosome (i.e., as fitness value) achieved in the last chromosomal generation represents usually, the solution provided by a genetic algorithm. However, it is very possible that a more performant individual to be already obtained for example, in the previous chromosomal population. To avoid this drawback and based on analogy with Gallant algorithm described in the machine learning theory, at each chromosomal stage, the best individual was kept into virtual *pocket*. Consequently, after a final sorting process (in descending order), the best solution will be certainly achieved etc.

More theoretical details about the involved genetic operators and other specific procedures can be found in [18, 20].

4. EXPERIMENTAL RESULTS

4.1. Database Design

To confirm the significant potential of the proposed decision fusion method related to other well-known decision fusion techniques (based on possibility/Dempster-Shafer theory and standard fuzzy integral, respectively), a concrete pattern recognition task (by HRR ATR type) was proposed to be solved. Consequently, the real data (given by an ISAR sensor) were obtained in the anechoic chamber of METRA (Bucharest, Romania) using the experimental setup illustrated in Fig. 3.

The eight targets were used in our experiment, and each target represents an (military) aircraft scale-reduced model (1 : 52) made by plastic with a metallic coating (Fig. 4).

In the acquisition phase, each target was illuminated with a frequency stepped signal. The data snapshot contained 32 frequency

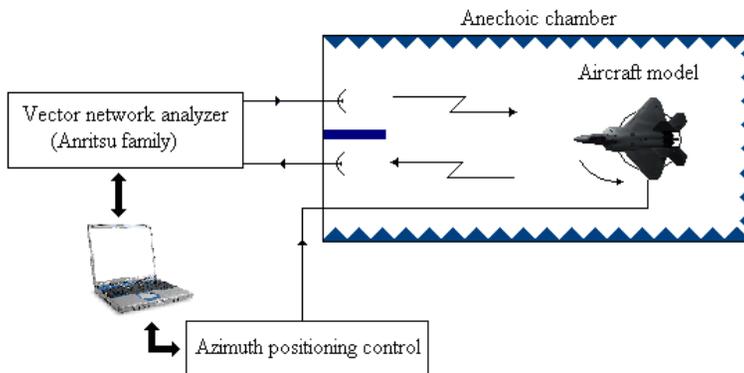


Figure 3. Primary database acquisition experimental setup.



Figure 4. Scale-reduced aircraft models used into anechoic chamber experiment.

steps, uniformly distributed into $[12, 18.4]$ GHz range, which results in a frequency increment of 200 MHz. Consequently, the slant range resolution had the value of 2.3 cm and the ambiguity window had the value of 0.75 m, respectively.

To generate the target HRR images, a specific procedure based on superresolution ESPRIT-2D algorithm was used [21]. Consequently, the main stages involved in the generation of the target scattering centre locations by ESPRIT-2D method are given below:

- (1) 2D array complex data acquisition;
- (2) data reformatting (resampling and interpolation);
- (3) estimation of the autocorrelation matrix using the spatial smoothing method;
- (4) eigenanalysis of the estimated autocorrelation matrix and identification of the eigenvector matrices corresponding to the signal subspace, for the case when the data are processed column by column and row by row respectively;
- (5) ESPRIT-2D reconstruction of the target image (i.e., estimation of the target scattering centre coordinates) by applying of a suitable diagonalization transform on the above determined eigenvector matrices etc.

More theoretical details about the effective structure of ESPRIT-2D superresolution algorithm can be found in [18, 22].

Consequently, 90 HRR images/target (or input class) were generated for aspect angles between 0° and 90° , with an angular increment between two consecutive images of 1° . Each image (Fig. 5) is obtained from the complex profiles acquired over an angular sector

of 10° , with an angular shift of 1° . In addition, to apply the above described decision fusion techniques, four types of complex HRR signatures were available (i.e., HH, HV, VH and VV).

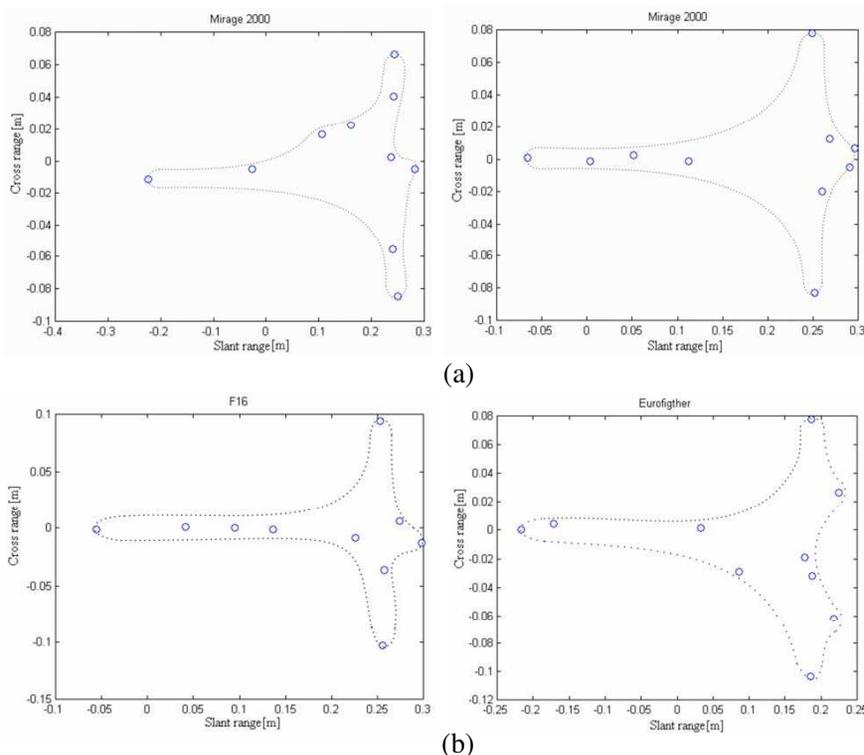


Figure 5. Target images from available HRR database (with interpolation of the scattering points). (a) Target HRR images for 0° angle of sight and VV/HH polarization. (b) Target HRR images for 0° angle of sight and HH polarization.

To effectively implement the classification chains, the *polygonal contour* obtained from a suitable interpolation of the target scattering centres was used (Fig. 5). In addition, as a feature extraction method, the generalized Flusser invariants described in [18] were used (i.e., 11 invariants were calculated and stored for the final classification stage), and as a feature selection method, the standard Sammon projection algorithm was also used (i.e., implementing a feature projection by $R^{11} \rightarrow R^n$ type). Consequently, after the feature selection stage, the feature matrix assigned to each input class had a dimension of $(n \times 90)$, one for each available radar data set.

More details about the modality to generate HRR database can be found in [18].

4.2. Simulation Results

The main objective of the experimental part of this paper was to demonstrate the superiority of the genetic optimized version of Sugeno's fuzzy integral related to its standard form and other well-known decision fusion techniques (i.e., possibility and Dempster-Shafer theory-based decision fusion methods), respectively. In addition, the robustness of the proposed decision fusion method at the noise action was also investigated.

Using the above described HRR database, a supervised ART neural network (SART) was next used to obtain the classification performances for each of the four available HRR information flows. Consequently, the block-diagram of the decision fusion experimental setup is illustrated in Fig. 6.

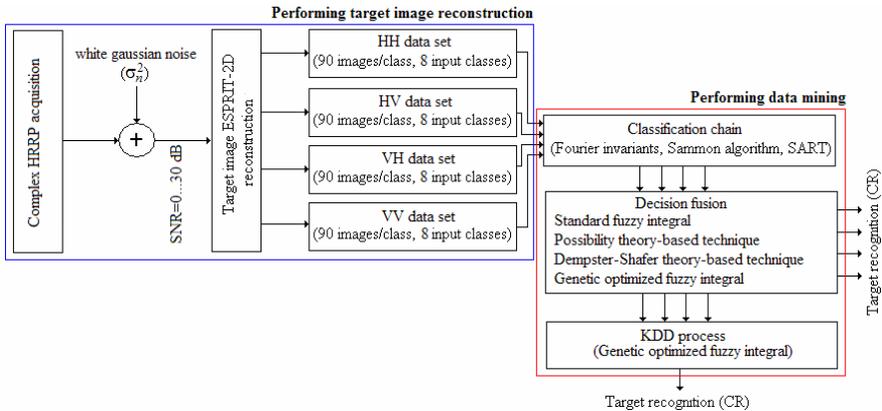


Figure 6. Decision fusion experimental setup.

As can be seen from Fig. 6, to study the robustness of the proposed decision fusion technique, the primary complex HRRPs were corrupted by white gaussian noise. By fitting of the noise squared variance σ_n^2 , SNRs between 0 and 30 dB were generated (afterwards, ESPRIT-2D algorithm was employed to achieve the target radar images). In addition, to obtain a high-quality target recognition process, the final fusion of the four available fusion models was also made using the proposed version of Sugeno's fuzzy integral. Finally, unlike the two versions of Sugeno's fuzzy integral and possibility theory-based

method, Dempster-Schafer theory-based technique was applied on the decision of SART neural classifier (for each available recognition chain), and not on the effective (numeric) output of this.

According to [23], the neural SART classifier uses a similar way as well as ART neural networks, to generate the prototypes, but in a specific *supervised* manner. In addition, its capacity to learn patterns is faster because of the concrete modality to design local approximations of the input classes and its working mechanism does not depend on the any chosen parameters, respectively.

The basic learning process flowchart of SART neural classifier is illustrated in Fig. 7.

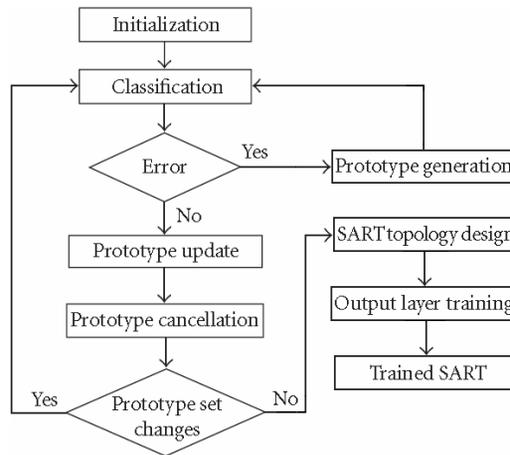


Figure 7. Basic learning process flowchart of SART neural classifier.

The training algorithm of SART neural classifier starts by randomly setting of one prototype for each input class. During this process, a new prototype for a class is created whenever the actual set of prototypes is not able anymore to classify the training data set satisfactorily using the well-known nearest prototype rule. In addition, this updating procedure is repeated as long as there are classification errors (ε_{\max}) on the training pattern set and as long as it dynamically changes the position of the prototypes, respectively.

Generally, the neural connectivity of SART classifier is similar to the one used in case of RBF or LVQ neural networks (i.e., the number of the neurons from the hidden layer (n_h) is equal to the number of prototypes, and each neuron from output layer is assigned to an input class etc.). However, very useful, the internal operation of this

supervised classifier needs no a priori setting of code book vectors or some system parameter initialization. In addition, unlike the RBF or LVQ neural networks, the (optimal) number and the final values of the prototypes are automatically found during the training process of SART classifier.

More theoretical aspects about the neural SART classifier can be found in [18, 24].

To assure the learning process of the supervised SART classifier, for each input class, and using an appropriate interlacing splitting technique, the feature matrix was divided in two parts: one matrix for training and other for testing, respectively. In addition, for each input HRR data flow, as the most significant performance indicator, the *classification rate* (CR) was also computed.

To achieve a very good estimation of the performance level for each classification chain, the training process was repeated 15th times, and finally, CRs were calculated as mean of the obtained partial classification results.

Based on the available HRR data sets and the above described decision fusion techniques, the achieved average classification (and decision fusion) results (also, the running parameters of the genetic algorithm) are presented in Table 1, and synthetically illustrated in Fig. 8. In addition, the output values of standard fuzzy integral and its genetic optimized version are comparative indicated in Fig. 9. Finally, two examples related to the performance level (e.g., confusion matrix and other SART training parameters etc.) assigned to each

Table 1. Simulation results.

HRR image database	Classification rate (CR [%])								
	1st class	2nd class	3rd class	4th class	5th class	6th class	7th class	8th class	Mean
HH	92	87	90	91	90	93	91	90	90.5
HV	90	85	83	91	92	89	92	88	88.8
VH	87	91	89	90	92	91	89	91	90.0
VV	91	92	94	92	89	93	92	93	92.0
Standard fuzzy integral/SFI	93.7	93.1	94.3	92.7	93.1	94.7	95.1	93.3	93.8
Possibility theory-based decision fusion/PT (using mean operator)	93.4	93.8	95.0	93.3	93.8	95.3	94.5	95.0	94.2
Dempster-Shafer theory-based decision fusion/DST	94.1	94.5	95.7	94.0	94.3	96.0	95.5	95.7	95.0
Genetic optimized fuzzy integral/GFI	94.7	95.1	96.3	95.0	95.3	96.5	96.1	97.0	95.8
	$N_g = 4, M = 8, p_c = 0.75, k = 0.8$ $\max pop = 75, \max gen = 200, \max string = 32$								
Final decision fusion/FDF	96.1	95.7	97.4	96.3	96.7	98.1	97.4	98.5	97.0

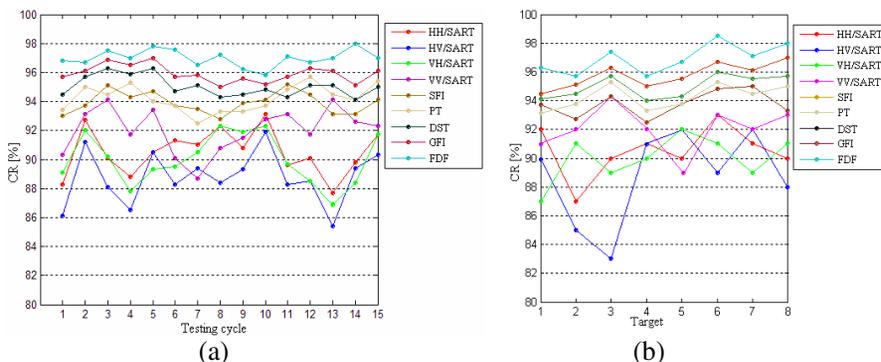


Figure 8. CR means calculated after the simulation process. (a) For each testing cycle. (b) For each input target (after 15 testing cycles).

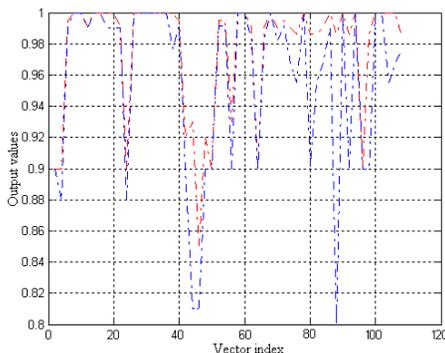


Figure 9. A comparative view of the output values assigned to the tested decision fusion techniques — fuzzy integral (blue), its genetic optimized version (red).

HRR classification chain are also shown in Fig. 10.

As can be observed from Table 1, all tested decision fusion techniques give better results in average than every available classification chain. At individual level, the best CR (about 95.8%) is obtained in the case of proposed decision fusion method. In addition, the final decision fusion process leads to a CR of 97% that means an average increase of 2.3% related to the four tested decision fusion techniques. Finally, for all the 15th testing/running cycles, the genetic version of Sugeno’s fuzzy integral gives the best CRs related to the same techniques (Fig. 8(a)).

On the other hand, CR means were calculated for each input

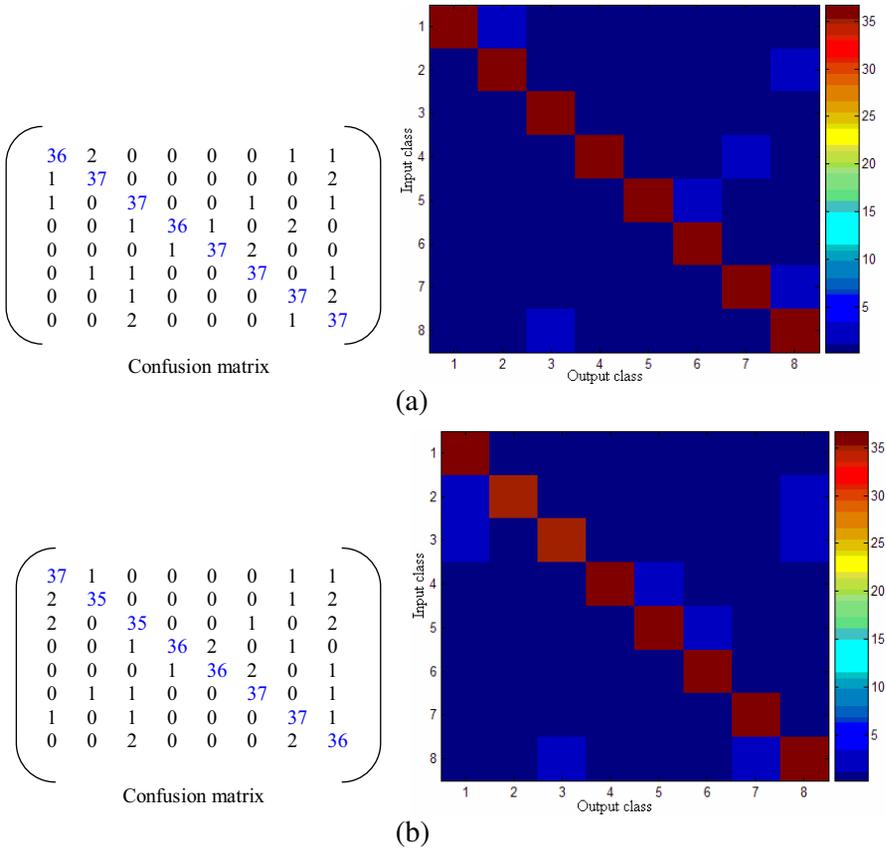


Figure 10. Classification results obtained in the case of the most two performant HRR data sets (only for testing phase of SART classifier). (a) VV data set ($n = 8$, $M = 8$, 40 vectors/class, $CR \cong 92\%$, SART: $n_h = 32$, $\varepsilon_{\max} = 0.01$, $\eta = 0.1$, 8.4 s). (b) HH data set ($n = 9$, $M = 8$, 40 vectors/class, $CR \cong 90\%$, SART: $n_h = 37$, $\varepsilon_{\max} = 0.01$, $\eta = 0.1$, 13.5 s).

target. In this case, the best CR is also given by the proposed decision fusion method. In addition, for all eight input targets, the genetic version of Sugeno's fuzzy integral gives the best CRs related to the same techniques (Fig. 8(b)). Finally, the problematic targets are not the same for each available classification chain. For example, the Tornado is better recognized using VV dataset, and it is the contrary for the B-2 etc. Consequently, by fusion of the tested models, these differences can be exploited well to obtain the best classification results.

Generally, in case of the proposed genetic version of fuzzy integral, an average CR increase of 5.5% related to singular use of each available HRR data set is achieved. In addition, related to its standard version, this average increase is 2% (Fig. 9). Not lastly, related to other similar pattern recognition experiments indicated in radar literature [7–19, 16, 22, 24], an important increase of performance level (in fact, of CR) in radar target classification (i.e., around of 3%) was achieved.

Using the previous described modality to generate noise inside HRR ATR system (Fig. 6), a comparison as robustness at the noise action (i.e., measured as mean (classification) error rate by SNR) between proposed genetic version of Sugeno’s fuzzy integral (including the final decision fusion technique) and its standard form is illustrated in Fig. 11. Strong connected with this noise robustness test, an interesting approach related to influence of the noise on the positioning error of the target scattering points (i.e., measured as MSE by SNR/for VV data set) using ESPRIT-2D algorithm is also indicated in Fig. 12.

As can be observed from Fig. 11, the robustness superiority of the proposed fusion method either as singular decision fusion method or as fusion method of models, related to its standard version is thus demonstrated. In addition, in quantitative terms, the final decision fusion procedure leads to an average robustness increase of 4 dB related to the tested methods (estimated at 0.5 level), a possible explanation could be connected by the nature of its internal (optimal) working mechanism and the individual robustness of each available data fusion model etc.

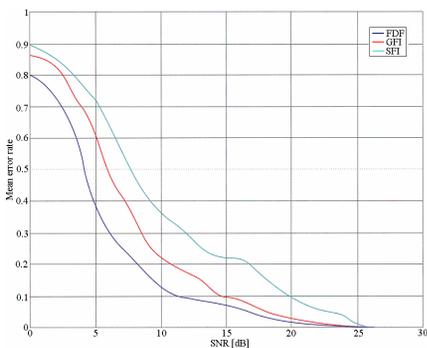


Figure 11. Decision fusion results in the case of noisy classification environment.

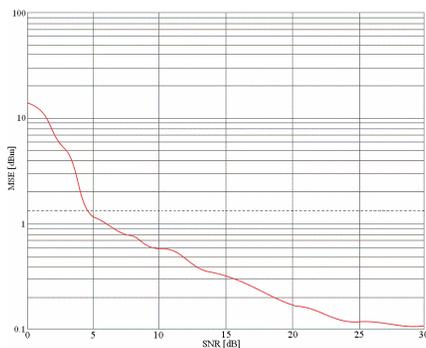


Figure 12. Positioning error of the target scattering points using ESPRIT-2D algorithm (for VV data set).

Despite the dependency from Fig. 12 is obtained into particular case of VV data set (but the most performant as CR level), it can be remarked the accurate estimation of the scattering centre locations assured by this superresolution algorithm. In addition, a logical link can be made between these two figures because the both indicate a similar robustness to noise limit, located around of 4 dB. Consequently, the robustness of ESPRIT-2D algorithm doubled by an adequate selection of the classification chain structure and data fusion technique, leads to a high-strength of the designed HRR ATR system into a noisy (in fact, real) action environment.

All the applications described in this experimental section of the paper were implemented into Matlab 7 package using specific functions from *nnet* and *gaot* toolboxes.

5. CONCLUSION

This paper presents a novel and proper genetic optimized version of Sugeno's fuzzy integral used to improve the classification function assigned to an ATR system. Based on a real HRR database, the achieved experimental results confirmed an important increase of CRs related to its standard version and other well-known decision fusion models. In addition, related to each available information flow and other fusion techniques, the robustness level of a radar system incorporating this pattern recognition algorithm was also significantly improved. Finally, the classification results achieved by simulations were quite similar to the ones reported with other interesting approaches from radar classification theory, and consequently, fully justify an effective integration of the discussed processing ATR technique in a concrete radar application.

On the other hand, the required computing resources to implement this improved decision fusion technique are reasonable and thus, using dedicated processing hardware tools (e.g., DSP, FPGA, technology etc.), its practical implementation can also become an acceptable task.

In summary, the proposed decision fusion technique has been demonstrated to be an effective algorithm to improve the performance level assigned to a radar ATR system, having a great area of applicability in the modern radar systems. In addition, this genetic optimized version of Sugeno's fuzzy integral can represent a good starting point into investigation of new decision fusion models applied on different radar classification chains.

REFERENCES

1. Outhouse, M., A. Beach, and A. Parslow, "Automatic target recognition," *Proceedings of SEAS DTC Technical Conference*, A2, 2010.
2. Nebabib, V. G., *Methods and Techniques of Radar Recognition*, Artech House, London, 1994.
3. Tait, P., *Introduction to Radar Target Recognition*, IET Radar and Sonar Navigation Series, No. 18, 2005.
4. Duda, R. O., P. O. Hart, and D. G. Stork, *Pattern Classification*, John Wiley & Sons, New York, 2001.
5. Lee, C. K., C. W. Huang, and M. C. Fang, "Radar target recognition by projected features of frequency-diversity RCS," *Progress In Electromagnetics Research*, Vol. 81, 121–133, 2008.
6. Park, S. H., J. H. Lee, and K. T. Kim, "Performance analysis of the scenario-based construction method for real target ISAR recognition," *Progress In Electromagnetics Research*, Vol. 128, 137–151, 2012.
7. Quinquis, A., E. Radoi, and F. Totir, "Some radar imagery results using superresolution techniques," *IEEE Tran. on Antennas and Propagation*, Vol. 52, No. 5, 1–15, 2004.
8. Anton, L., *Signal Processing in High Resolution Radars*, MTA Press, Bucharest, 2008.
9. Han, S. K., H. T. Kim, and S. H. Park, "Efficient radar target recognition using a combination of range profile and time-frequency analysis," *Progress In Electromagnetics Research*, Vol. 108, 131–140, 2010.
10. Hall, D. L. and J. Llinas, *Handbook of Multisensor Data Fusion*, CRC Press, Boca Raton, 2001.
11. Vizitiu, I. C., *Fundamentals of Electronic Warfare*, MatrixRom, Bucharest, 2011.
12. Molder, C., *Pattern Recognition: Classification Algorithms*, MTA Press, Bucharest, 2004.
13. Ng, G. W., *Intelligent Systems-fusion, Tracking and Control*, RSP Press, Hertfordshire, 2003.
14. Mangai, U. G., S. Samanta, and P. R. Chowdhury, "A survey of decision fusion and feature fusion strategies for pattern classification," *IETE Technical Review*, No. 27, 293–307, 2010.
15. Martin, A. and E. Radoi, "Effective ATR algorithms using information fusion models," *Proceedings of International Conference on Information Fusion*, 161–166, 2004.

16. Vizitiu, I. C. and I. Nicolaescu, "More efficient ATR system using the decision fusion between HRR and video imageries," *Proceedings of IEEE International MRRS Conference*, 272–275, 2011.
17. Alam, H., R. Hartono, and M. Fairhurst, "Use of genetic algorithms for optimizing a decision fusion framework," *Proceedings of IEEE International Conference on Information Fusion*, 831–837, 2003.
18. Vizitiu, I. C., *Neuro-fuzzy-genetic Architectures: Theory and Applications*, MTA Press, Bucharest, 2011.
19. Cui, M., *Genetic Algorithms Based Feature Selection and Decision Fusion for Robust Remote Sensing Image Analysis*, ProQuest, Cambridge, 2012.
20. Eiben, A. E. and J. E. Smith, *Introduction to Evolutionary Computing*, Springer, Berlin, 2008.
21. Roy, R. and T. Kailath, "ESPRIT-estimation of signal parameters via rotational invariance techniques," *IEEE Tran. on Acoustic Speech, Signal Processing*, Vol. 37, 984–995, 1986.
22. Radoi, E., A. Quinquis, and F. Totir, "Superresolution ISAR image classification using Fourier descriptors and SART neural network," *Proceedings of the European Conference on Synthetic Aperture Radar*, 241–244, 2004.
23. Carpenter, G., S. Grossberg, and J. H. Reynolds, "ARTMAP: Supervised real-time learning and classification of nonstationary data by a self-organizing neural network," *Neural Networks*, Vol. 4, 565–588, 1991.
24. Radoi, E., A. Quinquis, and F. Totir, "Supervised self-organizing classification of superresolution ISAR images: An anechoic chamber experiment," *EURASIP Journal on Applied Signal Processing*, Vol. 2006, 1–14, 2006.