A Multi-objective Repository-based Genetic Algorithm for Ultra-wideband Antenna Optimization

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Abstract—**This paper presents an application of a machine learning technique to enhance a multi-objective genetic algorithm to estimate fitness function behaviors from a set of experiments made in laboratory to analyze ultra-wideband antennas. These experiments are stored in a web repository server that represents the knowledge of the antenna behavior using XML information. The algorithm is also self-organizing since it is a client application that always learns from the repository information before it defines its fitness function. The results were compared with the ones obtained with a real prototype antenna built from the optimal values obtained after the optimization. The final comparison has shown a promising gain for the designed antenna in the analyzed frequencies.**

Index Terms—**Ultra-wideband antennas, Genetic algorithms, Optimization methods, Microstrip antennas.**

I. Introduction

The recent widespread of ultra-wideband (UWB) systems has aroused interest in the subject of UWB antenna design. This design task normally has several, possibly conflicting, objectives [1]. In terms of optimization, multiple objectives usually involve multiple fitness functions that have to be considered simultaneously to solve a specific problem. These diverse considerations has made UWB antenna design an interesting domain to computational intelligence methods. However, construction of microstrip antennas with these characteristics without loss of performance is still a challenge to current research. A typical UWB antenna consists of a thin metal layer of some geometry that acts as a radiator element, separated from its ground plane by a dielectric substrate layer. This work presents a client application for a UWB antenna knowledge repository. It is a multi-objective genetic algorithm based on a technique that adopts a machine learning process to estimate fitness function behaviors from the information stored in the repository server. It is an evolution of three previous works [3][4][5] that have been basically enhanced in three aspects. In the first one of these, it was used a larger data set of empirical data sets to drive a learning process necessary to optimize slit dimensions of the ground plane, in the second one, a web repository is implemented to store experiments for different XML representations for UWB antennas, and in the third one, a color visualization technique was applied to graphically track the throughout optimization process.

II. Machine Learning and Genetic Algorithms

Machine Learning (ML) refers to the use of formal structures (machines) to make inference (learning). This includes the construction of models proposing mathematical expressions that encapsulate the mechanism by which a physical process gives rise to observations [2]. ML can be used in various contexts and applications. One of them is the Evolutionary Algorithms (EA). Algorithms in evolutionary computation typically produce databases of sufficient size to obtain knowledge and improvement of the algorithm itself, allowing the use of ML techniques such as: statistical methods, interpolation, artificial neural networks and others.

III. Metadata Repositories

Metadata is known as data about data. They describe concepts, including their attributes and even relationships to other metadata. Metadata are maintained in repositories. The Antenna repository is used to store all the parts and pieces of a typical UWB antenna, such as its geometry and to associate experiments for a specified antenna concerning to an optimization objective. Many metadata repositories now use semantic technologies, such as XML languages known as Resource Description Framework (RDF) and Web Ontology Language (OWL) to create full descriptions of components and their relationships.

IV. Implementation and Results

A classical Genetic Algorithm (GA) was modified in the initial population generation step and in the fitness calculation step to be enhanced by the ML technique. See Figure 1.

A spline interpolation variant (ML Technique) was used for each objective considered and its combination inside a weighted aggregate function. Spline interpolation is a form of interpolation where the interpolant is a type of piecewise polynomial named spline. The special case used here is the bicubic interpolation, in which a bicubic spline "S" interpolates (xi,yj,zij) points and S(xi,yj) is equal to zij for all i=1,..,nx and j=1,..,ny. Each objective is associated with a different S(x,y), where x and y would be the antenna optimization parameters Ls and Ws (two antenna geometry dimensions). S1(Ls,Ws) is the interpolation for bandwidth, S2(Ls,Ws) is the interpolation for return loss and S3(Ls,Ws) is the interpolation for central frequency deviation. The compound aggregate objective function (AOF) is:

$$AOF(L_s,W_s) = w_1.S_1(L_s,W_s)+w_2.S_2(L_s,W_s)+w_3.S_3(L_s,W_s)$$

Where, wi (for i=1,2 and 3) are the empirical weights and the other GA parameters consist of simultaneous binary genetic operations over a population consisting of individuals with two binary parts (one for each optimization dimension) with elitism, mutation (5%) and crossover (90%) genetic operators. The prototype implemented was tested for different datasets considering a ring monopole microstrip antenna and a set of restrictions empirically defined (Table I).

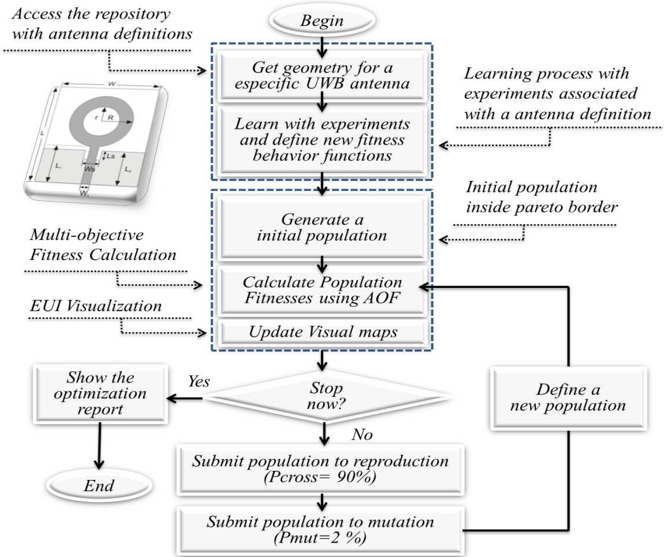

Fig. 1 - Evolutionary algorithm

TABLE I
OPTIMIZATION RESULTS FOR DIFFERENT DATA SET SIZES

Datasets	L_S (mm)	W_S (mm)	BW(GHz)	RL (dB)	CFD(Hz)
72	1.89	4.02	9.27	- 25.21	0.35
119	2.30	3.69	9.32	- 20.12	0.35
170	4.18	1.49	9.36	-32.66	0.34

These datasets contain a different number of experiments to demonstrate that, as the number grows, the prototype algorithm increases its perception on the behavior of the objectives and its joint behavior of the whole. For all the datasets, the restrictions have been met and the best results were obtained with the last set of experiments. The one with 170 experiments and presents the best results for all the objectives considered: bandwidth (9.36), return loss (-32.66) and central frequency deviation (0.34).

In Figure 2, the optimum values for Ls and Ws are shown graphically using a surface chart that associate different colors to different values of aggregated fitness function values. The aggregated fitness function value associated to the optimum values is 79.13 and it is indicated in Figure 3 by a black arrow and by the crossing point of two straight lines. Since new data is experimentally obtained over time to show the behavior of an antenna with respect to analyzed objectives, the shape of both graphs changes and may result in the choice of new optimum values for the slit dimensions considered. This aspect shows how the algorithm could learn (and adapt itself) to improve its perception as soon as new information is available in the repository in which the experiments are stored.

It is interesting to note that Figure 2 also shows the pareto boarder in which the population individuals were defined. For a nontrivial multi-objective optimization problem, there does not exist a single solution that simultaneously optimizes each objective. In that case, the objective functions are said to be conflicting, and there exists a set of Pareto optimal solutions.

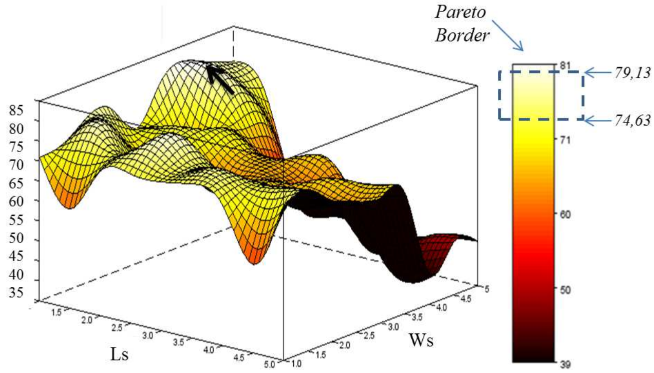

Fig. 2 - Final optimal values for AOF function visual map

A solution is said to be in Pareto border if none of the objective functions can be improved in value without impairment in some of the other objective values. Without additional preference information, all Pareto optimal solutions can be considered mathematically equally good.

V. CONCLUSIONS

An antenna for UWB operation was constructed and optimized by a repository-based genetic algorithm prototype improved by an interpolation ML technique. This ML technique enabled a dynamic estimation of an aggregated compound fitness function used in a prototype algorithm that made it possible to learn with a set of experiments stored in a web system repository. The final optimal values found allowed the construction of a prototype UWB antenna that presented a reasonable gain in the analyzed frequencies of 3.5, 6.0 and 9.5 GHz. An important aspect to consider in this work is its potential for the development of new algorithms and strategies based in knowledge stored in the repository used, since the web service implemented here can be easily extended to enable new approaches to treat the experiment data sets already available in the repository.

VI. REFERENCES

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