An Evolution of Geometric Structures Algorithm for the Automatic Classification of HRR Radar Targets

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Abstract. This paper presents a novel approach to solve multiclass classification problems using pure evolutionary techniques. The proposed approach is called Evolution of Geometric Structures algorithm, and consists in the evolution of several geometric structures such as hypercubes, hyperspheres, hyperoctahedrons, etc. to obtain a first division of the samples space, which will be re-evolved in a second step in order to solve samples belonging to two or more structures. We have applied the EGS algorithm to a well known multiclass classification problem, where our approach will be compared with several existing classification algorithms.

1 Introduction

Genetic algorithms have been widely used for solving very different problems, the majority of times related to optimization. In this field the research work has been massive in the last years and powerful algorithms based on evolutionary computation have been developed.

However, there are other fields in artificial intelligence in which the genetic approach has not been so successful. In classification problems for example, the different evolutionary computing techniques have always played a secondary role: training of neural networks [2]-[7], or generation of fuzzy rules [8], but it is difficult to find a pure evolutionary technique applied to the complete resolution of the problem. The Genetic Programming technique [9] has been applied to some classification problems with some success, though its results in multiclass classification have not been so promising.

The idea behind this paper is to propose a pure evolutionary technique to tackle multiclass classification problems. We have called this technique "Evolution of Geometric Structures Algorithm" (EGS), since it is based on evolving a set of geometric structures (hypercubes, hyperspheres, hyperoctahedrons, etc) to cover the samples space, and then using another evolutionary algorithm to combine them into a single classifier. As will be shown, the idea is to run a genetic algorithm encoding a set of geometric structures for each class, in such a way that the position and size of the geometric structure is evolved. A fitness function counting the number of correct classification of samples for each class is used to guide the search. In a second step, another evolutionary algorithm is used to decide the classification of the samples within two or more geometric structures. As can be seen, only evolutionary techniques are used to solve the problem. Also, the EGS algorithm is adequate to be implemented in a parallel way, since several genetic populations must be run in the first step of the algorithm.

In this paper we apply the presented technique to the automatic classification of high range resolution radar (HRR) targets, which is a hard problem of classification solved previously in the literature [11]. This kind of radar uses broad-band linear frequency modulation or step frequency waveforms to measure range profiles (signatures) of targets [11], [12]. HRR radar profiles are essentially one-dimensional images of radar targets. A range profile is defined as the absolute magnitude of the coherent complex radar returns, and all phase information is usually discarded. If a range profile is measured with sufficient resolution, the parts of the aircraft that strongly reflect the radar energy, are resolved. Therefore, range profiles provide information about the geometry and structure of the aircraft, and so they are suitable features for automatic aircraft classification. Figure 1 shows an example of the generation of a HRR signal associated to a target in two different orientations. The number of samples with information is related to the maximum size of the target. Data sets of HRR radar profiles can be generated by recording measurements of each target over the values of azimuth and elevation considered.

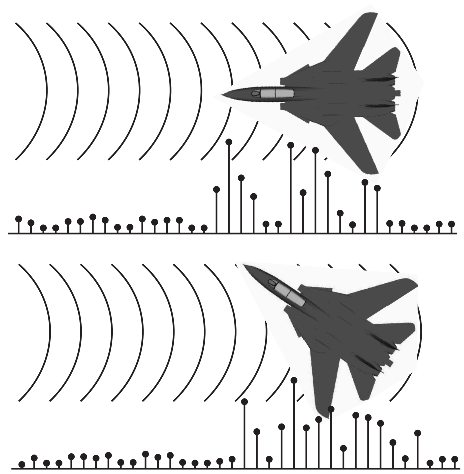


Fig. 1. HRR radar signal example for two different orientations of the target.

In the literature, this task is called "Automatic Target Recognition" (ATR) [12]. The ATR problem can be formulated as a multiclass classification problem. The objective is to be able to classify an arbitrary target, based on knowledge derived from previous samples. The Probability Density Functions (PDFs) of the classes are usually unknown, and only a finite set of well defined cases (training set) is available. Several techniques based on different approaches to the problem and its solution have been developed, all of them having some disadvantages either in terms of accuracy or complexity.

The structure of the rest of the paper is the following: next Section presents the EGS algorithm, describing its different steps and possible modifications for a better performance. Section 3 shows an example of application of the EGS to the ATR problem. Section 4 closes the paper with some final remarks.

2 An evolution of geometric structures algorithm for classification

Definitions:

1. *Hyper-structures:* the set of points $x \in S$ (S features space of dimension w) such that

$$a_i \cdot p_i \cdot |c_i - x_i| \leq R, \ \forall \ i, \tag{1}$$

   this equation defines a hypercube.

$$\sum_{i=1}^{w} a_i \cdot p_i \cdot (c_i - x_i)^2 \leq R, \tag{2}$$

   this equation defines a hypersphere.

$$\sum_{i=1}^{w} a_i \cdot p_i \cdot |c_i - x_i| \leq R, \tag{3}$$

   this equation defines a hyperoctahedron.
   In all the structures presented, the parameters c_i, $i = 1, \cdots, w$ stands for the coordinates of the center of the geometric structure, p_i, $i = 1, \cdots, w$ is a positive scale factor and $a_i \in \{0, 1\}$, $i = 1, \cdots, w$, are binary numbers which reduce the dimensionality of the geometric structure.

2. *Genetic Individual:* A set of N hyperstructures. Each hyperstructure is defined by the equations shown above, with parameters R, $\mathbf{c}$, $\mathbf{a}$ and $\mathbf{p}$.

3. *Genetic Population:* A set of M genetic individuals focussed in a given class C. An point x is decided to belong to class C if this point is inside the structure defined for this class.

With these definitions, the EGS algorithm is constructed in two different steps:

Step 1:

In this step, C genetic algorithms (one per class) are launched. Each genetic algorithm is formed by M individuals representing geometric structures in the way defined above. The fitness function of the genetic algorithm is defined as:

$$f(x) = \nu_1 \cdot A + \nu_2 \cdot B \tag{4}$$

where A stands for the percentage of correct answers when classifying a point x as belonging to the corresponding class of the geometric structure, and B is the percentage of correct answers when classifying a point x as not belonging to the corresponding class of the geometric structure. Parameters ν_1 and ν_2 weight the importance of classifying correctly the points belonging and not belonging to the class of the geometric structure. It is important to note that we are evolving a number $N * C$ of structures (N structures per class), but, at this stage, each class is evolved in a different genetic population.

Evolutionary Algorithm dynamics: Once each individual of the population has assigned its fitness value, the mean value for the population is calculated. The individuals with associated fitness values over this value are maintained, whereas the individuals with fitness values under the mean are substituted by new individuals obtained from the crossover of maintained individuals.

The crossover operation is implemented in the following way: Starting from two parents P_1 and P_2, a single offspring individual will be generated. To do this, for each of the N geometric structures encoded in the individuals we can do the following actions:

- Copy the structure of P_1, with probability 0.25.
- Copy the structure of P_2, with probability 0.25.
- Form a new individual as follows: the new radio is the mean value of the P_1 and P_2 radios. The same operation is carried out to obtain the centers and scale factors of the individual. Regarding the parameter a, it is calculated using the logical operation "or" between vectors $\mathbf{a}$ of P_1 and P_2, with a probability of 0.5, and the logical operation "and" with the same probability.

The mutation operator is applied to all the individuals of the population after the crossover operator, with a low probability:

- The radio is modified using a small noise from a uniform distribution $[-0.1, 0.1]$. Choosing randomly a direction, the center is moved towards this direction using a uniform noise in the range $[-1.0, 1.0]$.
- The scale factor of each geometric structure is modified adding an noise from a uniform distribution $[-1.0, 1.0]$.
- Finally, the vector $\mathbf{a}$ is modified applying a flip operation to some of its components.

Step 2:

After evolving the set of geometric structures for each class, we have to merge them into a single classifier. This is problematic, since structures may overlap, and thus a sample may be into structures belonging to different classes. In this second step we use a genetic algorithm for assigning a real weight (ω) to each structure, in such a way that the number of correct classifications to be maximum (we consider the real numbers in the interval $\omega \in [-1, 1]$). A voting scheme is carried out, and the samples belonging to two or more geometric structures are assigned to the structure with largest weight (if a sample belongs to two structures of the same class, their values are added). As mentioned, the fitness value of each individual is the total number of correct classifications.

This process can be done in a soft way, by defining variable weights, in such a way that the value of the weight is ω in the center of the hyperstructure, and it has a lower value near the border of the hyperstructure. To do this we define the following weight:

$$\omega^* = (\omega - d \cdot Q) \cdot h(\mathbf{x}), \tag{5}$$

where Q is a value in $(0, 1)$, d is the distance from the center of the geometric structure and $h(\mathbf{x})$ is a binary value which indicates if the point $\mathbf{x}$ is inside the structure ($h(\mathbf{x}) = 1$) or out of the structure ($h(\mathbf{x}) = 0$). An example in a two-dimensional structure (octahedron) is given in Figure 2.

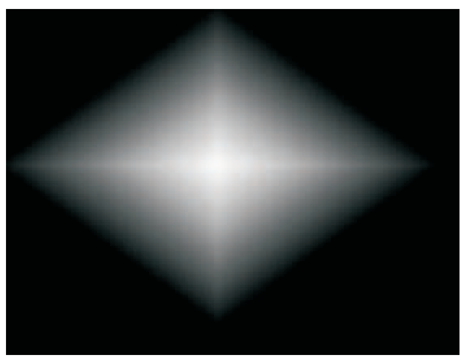


Fig. 2. Example of the soft version in the case of samples shared by two or more structures. In this case an octahedron with a different value in its weight (linear variation following Equation (5)) is considered. The value of the weight is related with the intensity of the hyperstructure: the closer the sample is to the center of the hyperoctahedron, the largest is the associated weight.

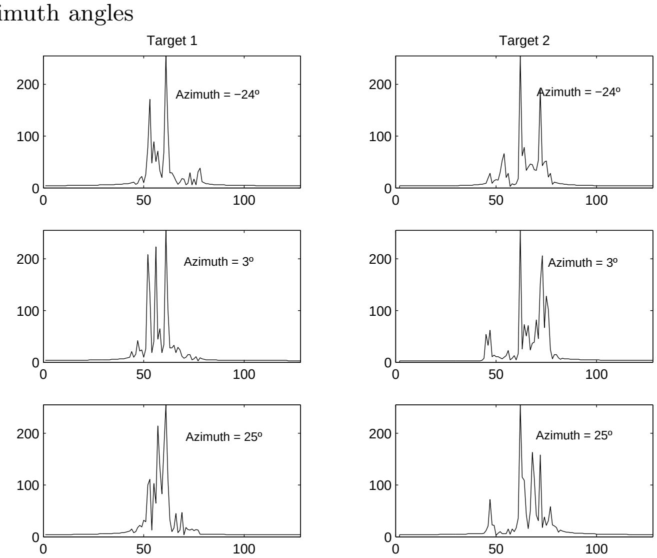
If we use this soft version of the weights, the genetic algorithm must search for values ω and Q for each structure, instead of only for ω as in the former case.

3 Experiments and results

As we mentioned before, we test the propose EGS algorithm in the ATR problem. The term ATR "Automatic Target Recognition" was originated in the early 1980s within the Low Altitude Navigation and Targeting Infra-Red for Night (LANTIRN) program belonging to the U.S. Defense Agency. One of its objectives was to develop a system capable of distinguishing tanks from trucks, jeeps, and other less important targets. In 1988, the United States Defense Advanced Research Projects Agency (DARPA) conducted a study of neural networks and selected ATR as one of the four areas for which application of neural network technology was to be evaluated [13].

A database containing HRR radar profiles of six types of aircrafts (six classes) is used. These signals have been generated using a ray tracing algorithm, and they are the same signals used to generate the results presented in [14]. The assumed target position is head-on with an azimuth range of $\pm 25^o$ and elevations of -20^o to 0^o in one degree increments totaling 1071 radar profiles per class. The length of each profile is 128. These profiles have been aligned using the position of the maximum sample in each vector, and they have been energy normalized and Box-Cox transformed with $\alpha = 0.65$. Once the profiles have been aligned, most of the information is concentred in the central part of the vector, so only $L = 53$ central samples are selected to classify each pattern. Figure 3 shows radar profiles of two different targets, illustrating the magnitude of variation of the radar signature caused by changes in orientation.

Fig. 3. Radar signatures of two different targets for an elevation angle of -20^o and different azimuth angles



The performance of the classifier will be specified by both the error rate and the computational cost after training. The error rate is defined as the percentage of overall classification errors, and the computational cost after training is defined as the average number of simple operations (sums, products, comparisons, etc) needed to classify each test pattern.

For each experiment carried out, two subsets are used: a training set composed of 960 profiles (160 per class), randomly selected from the original data set (the poses could be different for different targets), and a test set, composed of 1710 profiles. The test set is used to assess the classifier's quality after training. Both sets of data correspond to a value of Signal to Noise Ratio of 20 dB. Recall that the SNR is defined using the peak energy of the signal, given by equation

$$SNR(dB) = 10 \log \left(\frac{\max\{|\mathbf{x}|\}^2}{\sigma^2} \right) \qquad (6)$$

The proposed algorithm is going to be tested in this problem, using three different geometric structures, hypercubes, hyperspheres and hyperoctahedrons. We will compare the results obtained with the results of several different algorithms applied to the problem: Diagonal Linear Discriminant Analysis (DLDA), Diagonal Quadratic Discriminant Analysis (DQDA), 1-nearest neighbor (1NN), 3-nearest neighbor (3NN),5-nearest neighbor (5NN), a Multi Layer Perceptron with gradient descent momentum and adaptive learning rate (MLP) and finally a RBF network (RBFN).

Table 1. Comparison of the results (error rate) obtained by the EGS algorithm and other classification algorithms in the ATR problem tackled.

Algorithm	DLDA	DQDA	1NN	2NN	3NN	MLP	RBF	EGS-HC	EGS-HS	EGS-HO
Error rate	24.62%	21.11 %	21.99%	19.53%	19.42%	19.88%	14.97%	31.77%	27.12%	17.87%

Table 2. Computational complexity of the algorithms in terms of the number of basic operations needed to classify a single pattern.

Algorithm	DLDA	DQDA	1NN	2NN	3NN	MLP	RBF	EGS-HC	EGS-HS	EGS-HO
# of Operations	953	1271	152645	153604	154562	10959	110085	4229	3457	4230

Tables 1 and 2 sumarize the results obtained by the EGS algorithm proposed, with different geometric structures implemented, and the comparison with several other classification techniques in the tackled ATR problem. The first result that can be extracted from the tables refers to the behavior of the different type of structures involved in the EGS algorithm. Note that the hyperoctahedron structure is the one which obtains a best result in terms of error rate of classification. Other structures such as hyperspheres or hyperplanes do not provide such a good results as the hyperoctahedrons, as can be seen in Table 1. All the tested EGS algorithms obtained a similar computational cost, measured as the number of basic operation needed to classify a single pattern.

Regarding the comparison with other techniques, it is interesting to check that the EGS algorithm using hyperoctahedrons (EGS-HO) improves the results of the compared classification methods. In the case of discriminant analysis algorithms, our EGS-HO approach obtains better error rates than DLDA and DQDA algorithms (24.62% and 21.11% versus 17.87% obtained with the EGS-HO). The computational cost of the DLDA and DQDA approaches, is, on the other hand, slightly smaller than the EGS-HO's: 953 and 1271 operations versus 4230 of the EGS-HO. Our EGS-HO algorithm also improves the results of the nearest neighbors classifiers tested, both in error rate and in computational cost of the algorithm. The MLP approach obtains a good error rate, comparable with those from the NN algorithms, but worse than the EGS-HO approach. The computational cost of this algorithm is also worse than the EGS-HO (10959 operations versus 4230 with the EGS-HO). Finally, the RBF network is the only compared approach which have obtained a slightly better result than the EGS-HO in terms of error rate in classification (14.97% versus 17.87% with the EGS-HO), on the other hand, the RBF network shows a much worse computational cost (110085 operations versus 4230 of the EGS-HO).

4 Conclusions

In this paper we have presented a novel evolutionary-type algorithm for multiclass classification problems, called Evolution of Geometric Structures algorithm. We have analyzed the main characteristics of the algorithm and applied it to the resolution of a well known multiclass classification problem, the Automatic classification of High Range Resolution radar targets, ATR problem. We have shown that our approach is able to obtain results which improves the results of other different classification techniques such as discriminant analysis, k-neares neightbours or a multilayer perceptron. As a final conclusion, the proposed method presents an interesting trade off between error rate and computational cost after training, which might be very beneficial in those applications in which embedded real time implementation is required.

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