International Journal of Electronics and
Communication Engineering (IJECE)
ISSN(P): 2278-9901; ISSN(E): 2278-991X
Vol. 2, Issue 5, Nov 2013, 65-72
© IASET

International Academy of Science, Engineering and Technology
Connecting Researchers; Nurturing Innovations

PERFORMANCE EVALUATION OF NON-UNIFORM PRF RADAR SIGNALS USING MOGA

B JITHENDRA KUMAR REDDY[1] & G MANMADHA RAO[2]

[1]Research Scholar-DECS, GMR Institute of Technology, Rajam, Andhra Pradesh, India

[2]Associate Professor, Department of ECE, GMR Institute of Technology, Rajam, Andhra Pradesh, India

ABSTRACT

In this paper a novel method for solving the multi-function optimization problems have been proposed. Radar is mainly used to detect the targets in different environments by analyzing the echo signal from the target. One method of distinguishing multiple-time-around echoes from unambiguous echoes is to operate with a varying pulse repetition frequency. The different pulse repetition frequencies also allow eliminating the blind speeds in finding the moving targets information. The use of more than one PRF offers additional flexibility in the design of MTI radars. The detection level of the target can be decided by the performance factors called merit factor and discrimination factors. The performance factors are varying with the variation of PRI sequence. Hence we are generating the non-uniform PRI sequence to maximize both the performance factors using multi objective genetic algorithm optimization technique.

KEYWORDS: PRF, PCW, Merit Factor, Discrimination Factor, GA, MOGA

INTRODUCTION

The objective of this paper is to optimize non-uniform PRI parameters of radar signals by multiple-objective optimization methods using genetic algorithms (GA). For multiple-objective problems, the objectives are generally conflicting, preventing simultaneous optimization of each objective. Many, or even most, real engineering problems actually do have multiple-objectives, i.e., minimize cost, maximize performance, maximize reliability, etc. These are difficult but realistic problems. GA are a popular meta-heuristic that is particularly well-suited for this class of problems. Traditional GA is customized to accommodate multi-objective problems by using specialized fitness functions and introducing methods to promote solution diversity.

The general approach to multiple-objective optimization is to determine an entire Pareto optimal solution set or a representative subset. A Pareto optimal set is a set of solutions that are non-dominated with respect to each other. While moving from one Pareto solution to another, there is always a certain amount of sacrifice in one objective(s) to achieve a certain amount of gain in the other(s).

The objective of this paper is to optimize the parameters of radar signals by multiple-objective optimization methods using genetic algorithms (GA). For multiple-objective problems, the objectives are generally conflicting, preventing simultaneous optimization of each objective. Many, or even most, real engineering problems actually do have multiple-objectives, i.e., minimize cost, maximize performance, maximize reliability, etc.

These are difficult but realistic problems. GA is a popular meta-heuristic, that is particularly well-suited for this class of problems. Traditional GA is customized to accommodate multi-objective problems by using specialized fitness functions and introducing methods to promote solution diversity.

The general approach to multiple-objective optimization is to determine an entire Pareto optimal solution set or a representative subset. A Pareto optimal set is a set of solutions that are non-dominated with respect to each other. While moving from one Pareto solution to another, there is always a certain amount of sacrifice in one objective(s) to achieve a certain amount of gain in the other(s).

MULTI-OBJECTIVE OPTIMIZATION FORMULATION

Consider a decision-maker who wishes to optimize K objectives such that the objectives are non-commensurable and the decision-maker has no clear preference of the objectives relative to each other. Without loss of generality, all objectives are of the minimization type - a minimization type objective can be converted to a maximization type by multiplying negative one. A minimization multi-objective decision problem with K objectives is defined as follows:

Given an n-dimensional decision variable vector $x = \{x_1,...., x_n\}$ in the solution space x, find a vector x* that minimizes a given set of K objective functions $z(x^*) = \{z\ (x^*),....z_k(x^*)\}$.The solution space x is generally restricted by a series of constraints, such as $g_j(x^*) = b_j$ for j=1.., m. and bounds on the decision variables.

In many real-life problems, the objectives under consideration are conflict with each other. Hence, optimizing *x* with respect to a single objective often results in unacceptable results with respect to the other objectives. Therefore, perfect multi-objective solution that simultaneously optimizes each objective function is almost impossible. A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution.

If all objective functions are for minimization, a feasible solution *x* is said to dominate another feasible solution *y* (*x*>*y*), if and only if, $z_i(x) \le z_i(y)$ for *i*=1,....,*K* and $z_j(x) < z_j(y)$ for least one objective function j. A solution is said to be a pareto optimal if it is not dominated by any other solution in the solution space. A Pareto optimal solution cannot be improved with respect to any objective without worsening at least one other objective. The set of all feasible non-dominated solutions in *X* is referred to as the Pareto optimal set, and for a given Pareto optimal set; the corresponding objective function values in the objective space are called the Pareto front. For many problems, the number of Pareto optimal solutions is enormous (perhaps infinite).

The ultimate goal of a multi-objective optimization algorithm is to identify solutions in the Pareto optimal set. However, identifying the entire Pareto optimal set, for many multi-objective problems, is practically impossible due to its size. In addition, for many problems, especially for combinatorial optimization problems, proof solution optimality is computationally infeasible. Therefore, a practical approach to multi-objective optimization to investigate a set of solutions (the best-known Pareto set) that represent the Pareto optimal set as well as possible. With these concerns in mind, a multi-objective optimization approach should achieve the following three conflicting goals [1].

The best-known Pareto front should be as close as possible to the true Pareto front. Ideally, the best-known Pareto set should be a subset of the Pareto optimal set.

Solutions in the best-known Pareto set should be uniformly distributed and diverse over of the Pareto front in order to provide the decision-maker a true picture of trade-offs.

The best-known Pareto front should capture the whole spectrum of the Pareto front. This requires investigating solutions at the extreme ends of the objective function space.

MULTI-OBJECTIVE GA

Being a population-based approach, GA are well suited solve multi-objective optimization problems[2]. A generic single-objective GA can be modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex, discontinuous, and multi-modal solutions spaces. The crossover operator of GA may exploit structures of good solutions with respect to different objectives to create new non-dominated solutions in unexplored parts of the Pareto front. In addition, most multi-objective GA do not require the user to prioritize, scale, or weigh objectives. Therefore, GA have been the most popular heuristic approach to multi-objective design and optimization problems. Jones et all reported that 90% of the approaches to multi objective optimization aimed to approximate the true Pareto front for the underlying problem. A majority of these used a meta-heuristic technique, and 70% of all met heuristics approaches were based on evolutionary approaches.

DESIGN ISSUES AND COMPONENTS OF MULTI-OBJECTIVE GA

- Assign no. of PRI’s(n),
- Assign no. of bits (b).
- Assign no. of variables to optimize (m).
- **Initialization of Population:**

Generate population by using a random function and this random function values multiply with the R_{max} and R_{min} values such that the generated random values become with in specified range.

r= rand(n, m*b)-0.5;

P=(R_{min})+((R_{max}-R_{min})/1023)*r;

The generated population acts as chromosomes.

- Calculate the fitness values i.e., merit factor and discrimination factor,
- Assign the rank based on fitness values.
- Calculate crowding distance

$$i_{C.D} = \sum_{m} \left(\frac{f[i+1]_m - f[i-1]_m}{f_m^{\max} - f_m^{\min}} \right) \quad (1)$$

Where $i = 2,3,\ldots(l-1)$

Where $f[i]$m represents m^{th} objective value of i^{th} solution and $f_m^{\max}$ is the maximum value of function in the pareto front.

- Selection is performing to chosen the individual population for crossover operation.
- Crossover operation is done by combining two parents to produce Childs

$$b = \begin{cases} (2*r)^{\left(\frac{1}{\mu+1}\right)} & if \quad r \le 0.5 \\ \left(\frac{1}{2*(1-r}\right)^{\left(\frac{1}{\mu+1}\right)} & if \quad r > 0.5 \end{cases} \tag{2}$$

Where *r* is a random number {0,1}, μ is a crossover operator, *j* represent dimension of individual. Generation of Childs by using the formula as shown in below

$$child_1(j) = \frac{1}{2}((1+b)*parent_1(j) + (1-b)*parent_2(j)) \tag{3}$$

$$child_2(j) = \frac{1}{2}((1-b)*parent_1(j) + (1+b)*parent_2(j))$$

- Mutation operation is done to alters one or more gene values in a population In polynomial mutation child's are generated as below formulae

$$child(j) = parent(j) + d \tag{4}$$

$$d = \begin{cases} (2*r)^{\left(\frac{1}{\eta+1}\right)} - 1 & if \quad r \le 0.5 \\ 1-(2*(1-r))^{\left(\frac{1}{\eta+1}\right)} & if \quad r > 0.5 \end{cases} \tag{5}$$

Where r is a random number {0,1}

η is a mutation operator

j is represented dimension of individual

- Selection of population for next generation is based on rank assign to the population.

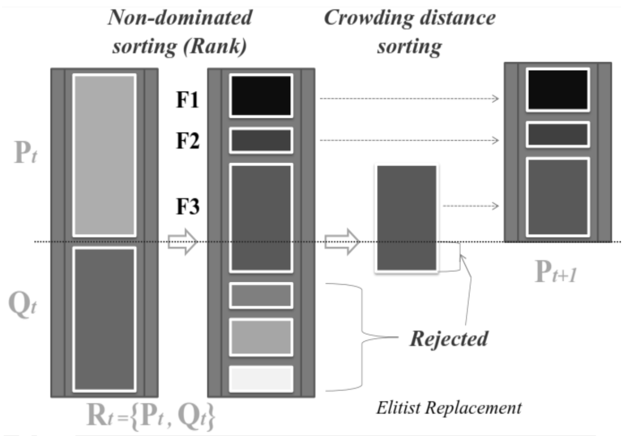

Figure 1: Selection Process of Chromosomes for Next Generation

- Merit factor can be calculated as by

$$F = \frac{r^2(0)}{2\sum_{k=1}^{N-1} r^2(k)} \tag{6}$$

Where $r^2(0)$ indicates energy of the main peak and $r^2(k)$ indicates energy of the side lobes.

- Discrimination Facto can be calculated as

$$D = \frac{r(0)}{_{k \neq 0} r(k)_{\max}} \tag{7}$$

Where $r(0)$ indicates main peak at $\chi(0,0)$ and $r(k)_{\max}$ indicates maximum side lobe.

The process of entire operation gives the following flow chart diagram, it specify the step by step procedure in the algorithm.

The flow chart for MOGA is

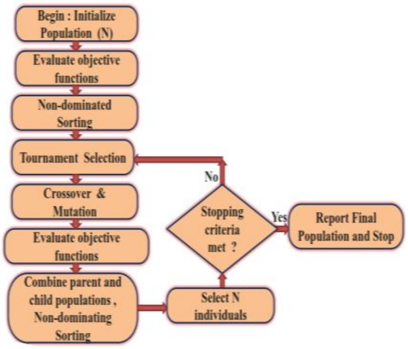

Figure 2: Flow Chart of MOGA

RESULTS

The MOGA tests optimal solutions for our problems. The respective pareto front is plotted in the Figure 3. The ambiguity plot using optimal non uniform PRI sequence for PCW signal is illustrated in Figure 4.

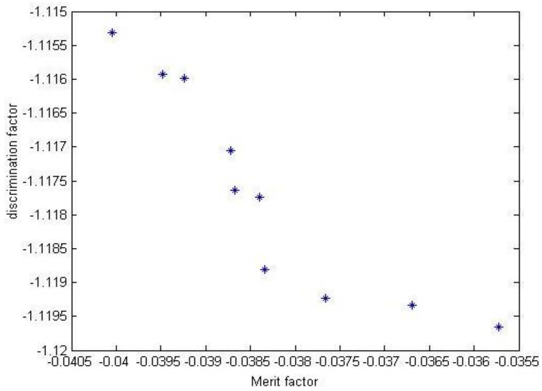

Figure 3: Pareto Front of PCW Radar Signal

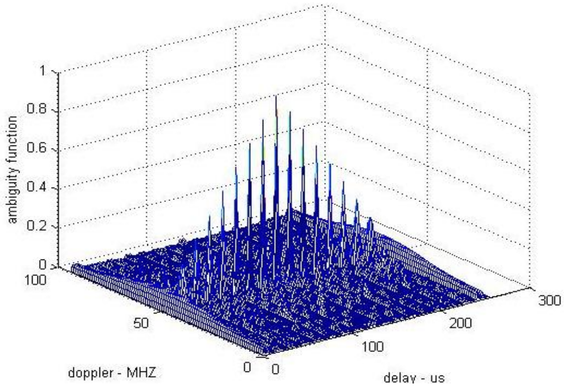

Figure 4: Ambiguity Plot of Non-Uniform PRI PCW Pulse Train

Table 1: PCW Signal with Uniform and Non Uniform PRI Performance Results

		Discrimination Factor	Merit Factor	PSLR(dB)	ISLR(dB)
Uniform PRI		1.1191	0.0059	-0.9776	22.2848
Non-Uniform PRI	Ascending	1.1333	0.0066	-2.2027	50.1799
	Descending	1.2431	0.0066	-4.3516	50.2189
	MOGA	1.3731	0.0230	-3.1934	37.7041

CONCLUSIONS

This paper consists non uniform PRI PCW radar signalas the non-uniform PRI avoids the blind speeds. Using multi objective genetic algorithm merit factor and discrimination factors have been set as two object functions using MOGA approach better results have been obtained for PSLR, ISLR, with compared to conventional uniform and non-uniform(ascending, descending and random) PRI strategies

REFERENCES

1. K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan, “A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II,” in Proc Parallel Problem Solving from Nature VI, 2000, pp. 849–858.
2. G. Manmadha Rao, Prof K. Raja Rajeswari, “Optimization of Radar signals performance using Genetic and Differential Evolution Algorithms” EngineeringScience and Technology: International Journal (ESTIJ),Vol.3.No.03, June-2013.
3. Osycza and S. Kundu, “A new method to solve generalized multicriteria optimization problems using the simple genetic algorithm,” Struct. Optimiz., no. 10, pp. 94–99, 1995.
4. A New Optimal Design Method of Rotor Slot of Three-Phase Squirrel Cage Induction Motor for NEMA Class D Speed-Torque Characteristic Using Multi-Objective Optimization Algorithm: IEEE Trans.2012. Dianhai Zhang, Chang Soon Park, and Chang Seop Koh
5. K. Rasheed and H. Hirsh, “Informed operators: Speeding up genetic-algorithm- based design optimization using reduced models,” in Proc. Genetic and Evolutionary Computation Conf. (GECCO’2000), 2000, pp. 628–635.
6. C. M. Fonseca and P. J. Fleming, “Genetic algorithms for multiobjective optimization: Formulation, discussion and generalization,” in Proc. 5th Int. Conf. Genetic Algorithms, S. Forrest, Ed. San Mateo, CA: Morgan Kauffman, 1993, pp. 416–423.
7. D. E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning. Reading, MA: Addison Wesley, 1989
8. Multi-objective optimization using genetic algorithms: Abdullah Konak, David W.Coit, Alice E.Smith
9. Multi-Objective Optimization by Genetic Algorithms: A review by Hisashi Tamaki, Hajinme Kita, Shigenobu Kobayashi
10. An introduction to Genitic algorithm: PP 24-63 by Melanie Mitchell.
11. Introduction to Radar Systems by Merrill I. Skolnik, 3rd Edition, McGraw-Hill publications-2006, Pages456-487.
12. Goldberg, D. E. (1989), Genetic Algorithms in search, optimization and machine learning, Addison-Wesley, Massachusetts.

AUTHOR'S DETAILS

Mr. B. JITHENDRA KUMAR REDDY received his B.E. degree in Electronics and Communication Engineering and pursuing M.Tech in Digital Electronics And Communication systems in GMR Institute of Technology. Member of IEEE

Mr. G. ManmadhaRao received his B.E. degree in Electronics and Communication Engineering and M.E in Electronic Instrumentation from College of Engineering; Andhra University in 1998 and 2003 respectively. He is working for his Ph.D as a part-time research Scholar at Andhra University. He worked in different industries for 9 years. He is in teaching profession for more than 11 years. Presently he is working as Associate Professor in the Department of Electronics and Communication Engineering, GMR Institute of Technology, Rajam, Srikakulam, India. He has published a pulse and digital circuits book with pearson Education in 2010.