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APPLICATION OF FUZZY LOGIC IN THE QUALITY OF A FUZZY IN IDENTIFYING A DYNAMIC TARGET

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Abstract

A stage of an "intelligent" system for identifying a flying target (airplane), making a classification according to features taken down from a contour via a neural network is treated in this paper. Aiming at correct and true coding of the input data of the neural network for all the intervals of the values of the features, a FUZZY system, which uses the Mamdani algorithm, is synthesized in its quality of a fuzzy inference.

Key words: *features, intervals, coding, fuzzy inference, fuzzy logic*

1.Introduction

An important factor for a correct classification at solving problems connected with identification is the preceding preparation, ensuring optimal setting of the intervals of the features. A particular radio-location problem is treated, connected with identification via a classification of dynamic targets (airplanes) according to features taken down from a contour drawn at processing a radioholographic image. [3] It is possible, due to the great variety of flying devices, planes with values of a certain feature close to the limits of a respective interval but beyond them or getting into an interval characteristic of another group of planes not to be classified or to be classified incorrectly, i.e. a correct coding cannot be realized. This problem is solved by applying fuzzy logic in the quality of fuzzy inference. The fuzzy system guarantees a correct coding in cases where there are uncovered intervals or coinciding (overlapping) intervals. In the rest of the cases it reacts as a fuzzy inference.

2.Theoretical part

Definition: *Fuzzy logic inference* means reaching a conclusion in the form of a fuzzy multitude, corresponding to respective values of the input, using a fuzzy data base of knowledge and fuzzy operations.

The fuzzy inference is on the grounds of Zadeh's compositional rule. [1]

Definition: Lotfi *Zadeh's compositional rule of the conclusion is formulated as follows:*

if the fuzzy ratio $\tilde{R}$ between the input variable (x) and the output variable (y) are known, then when the fuzzy value of the input variable $x = \tilde{A}$, the fuzzy value of the output variable is defined by the expression:

(1) $y = \tilde{A} \circ \tilde{R}$

where o -is the maxmin. composition.

The fuzzy logic inference according to *Mamdani* 's algorithm is as follows [1]:

(2) $\bigcup_{p=1}^{k_j}[\bigcap_{i=1}^{n} X_i = a_{i,jp}.w_{jp}] \rightarrow y = d_j$

$j = 1 \div m$

Let us assume that $\mu_{jp}(x_j)$ is the membership function of the input x_i Fuzzy term $a_{i,jp}$, i.e.

(3) $a_{i,jp} = \int_{\underline{x}_i}^{\overline{x}_i} \mu_{jp}(x_i)/x_i$, $x_i \in [\underline{x}_i, \overline{x}_i]$

$\mu d_j(y)$ -is membership function of the output y of the fuzzy term d_j, i.e. $d_j = \int_{\underline{y}}^{\bar{y}} \mu d_j(y)/y,$,

(4) $y \in [\underline{y}, \bar{y}]$

The degree of membership of the input vector $X^* = (x_1^*, x_2^*, ..., x_n^*)$ of the fuzzy term d_j is defined as follows:

$$\mu_{d_j}\left(X^*\right) = \bigvee_{p=\overline{1,k_j}} w_{jp} \cdot \bigwedge_{i=\overline{1,n}} \left[\mu_{jp}\left(x_i^*\right)\right], \ j = \overline{1,m} \tag{5}$$

where $\vee(\wedge)$ -are the logic operations OR (AND). This results into a fuzzy multitude $\tilde{y}$, corresponding to the input X^*:

$$\tilde{y} = \frac{\mu_{d_1}(X^*)}{d_1} + \frac{\mu_{d_2}(X^*)}{d_2} + \ldots + \frac{\mu_{d_m}(X^*)}{d_m}. \tag{6}$$

For a transition from a sub-multitude of the universal multitude of the fuzzy terms $\{d_1, d_2, ...d_m\}$ to the fuzzy multitude of an interval $y \in [\underline{y}, \bar{y}]$ it is necessary: to "cut" (agg) the function of belonging $\mu d_j(y)$ at level $\mu d_j(X^*)$, and to join the resulting fuzzy multitudes, which can be written down as follows:

$$\tilde{y} = \underset{j=\overline{1,m}}{\operatorname{agg}} \left(\int_{\underline{y}}^{\bar{y}} \min\left(\mu_{d_j}(X^*),\ \mu_{d_j}(y)\right) / y \right) \tag{7}$$

The crisp (non-fuzzy) value of the output y, corresponding to the input vector X^* is determined as a result of a defuzzification of the fuzzy multitude $\tilde{y}$. Defuzzification is applied mostly in accordance with the method of the weight centre.

$$y = \frac{\int_{\underline{y}}^{\overline{y}} y \cdot \mu_{\tilde{y}}(y)dy}{\int_{\underline{y}}^{\overline{y}} \mu_{\tilde{y}}(y)dy},$$

3. Methodology for creating a Fuzzy system

3.1. General characteristic

One of the effective approaches for choosing an optimal decision to which interval to consider the values of a given feature is the so-called approach for the logic conclusion in the conditions of obscurity and inconclusiveness (fuzzy logic inference).

The methods of the fuzzy multitudes are applied in the quality of a formal apparatus. To be more exact, fuzzy relations are introduced about quality values of the area factors and the target function (the criterion for optimality). A fuzzy relation is characterized by a membership function, which is a subjective measure of the degree of fulfillment (truthfulness) of the factor-criteria ratio. Using the Bellman-Zadeh compositional rule, the fuzzy ratio is applied for calculating the value of the conclusion (the so-called composition -based inferencing).

A suitable apparatus for formal description of the conclusion are the multi-valued logic probabilities and respectively the fuzzy multi-valued logic functions. They are based on the multi-valued logic (k-valued logic), $k \geq 2$, which is a generalization of the two-valued logic.

The functions of the ê-valued logic $f(x_1, ... x_i ..., x_n)$, x_i, $i = 1 \div n$, where for each x_i there are k number of logic truth values, can be presented in a table or analytically.

3.2.Application of a fuzzy inference for a given localizing task.

3.2.1.Formulating the task:

Digital radioholographic images of ten types of airplanes are treated: F16, An 124, McDowell, B52, Bucaneer, F117, Jaguar, Mig 29, Miraj 2000, Su 34. A filtration of the noisy images is done using a CNN neural network. *Candy* software is used to achieve the filtration via a CNN neural network.[2]

The method used for taking down a contour from the filtered radio-holographic image of the target is Robert's method because it provides the biggest number of points of the contour, therefore it is the most informative: the contour only gets thinner but is not broken.

For identifying particular types of planes (specific "Stealth"; military and transport) the following vector of features is synthesized from the produced contour:

1. Ratio A of the width to the length of the target, where the width is the distance between the endmost points of the wings and the length - the distance between the endmost points of the fuselage axis:

2. Slope α of the line linking the centroid (the mass centre) and the endmost point of one of the wings, toward the fuselage axis:

3. The position of the mass centre in relation to the geometric centre of the fuselage axis The subtraction "geometric centre – mass centre" - L_r is calculated.

4. Width of the wings of the plane – L_k.

The characteristic values are calculated for the respective features of the given types of planes.

The following classification of planes is done according to the formulated features and the values calculated for the particular type of plane:

- According to the feature 'relation', the planes can be classified in three groups: specific, military and transport.

- According to the feature 'position of the mass centre in relation to the geometric centre of the fuselage axis', the second group of planes can be divided into bombers, exterminators, and unmanned.

Due to the fact that the unmanned planes have characteristic value of the ratio A, different from the value of the other types of planes, this group of planes could be classified correctly as a separate one according to this ratio.

- According to the feature 'A', the transport planes can be identified either as type *An* or as type *Boing.* According to the feature width of the wings, the number of the plane engines could be identified as those with more engines, e.g. 4, 6, have a larger width of the wings.

The confidence intervals of the features of the separate types of planes, shown in tables 1, 2, 3, 4, 5, are given by means of statistic methods.

Table 1.
Confidence intervals and limiting relative error for the feature 'A'.

Type of plane	Lower limit	Upper limit	*, % **
Stealth	0.7575	0.8077	
Military			
Fighters	0.56	0.6789	
Bombers	0.486	0.647	
Unmanned	1.4706	1.9238	
Transport			
Boing	0.912	0.9814	
An	1.0524	1.1361	

*= $\Delta_{\gamma;k}$; **= $\gamma = 0{,}95$

Table 2. Confidence intervals and limiting relative error for the feature α :

Type of plane	Lower limit	Upper limit	*,% **	*, % ***
Other types of planes	78,9316	85,9434	4,2529	7,8103
Unmanne-d planes	90			

$*=\Delta_{\gamma;k}$; $**=\gamma=0{,}95$; $***=\gamma=0{,}99$

Table 3.
Confidence intervals and limiting relative error for the feature L_{γ}

Type of plane	Lower limit	Upper limit	*,% **	*, % ***
Fighter	34.915	46.585		
Bomber	9	24		

$*=\Delta_{\gamma;k}$; $**=\gamma=0{,}95$; $***=\gamma=0{,}99$

Table 4.
Confidence intervals and limiting relative error for the feature $L_{\acute{e}}$

	Boeing		
	2 engines	4 engines	
Lk	<56.02	>56.02	

Table 5.
Confidence intervals and limiting relative error for the feature $L_{\bar{\varepsilon}}$.

	An		
	2 engines	4 engines	6 engines
Lk	<48.145	80.85<Lk<-48.145	>80.85

The *Matlab* programme medium is used for getting these intervals [3].

On Table 1 it is seen that the intervals of the feature ratio A, determined for each type of plane have both overlapping and not overlapping plots. For example:

1. When the ratio A is in the interval from 0.677 to 0.748, a concrete decision cannot be imposed how to code the input of the neural network – it could go into group 2 or into group 1.
2. When the ratio A is in the interval from 0.8056 to 0.8904 – it could go into group 3 or into group 1.
3. When the ratio A is in the interval from.1324 to 1.2516 – it could go into group 3 or into group 2.

Because of this, a great deal of planes, which have values of a certain feature close to the limits of a respective interval but beyond them or get into an interval characteristic for another group of planes, cannot be classified or can be classified incorrectly, as a correct coding cannot be realized.

In order to eliminate this problem a second feature is introduced: the angle α, defined in (10) and Fuzzy Logic is used with the aim of covering a larger interval of the values of the feature.

3.2.2. Getting optimized values for the feature 'A'.

The input variables for the Fuzzy system are the two features: the ratio A and the slope α. The membership functions of A are set by 9 linguistic variables in the range from 0.4617 to 2.016. The limits are chosen in accordance with the following:

- the lowest value of the ratio is 0.486 which corresponds to a plane type "Military". An admissible deviation from this value is set in the limits of 5% -- A=0.4617.

- the highest value of the ratio is 1.92 (type of plane "Military"). An admissible deviation of 5 % from this value is set – A=2.016.

The linguistic variables and their intervals of operation are shown on Table7.

The limiting values of the feature A for the three groups of planes are shown on Table 6 in ascending order.

Table 6. Limiting values of A for the types of planes:

Type of plane	Limiting values of A	
	Min	Max
Military	0.486	0.6789
Stealth	0.7575	0.8077
Military	1.4706	1.9238
Transport	0.912	1.1361

For the linguistic variables A_3, A_5, A_7 and A_9 as a mean value is assumed the upper limit of each interval for the preceding type of plane enlarged by 5%. The linguistic variables A_2, A_4, A_6, and A_8 cover the interval for the respective type of plane.

The *Matlab 7.0* programme medium is used for modelling and simulation of fuzzy logic.[5] The ratio A as an input variable in fuzzy logic is shown visually in Fig.1

Table 7. Linguistic variables for A and their intervals

A	Intervals		
	Min	Mean	Max
A1	0.4617	0.486	0.5103
A2	0.486	0.599	0.7128
A3	0.677	0.7128	0.748
A4	0.7128	0.7804	0.848
A5	0.8056	0.848	0.8904
A6	0.848	1.02	1.192
A7	1.1324	1.192	1.2516
A8	1.192	1.556	1.92
A9	1.824	1.92	2.016

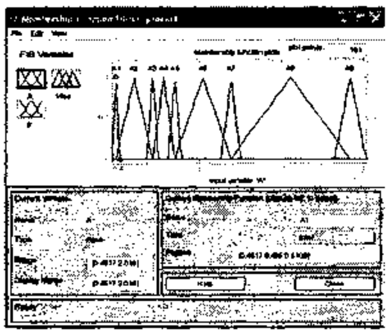

Fig.1. Fuzzy logic according to feature A.

The membership functions of the other input variable - the slope α are represented by 8 linguistic variables in the range 19.6745 ÷ 94.5. For each type of plane the values of α are shown on Table 8. The admissible intervals of the linguistic variables are shown on Table 9.

Table 8. Limiting values of α for each type of plane

Type of plane	*, °
Jaguar - Military	20.71
Stealth - Specific	41.25
Transport	54
Mirag 2000 - Military	60
Stealth - specific	66
Su - 34 - Military	72
F16 - Military	78
UAV - Military	90

*= α

This angle varies in small limits depending on the position of the plane in the frame. Due to that fact, overlapping of the limiting values is impossible to be set for the types of planes. Therefore, the intervals of that input variable are formed by the limiting value and an admissible deviation from it, ± 5 %.

Table 9. Linguistic variables for α and their intervals.

F	Intervals		
	Min	Mean	Max
F1	19.6745	20.71	21.7455
F2	39.1875	41.25	43.3125
F3	51.3	54	56.7
F4	62.7	66	69.3
F5	68.4	72	75.6
F6	74.1	78	81.9
F7	85.5	90	94.5
F8	57	60	63

Visually the relation α, as an input variable in fuzzy logic, is shown in Fig.2.

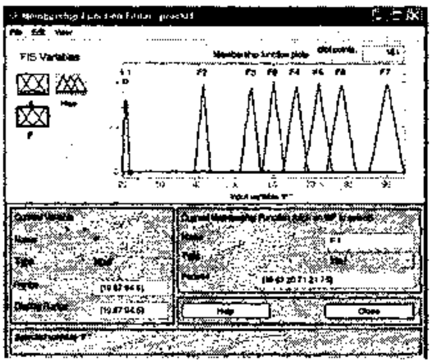

Fig.2. Fuzzy logic according to feature 'α'.

The output variable is determined by the discrete levels 1, 2, and 3, which correspond to the respective group of planes: Stealth, Military and Transport. It is shown in Fig.3

Triangular membership functions to the linguistic values of the variables are chosen. The transforming of the input variable into output ones is done by the algorithm of *Mamdani* [4]. Thirty-nine rules are introduced for control which are shown on Table 10.

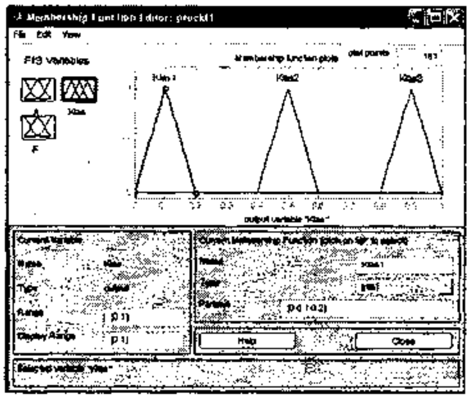

Fig. 3. Fuzzy logic for the output variable

These rules are introduced in the *Fuzzi Logic editor of Matlab* and can be visualized as follows :

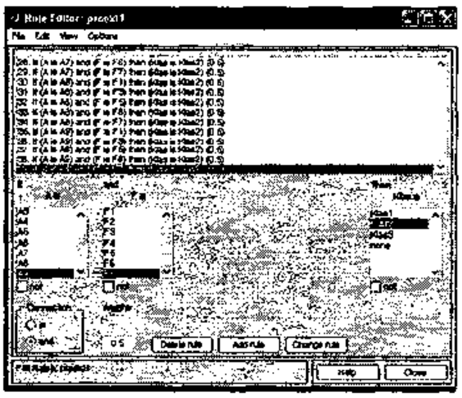

Fig.4. Fuzzy logic for introducing rules.

4.Computer simulation

The result from the operation of the *Fuzzy* system for the following input data is:

1. When A=0.69 and α=21° - the expected result is coding of the input into Group 2. The result from the *Fuzzy* system is shown in Fig. 5.

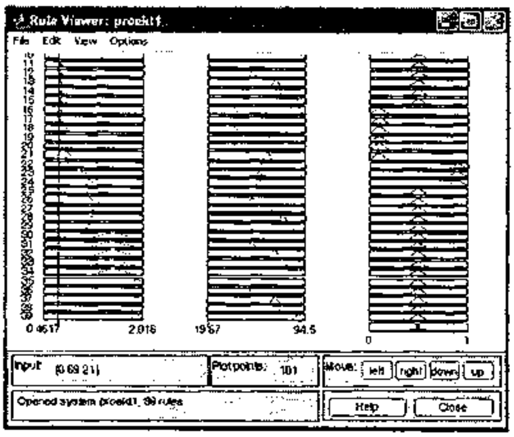

Fig.5. Result from the operation of Fuzzy logic

2. When A=0.73 and α=39° - the expected result is coding of the input into Group 1. The result from the *Fuzzy* system is shown in Fig. 6.

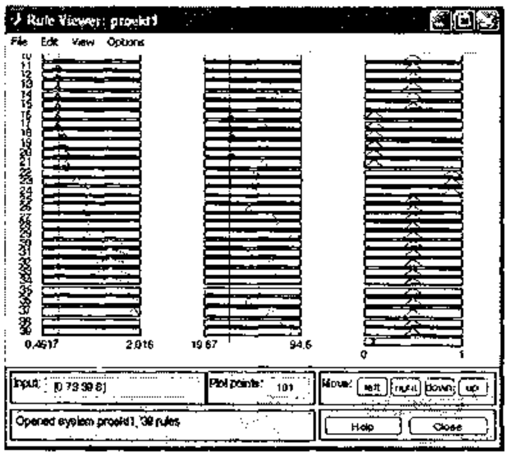

Fig.6. Result from the operation of Fuzzy logic.

3. When A=0.81 and α=63.1° - the expected result is coding of the input into Group 1. The result from the *Fuzzy* system is Group 1.

4. When A=0.856 and =59.7° - the expected result is coding of the input into Group 3. The result from the *Fuzzy* system is shown in Fig. 7.

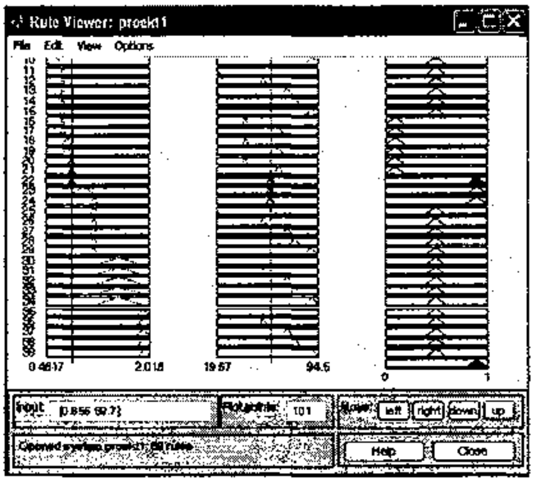

Fig. 7. Result from the operation of Fuzzy logic

5. When A=1.17 and α=62.4° - the expected result is coding of the input into Group 3. The result from the *Fuzzy* system is Group 3.

6. When A=1.21 and =73.8° - the expected result is coding of the input into Group 2. The result from the *Fuzzy* system is Group 2.

Table 10. Rules for getting input data for a fuzzy conclusion

A	F							
	F1	F2	F3	F4	F5	F6	F7	F8
A1	Klas2	-	Klas2	-	Klas2	Klas2	Klas2	-
A2	Klas2	-	Klas2	-	Klas2	Klas2	Klas2	-
A3	Klas2	Klas1	Klas2	Klas1	Klas2	Klas2	Klas2	-
A4	-	Klas1	-	Klas1	-	-	-	-
A5	-	Klas1	-	Klas1	-	-	-	Klas3
A6	-	-	-	-	-	-	-	Klas3
A7	Klas2	-	Klas2	-	Klas2	Klas2	Klas2	Klas3
A8	Klas2	-	Klas2	-	Klas2	Klas2	Klas2	-
A9	Klas2	-	Klas2	-	Klas2	Klas2	Klas2	-

Conclusion:

The use of Fuzzy Inference as an element of an intelligent classificatory on the basis of a neural network provides correct and true coding of the input data for all the intervals.

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ПРИЛОЖЕНИЕ НА FUZZY ЛОГИКА В КАЧЕСТВОТО НА РАЗМИТ ИЗВОД ЗА ОПТИМИЗИРАНЕ НА ВХОДНИ ДАННИ ПРИ РАЗПОЗНАВАНЕ НА ДИНАМИЧЕН ОБЕКТ

М. Костова

Резюме

Разглежда се етап от "интелигентна" система за разпознаване на летящ обект (самолет), извършваща класификация по признаци снети от контур.чрез невронна мрежа. С цел коректно и правилно кодиране на входните данни на невронната мрежа за всички интервали от стойности на признаците е синтезирана FUZZY система в качеството на размит извод, която използва алгоритъма на *Mamdani*.