Automatic recognition of radar targets using Case Based Reasoning

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***Abstract*— The main purpose of this paper to enhance the precision of radar target recognition, without reducing speed. Since the first detection method Case Based Reasoning (CBR) to improve the accuracy of nearest neighbor (with small k) is used for the detection time is not increased and rotating parts of the goals modulation (JEM) on the radar signal design and automatic recognition system of radar targets have been simulated using this method. In this way the the system performance somewhat different signal to noise ratios (SNR is improved), And radar as possible can help reduce the response time of decision.**

***Index Terms*—CBR, classification, recognition,JEM**

I. Introduction

A. Recognition of radar targets

An application of pattern recognition is Automatic Target Recognition (ATR) for continuous wave radars. Several approaches are presented for radar target recognition in literature. Radar Cross Section (RCS), natural resonance frequencies of targets, changes in polarizations of received electromagnetic radar wave and Jet Engine Modulations (JEM) have reported in [1], [2], [3] and [4] respectively.
We used this model to simulate backscattered signals in 200 elevation angles from ten flying objects, which have shown in Table I.

B. The raw Data Extraction

Raw data or unprocessed in the waveform returned from the target to the radar, which can be the same as the back of the goal in mind that in the process, process variations on primitive data occurs, a mathematical model accurately good to simulate signals the return of the rotating air targets relating paper Number One [5] is selected, it has been suggested. The theoretical model using the topological properties of rotating parts and some other parameters of the target signal return loses. [6] Using this model, the signal from 10 of reference [7] are simulated at different angles, which are the same reference purposes in Table I have been used.

TABLE I. Ten Targets as reference classes.

No.	Target	Application
1	F-3	Training
2	PC-7	Training
3	ANTONOV AN-12	Military
4	FFA AS ZZO118A	Training
5	BAE-248 SERIES 2B	Transport.
6	KJ 500-3S	Military
7	ROLLS ROYCE ALISON	Military
8	KUZNETSORNK-8-2	Transport.
9	TUMMANSKY R-11	Military
10	ROLLS ROYCE 535	Military

II. Case-Based Reasoning(CBR)[8]

The roots of CBR is found in the works of Roger Schank in1982.CBR is based on a model ofhuman cognition dealing with knowledge in form of concrete experienced examples: To solve a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation. It is a powerful and frequently applied way to solve problems for humans. Reasoning by retrieving past cases may succeed to solve a new problem by making full use of past information, it has two features as follows:

- In a CBR system, knowledge can be represented in case base ways, case is easier to acquire than acquisition of general knowledge.
- Maintenance of case base is easily, case base update can be implemented by deleting or repairing old cases or adding new cases.

III. CBR theory introduction [9]

CBR is a problem solving approach by recalling a previous experience suitable for solving the new problem. A widely accepted model of the CBR process is the CBR cycle proposed by Aamondt and Plaza which comprises four principle tasks: retrieve, reuse, revise, and retain, is called 4R model. In a word, a general CBR cycle may be described by the following four processes:

(1) RETRIEVE the most similar case or cases
(2) REUSE the information and knowledge in that case to solve the problem
(3) REVISE the proposed solution
(4) RETAIN the parts of this experience likely to be useful for future problem solving

In figure 1, this cycle is illustrated. An initial description of a problem defines a new case. This new case is used to RETRIEVE a case from the collection of previous cases. The retrieved case is combined with the new case -through REUSE -into a solved case, i.e. a proposed solution to the initial problem. Through the REVISE process this solution is tested for success,

e.g. by being applied to the real world environment or evaluated by a teacher, and repaired if failed. During RETAIN, useful experience is retained for future reuse, and the case base is updated by a new learned case, or by modification of some existing cases.As indicated in the figure, general knowledge usually plays a part in this cycle, by supporting the CBR processes. [10],[11],[12],[13].

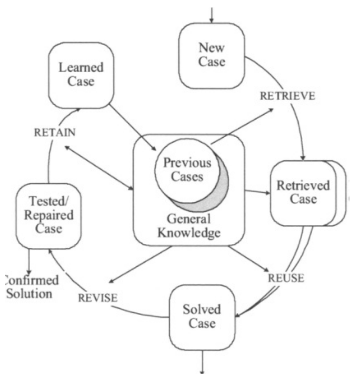

Fig. 1. The CBR Cycle

CBR is one of the most complex aspects of implementing a new method to compute the similarity of previously solved problems. Most methods that are used to calculate the degree of similarity The function used to match the nearest neighbor. Similarity of the methods in the new issue previous issues .The individual measures similarity measure is then obtained as the weighted average values between (1) of the criterion function can be calculated [14]

$$S_{IR} = \frac{\sum_{i=1}^{n} W_i \times sim(f_{Ii}, f_{Ri})}{\sum_{i=1}^{n} W_i} \quad (1)$$

In which:

S_{IR} Degree or index of similarity between the terms of the new I and the retrieved R ($0 \leq S_{IR} \leq 1$), where 1 represents the similarity hundred percent or the full implementation of Metrology less than 1, indicating matching or similar details. Define the parameters of equation (1) in Table II is shown.

TABLE II. PARAMETERS OF EQUATION (1)

I: Index attribute (criterion) (i = 1,2,3, ..., n)	R: : problem index retrieved	I: : New problem index
Sim: Function to calculate the similarity between two values f_Ii, f_Ri	W_i:Weight feature (standard) I'm (usually W_i = 1 Σ▒ 〖〗)	
f_{Ii}, f_{Ri}:The amount of feature points or I, respectively, and problem recovery problem New		

Sim-function for numerical values generally related to (2) is defined as:

$$S_{IK} = sim(f_{Ii}, f_{Ri}) = 1 \quad \frac{|f_{Ii} - f_{Ri}|}{\beta_i - \alpha_i}, f_{Ii}, f_{Ri} \subset [\beta_i, \alpha_i]$$
(2)

Which β_i, α_i respectively represent the lower and upper limit values are the criteria i., In some cases, reverse the "weighted

As equations (2) and (3) also show a similar assessment criteria - criteria that actually solved problem retrieving and using previous answer to a new problem - which is simply the distance measure values (parameters) in problem New Vmsalh are retrieved from positive (benefits) and negative (costs) of problem selection criteria of similarity retrieval (to solve a new problem) is not considered. [15]

IV. SIMULATION RESULTS

A. radar targets recognition by other methods

Table III ,IV shows the results of the detection algorithm to accurately identify the target radar with three Particle Swarm Optimization (PS), Multi-Layer Perceptron (MLP) and k-nearest neighbor (K-NN) is the minimum distance, FUZZY CONTROLLED PARTICLE SWARM CLASSIFIER(FCPS-CLASSIFIER) or INTELLIGENT PARTICLE SWARM CLASSIFIER (IPS-CLASSIFIER) [16],[17] it is shown

TABLE III. PERCENTAGE OF RADAR TARGET RECOGNITION ALGORITHM WITH THREE PS ,MLP ,K-NN [16]

SNR	-10	-5	0	5	10	15
PS-C	15	26.5	48.9	56.3	77.3	80.5
MLP	11.7	14.9	46.5	57.9	66.6	76.2
k-NN	7.7	17.0	50.5	62.5	79.0	79.5

TABLE IV. PERCENTAGE OF RADAR TARGET RECOGNITION ALGORITHM WITH THREE IPS,MLP,K-NN [17]

SNR	- 10	- 5	0	5	10	15
IPS-classifier	14/7	25/4	52/1	61/1	89/2	90/1
MLP	11/7	14/9	46/5	57/9	66/6	76/2
K-NN	7/7	17	50/5	62/5	79	79/5

B. Simulation Results CBR method

Results obtained in the three cases is shown in each case it is assumed that the target is unknown angle of ten degrees.

First case: frequency radar, none of the frequencies of the classes, not the viewing angle of the specified Nbashddrshkl 3 shows (Chart square.)

Second case: frequency radar is one of the frequencies corresponding to the subclass but radar detection angle of does not show. (chart positive.)

third: frequency of radar frequencies and angles of the subclass is also identified show. (Star charts).

Figure 2 shows the better performance of CBR in comparison to other methods shows. These methods of detection rates purposes unknown in the signal-to-noise above significantly improved due to The reason for this is the Classifier KNN no-action clustered only relies on comparing case of the CBR technique used to dispose of all specimens. Table IV to compare the proposed approach (CBR) with the results of sections A and B are used.

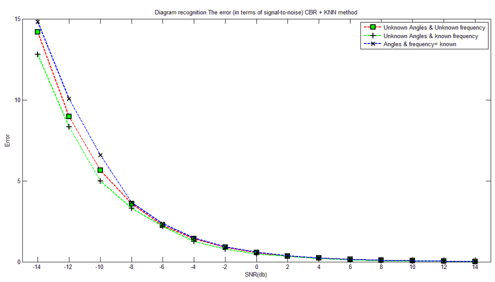

Fig. 2. displays the signal-to-noise ratio for the three modes of CBR

TABLE V. PERCENTAGE OF RADAR TARGET RECOGNITION ALGORITHM CBR

SNR	-10	-5	0	5	10	15
CBR	13.3	24.6	63.4	72.6	87.1	95.1

V. CONCLUSION

Detection methods Case Based Reasoning (CBR) to improve recognition accuracy of radar targets and the nearest neighbor (with small k) is used for the detection time is not increased. Results presented showed a unique feature of the method is shown CBR chair production responses with relatively high stability of the These features for classification particularly in critical applications such as medical or military when they are used, so the coefficient of the security classification system response raises And radar as possible can help reduce the response time of decision., One of the top targets in the design of a radar target identification system to enhance the ability of correct identification rate and the signal-to-noise ratio is lower.

This means that even in the presence of noise, the system is capable of high power, still has the power to determine the identity of the target. Performance of the system in this way is somewhat different ratios of signal to noise ratio (SNR has improved).

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