Fuzzy Fusion System for Radar Target Recognition

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ABSTRACT

Complex target recognition tasks rarely succeed through the application of just one classification scheme. Using the combination/fusion of different classifiers based on Inverse Synthetic Aperture Radar (ISAR) images usually explore complementary information. Thus, the each individual classifier results will be combined in order to improve the global recognition rate. Automatic target recognition systems mostly employ fusion strategies for this aim. The empirical evidence of the effectiveness of this approach makes it of the main current directions in target recognition research.

In this paper, the recognition combination will be presented using fuzzy fusion based on three classifiers: K- nearest Neighbors, Support Vector Machines and Multi-Layer Perceptron classifiers. In this purpose, we have used Sugeno and Mamdani models. To improve our approach, we have used an ISAR image database which was reconstructed from an anechoic chamber. All results of all individual and combined classifiers will be presented.

Keywords

Automatic Target Recognition, decisional fusion, classification, ISAR images, fuzzy fusion, fuzzy Sugeno integral, fuzzy Mamdani model.

1. INTRODUCTION

Today, multiple informations are being increasingly used in the design of automatic target recognizer to enhance performance and reliability of automatic target recognition (ATR) system. One of the important components in ATR system is its classifiers [1][12].

Traditional, target recognition (classification) task is achieved using a features vectors to describe and classify the true class of a given target. For radar target recognition problems, involving a large number of classes and noisy inputs, perfect solutions are often difficult to achieve. Recently, it has been observed that classifiers of different types complement one another in classification performance [4] ,[7]. This has led to belief that instead of finding the best classifier by exhaustively trying out all possible parameters. Consequently, using a classifiers fusion methods provide more efficient recognition accuracy.

In this study, we propose a classifier fusion model, particularly for SVM, KNN and MLP classifiers aiming to boost the performance of target recognition task [9]. A fuzzy fusion system is constructed to combine multiple classifiers in the light of the performance of each individual classifier. The choice of fuzzy model is justified by three principle reasons: Firstly, fuzzy methods can take into account both the uncertainty and imprecision associated with real data [3][6]. Secondly, they present a considerable flexibility due to the various choices of fuzzy membership functions and combination operators [7][5]. Finally, fuzzy models implementation is based on operators that are relatively simple and fast, which make them particularly suitable for practical applications [2].

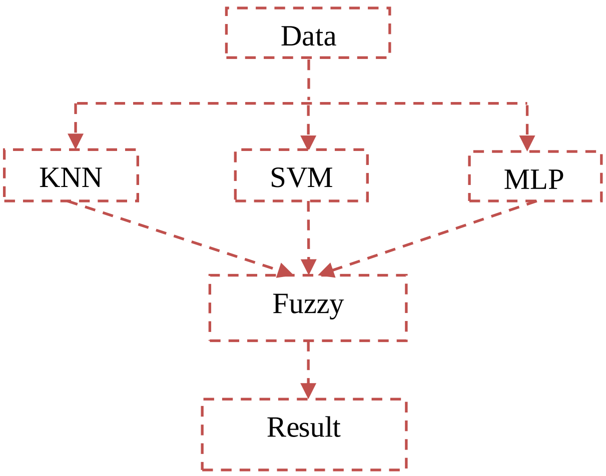

Fig 1: Multi classifier fuzzy fusion system

In this paper, in section II, we describe the three classifiers used to classify ISAR Images. Then, fuzzy system for decision fusion according two models: Mamdani and Sugeno Model; is introduced and discussed in section III. The experimental results and performance analysis are presented in section IV. Finally in section V, conclusions and perspectives will be drawn.

2. CLASSIFICATION STEP

2.1 K nearest Neighbors classifier (KNN)

A decision rule for KNN classifier is very simple and can be generalized for any number of classes [1]. It is a nonparametric probabilistic approach. For a problem of J classes, each object is labeled y_i. The decision function is defined as follows:

$$f(x) = y_j, Occ_k(y_i) > Occ_k(y_j), \forall i \neq j, i \in 1, \ldots J. \quad (1)$$

Where $Occ_k(y_i)$ is the operator defining the number of occurrences of y_i from the labels of KNN of x. The

y

neighborhood of x is defined by its k nearest individuals in the database.

In this method, the only parameters to be determined are the parameter k and the distance measure used to compare the subject to recognize and find the nearest neighboring objects. In this work, we have used the Euclidean distance.

2.2 Support Vector Machines classifier (SVM)

The SVM initiated by Vapnik [20] result from a linear approach of classification (separation into two classes).

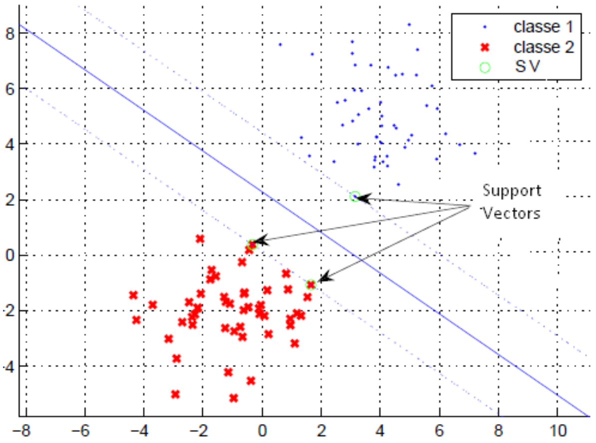

Fig 2: Support Vector Machine

If an hyperplane which split the two classes exist, the points of the hyperplane are described by the equation

$xi\, w + b = 0$ where w is the normal to the plan and $|b| = \|w\|$ is the distance between the hyperplane and the origin.

Let $d+$ (resp. d-) be the minimum distance between the hyperplane and the class of xi so that $yi = +1$ (resp. $yi = -1$). The optimal hyperplane is the one that maximize

$$d+ + d- = \frac{(1-b)}{\|w\|} - \frac{(-1-b)}{\|w\|} = 2/\|w\|. \quad (2)$$

This is rendering by the existence of a couple $(w, b) \in \mathcal{R}_d \times \mathcal{R}$ such as: $x_i w + b = 0$, for the points of the hyperplane with

$$yi(xi\, w + b \geq 0; with\ i = 1 \ldots l \quad (3)$$

So, the optimal hyperplane is determined minimizing $J(w) = \| w\|^2/2$ under the constraints in equation (3). Support vectors are points such as $yi\,(x_l.w + b) - 1 = 0$. It is a question of finding the constants w and b that confirm 1 which minimize $J(w)$. This system is simply resolved [ref], and shows that I order to estimate the class of x, we calculate $f(x)$:

$$f(x) = sign\,(\textstyle\sum_{VS} \alpha_i^0 y_i K_i(x_i x) + b_0) \quad (4)$$

where $\boldsymbol{VS}$ is the set of the support vector, K the Kernel and α_i^0 the solutions of KKKT (Karush Kuhn Tucker theorem) [10]. There are four most kernels used, the SVMs with the Gaussian (RBF) kernel are popular due to their practical use. In our simulation, we used the RBF Kernel (eq. 5) and the ‘‘one-against-one’’ approach in the multi-class classification. The Gaussian kernel is given by :

$$p(K(x, y) = e^{-\|x-y\|^2/2\sigma^2} \quad (5)$$

2.3 Multi Layer Perceptron classifier (MLP)

The multilayer perceptron [17] belongs to general family of feed-forward networks, that is, information propagates in one direction from input to output without any feedback.

The structure of a MLP contains three layers: an input layer, which is directly connected to the inputs. The size of this layer is determined by the size of characteristics vector, an output layer and one or more hidden layers that have an inherent value.

The MLP performs a matrix product between the inputs X and the parameter matrix

$$W: f(X) = t + XWb \quad (6)$$

where W is a weight matrix and b is biais. These two parameters, which represent knowledge about neurons, are estimated during the learning phase. This phase consists in finding best parameters from the training set.

To get output of a neuron in question, the activation functions H(x) such as the functions: Threshold, Hyperbolic tangent, Gaussian, Sigmoid are applied [17].

3. FUZZZY FUSION PROCEDURE

Fuzzy logic was introduced by Zadeh (Zadeh, 1965) and has demonstrated the powerful framework in manipulating the imprecision in real-world applications [18].

For integrating uncertainty reasoning, we used fuzzy rule and linguistic terms for knowledge representation. However, fuzzy rule base inference always results in fuzzy set with a support set (and consequently is uncertainty/imprecision) given by the union of the support set of the linguistic terms involved in the consequent of the active rules.

Fuzzy sets can be interpreted as membership functions μ_x that associate with each element x of the universe of discourse U, a number μ_x (x) in the interval [0,1]:

$$\mu_x : U \rightarrow [0,1] \quad (7)$$

This intrinsic characteristic of fuzzy rule based inference not only hinders the interpretation of the resulting fuzzy sets, but also hinders their use:

- as inputs to a new inference.
- to represent uncertainty propagation.

- if the size of the resulting support set is somehow important.
- as new linguistic terms of the consequent.

The set of statements comprise the fuzzy rule base, which is a vital part of a FLS[18] (figure 3).

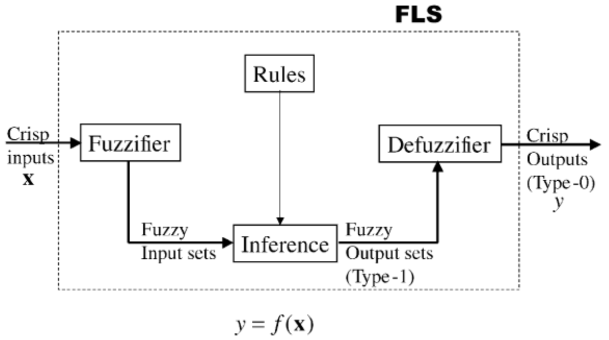

Fig 3: Structure of a fuzzy logic system.

The fuzzifier maps crisp inputs to fuzzy sets defined on the input space and the defuzzifier maps the aggregated output fuzzy sets to a single crisp point in the output space. The most widely used fuzzifier is the Singleton fuzzifier [XX][XX], mainly because of its simplicity and lower computational requirements. The proposed fusion system is designed by applying two fuzzy models: Mamdani [11] and Segueno [13] Models.

3.1 Fuzzy Fusion by Mamdani Model

The first fuzzy fusion system is designed by applying Mamdani Model [11] where the consequences of fuzzy rules are fuzzy sets. In the fusion system combining three classifiers, there are three accuracy inputs representing three classifier recognition-rates (a_i) for each classifier (SVM, KNN and MLP) and one output indicating the final decision from the fusion system for the example.

All the membership functions (MFs) of the inputs and output are defined as simple triangles shown in figure 3. Each a_i input is described by three fuzzy sets: {Low, Medium and High}.

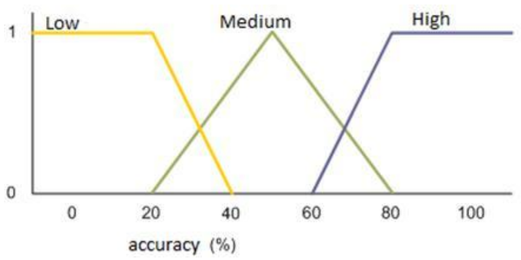

Fig 4 : Input Accuracy

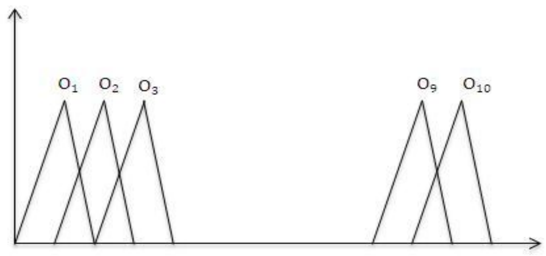

Fig 5 : Fuzzy fusion output

3.1.1 Fuzzy Rule Base

There are 27 rules in total each corresponding to one of 27 combinations of three inputs (33 = 27). The ith(i = 1. . . 27) fuzzy rule is defined as follows:

$$\textbf{\textit{IF}}\ a_1\ \textit{is}\ \boldsymbol{A}_{i1}\ \textit{and}\ a_2\ \textit{is}\ \boldsymbol{A}_{i2}\ \textit{and}\ a_3\ \textit{is}\ \boldsymbol{A}_{i3},$$
$$\textbf{\textit{THEN}}\ g_i\ \textit{is}\ \boldsymbol{O}_i(i = 1 \dots 27).$$

Where ai (can be input linguistic term or numerical value) denotes the ith recognition rate input $(i = 1 \dots 3)$. Aij$(j = 1 \dots 3)$ denotes the input fuzzy set in Low, Medium, High, and g i denotes an output fuzzy set in $O1 \dots O27$ for the ith rule.

3.1.2 Fuzzy system output and defuzzification

The system output is calculated by aggregating individual rule contributions:

$$y = \sum_{i=1}^{27} \beta_i\ g_i / \sum_{i=1}^{27} \beta_i\ . \ (8)$$

Where g_i is the output value of the ith rule and β_i is the firing strength of the ith rule defined by product t-norm:

$$\beta_i = \prod_{j=1}^{3} \mu_{A_{ij}}\ a_j\ (9)$$

Where $\mu_{A_{ij}}$ is membership grade of input aj in the fuzzy sets A_{ij}.

3.2 Fuzzy Fusion by Segueno Model

The fuzzy integral [13] constitutes a generalization of different fusion operators [14]. A fuzzy integral presents three elements in its mathematical expression. The values to be integrated are denoted by $h_i(x_i)$, where i=1,…,n and n is the number of information sources. The coefficients of the fuzzy measures, which are the membership functions used in the operator, are denoted by $\mu(A_i)$. The third element is the fuzzy connectives used in the operation of the two elements previously mentioned.

The used type of fuzzy connectives defines the type of fuzzy integral. Although there are several types of fuzzy integral [15], mainly two of them have been used in real applications. The first one uses a maximum $(\vee)$ and a minimum $(\wedge)$ operators are the fuzzy connectives. This integral is known as the Segeno Fuzzy Integral and presents the following expression:

$$S_\mu[x_1, \dots, x_n] = \vee_{i=1}^{n}[h_{(i)}(x_i) \wedge \mu(A_{(i)})]\ \ (10)$$

On the other hand, the Choquet Fuzzy Integral makes use of the sum $(\sum)$ and the product (.), as stated by:

$$C_\mu[x_1, \dots, x_n] = \sum_{i=1}^{n} h_{(i)}(x_i).[\mu(A_{(i)}) - \mu(A_{(i-1)]})\ (11)$$

Where $\mu(A_{(0)})$=0. In the radar target recognition, procedure described herein $x_i \forall i = 1,2,3$ denote the set of decisional elements (classifiers) used in fusion, h_i quantifies the decision taken by the classifier x_i concerning the membership of the unknown target to some class, and $\mu(A_i)$ the membership degree generated from each classification rate's classifier.

A fuzzy measure µ presents 2^n coefficient μ_{A_j} $\forall j = 1, \dots 2^n$, so many as subsets A_j can be formed among the number of classifier recognition rate input. From all these coefficients just n are taken into account in each fuzzy integration

$$\mu(A_{(i)}) = \mu(\{x_1, \dots, x_n\}) \forall j = 1, \dots, n \quad (12)$$

These are selected upon the sorting operation denoted by the enclosed subindices in expressions (2) and (3). If, for example the three classification rate input $x_3 > x_2 > x_1$, then x(1) = x3, x(2) = x2, and x(3)=x1. This operation involves taking the coefficients µ({x3}), µ({x2, x3})and µ({x1, x2, x3}) into account.

The fuzzy measure μ can be calculated in a recursive way using the following property of any fuzzy measure μ_{A_j}:

$$(\mathrm{P1}) \begin{cases} \mu_{A_j} = \mu(\{x1\}) = \mu^1 \\ \mu_{A_j} = \mu^i + \mu_{A_{j-1}} + \lambda\, \mu^i \ \mu_{A_{j-1}}\ j = 2, \dots, n. \end{cases}$$

Consequently, constructing the fuzzy measure requires the following steps:

a. The measure of each classifier performance and its fuzzy distribution function.

b. Calculating λ using the following equation :

$$\lambda + 1 = \prod_{i=1}^{n} (1 + \lambda \ \mu^i) \quad (13)$$

c. Establishing the fuzzy measure of each possible subset using the property (P1).

Once the fuzzy measure is calculated, we can calculate the fuzzy integral S_μ for each class according to equation (10). The final step, after that, is the decision on the membership of each target using combination operators (t-norm, t-conorm, median…). Whatever, the chosen operator, final decision is based on the maximum of membership coefficient:

$$x \in C_k \Leftrightarrow \mu_k = max_i[\mu_j(x)] \quad (14)$$

4. EXPERIMENTAL RESULTS

In the below results, we used cross-validation as a method of selecting the training database for each individual classifier. After, the fuzzy fusion system is applied on the output of all classifiers.

We prepare the validation data as follows: Each of n-fold training data is further divided m-fold. One fold of the data is treated as the validation data and all the other data are classified to get the validation accuracies. The average of m-fold classification will be used as the classifier's accuracy inputs in the fuzzy fusion model.

4.1 Dataset description

The effectiveness of the above mentioned algorithms was tested on two type of data sets, namely radar data [16] and Iris data.

Radar data is performed in ENSTA Bretagne's anechoic chamber (Figure 6). The dataset is MUSIC-2D 1 image of 10 scale reduced (1: 48) t data. It contains 1600 images of 10 aircraft targets (160 images per Target): Apache, F-14, Rafale, Harrier, Tornado, F117, F16, DC-3, Jaguar and Mirage [16].

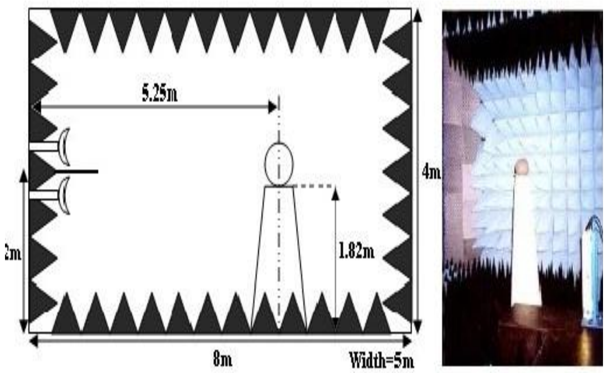

Fig 6 : Anechoic chamber of ENSTA Bretagne

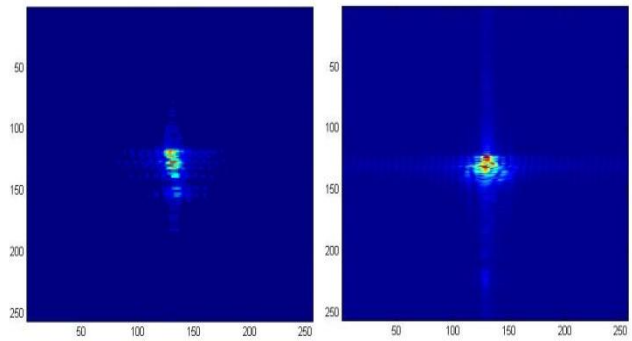

Fig 7 :Two images of rafale aircraft

In the first phase (figure 1), the data are classified using three classifier according the following parameters: for MLP classifier we employed a neuron with 2 hidden layers and hyperbolic tangent transfer function. Then, for K-NN classifier, the chosen value of k is 12. Finally for SVM classifier we chose a Gaussian Kernel with σ= 2-2, 63 and $C = 2^{13}$ [9].

4.2 Experimental environments

The data in phase I of the model are classified using K-NN, SVM and MLP classifier. The fuzzy classifier system to combine three classifiers has been implemented in Matlab program.

Decisions for each classifier were set by optimizing them for each performance measure over the validation data; that is, a classifier could have different accuracies for each of the separate performance measures. This ensures that the base classifiers are as competitive as possible across the fuzzy fusion system.

4.3 Experimental results

We present in Table 1 and figure 8 results of radar and iris data classification applying firstly individual classifiers (MLP, KNN and SVM) according to parameters previously described

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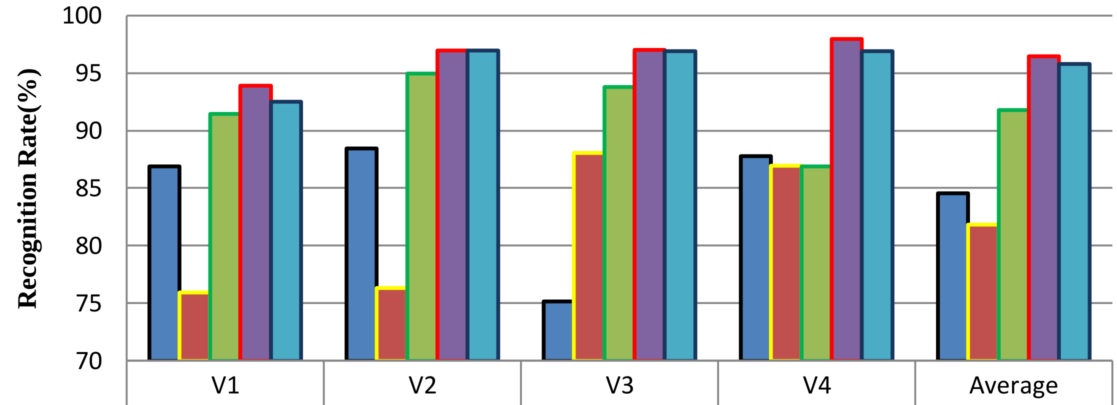
1 MUSIC-2D (Multiple Signal Classification) is a super resolution technique used in order to construct the target image.

and secondly Fuzzy fusion with Sugeno and Mamdani Models.



	V1	V2	V3	V4	Average
MLP	86.88	88.47	75.19	87.81	84.5875
KNN	75.94	76.34	88.08	86.96	81.83
SVM	91.47	94.94	93.82	86.91	91.785
F F S1	93.88	96.98	97.04	97.97	96.4675
F F S2	92.5	96.95	96.92	96.91	95.82

Fig 8 : Classification rates according individual classifiers (MLP, KNN and SVM) and fuzzy fusion model (FFS1: Sugeno Model, FFS2: Mamdani Model) using the 4-fold cross-validation scenario for radar data.

Table 1. Classification rates according individual classifiers (MLP, KNN and SVM) and fuzzy fusion model (FFS1: Sugeno Model, FFS2: Mamdani Model) using the 4-fold cross-validation scenario for iris data.

Data	**MLP**	**KNN**	**SVM**	**F F S1**	**F F S2**
V1	98,00	97,98	98,02	100,00	100,00
V2	98,00	97,98	98,00	100,00	100,00
V3	98,01	97,99	98,01	100,00	100,00
V4	98,00	98,00	98,02	100,00	100,00
Average	98,00	97,99	98,01	100,00	100,00

4.4 Performance analysis

From figure7 and table 1, we can see that in all the four tests, the fuzzy fusion performs better than the average of three individual classifiers. One more important result is that in some tests, the fuzzy classifier fusion model outperforms the best of its three composing individual classifiers and achieves higher accuracies. In general, the Sugeno model via fuzzy integral performs better than Mamdani model since the membership function of the second model is characterized by more parameters than the first one, so trying all possible parameters adapted to a particularly data to choose the best, is a penalizing process. Indeed the fuzzy integral model is able to deal with uncertainties in a better way.

Before closing this section, we must emphasize that applying fuzzy fusion on Iris data is not considerably important as well as for Radar data. This is due essentially to two reasons:

Firstly, we note that individual classifiers (MLP, KNN and SVM) present approximately the same recognition rate (98 ± 02 %). This means that there is no complementarity and diversity in classifiers results. Secondly, Radar data presents more imperfections in terms of uncertainty and imprecision compared with Iris data. These imperfections are reflected by different recognition rate of individual classifiers. In fact, the same classifier out performs other ones in some validation data and not for all (example: SVM presents best recognition rate for V1, V1, V3 but not for V4 (88, 91%) vs. MLP (87, 81%)). Which confirms, the absence of a best classifier so a unified classification method for different data.

5. CONCLUSION

Data fusion is a key technique to many engineering problems for its ability to provide more accurate results. A lot of literatures have reported the application and implementation of the data fusion based on the lowest level and the decision level. We presented a new scheme to combine ISAR images classifier‘s decision for the purpose of radar target recognition. Our scheme is decision-based, using fuzzy models (Mamdani and Sugeno). Experimental results improves recognition rate.

As a future work, we want to validate the results using other data base and we want also to study other combination schemes.

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