Automatic radar waveform design

Victor Manuel Hidalgo
Research and Development Department
DTS SpA, National Aeronautical Company of Chile
Santiago, Chile
vmhidalgo@ieee.org

Christian Muñoz
School of Engineering and Sciences
Diego Portales University
Santiago, Chile
christian.munoz1@mail.udp.cl

***Abstract*—Designing radar waveforms is complex as it involves a multi-objective optimization problem, featuring conflicting functions in a discontinuous and noisy landscape. Expanding the repertoire of radar waveforms aids other electronic warfare applications. Employing evolutionary algorithms is an attractive tool for solving this optimization problem, thus allowing scalable radar waveform design.**

***Index Terms*—Evolutionary computation, electronic warfare, radar waveform, multi-objective optimization**

I. Introduction

Radar waveform design is a complex task, as the underlying multi-objective optimization (MOO) problem involves many conflicting functions, forming a discontinuous and noisy optimization landscape. Also, the parameters defining a radar waveform, such as carrier frequency, pulse width, and pulse repetition interval create a rather large decision space. Nonetheless, a more comprehensive repertoire of radar waveforms would support the simulation of realistic electronic warfare scenarios, while also benefiting the development of more sophisticated signal processing techniques for electronic support. For example, deinterleaving algorithms are needed to separate and identify emitters, but they are impaired when agile pulse trains are interleaved, thus affecting the performance of these counter-measure algorithms. Automatic design of emission profiles for radars of interest is thus an attractive solution for several electronic warfare applications. Evolutionary algorithms have been used for automatic waveform design, focusing on pulse-repetition interval (PRI) as the parameter of interest [1]. In this way, MOO can be used to automatically find the solutions that offer the best performance on range and velocity resolution, which corresponds to the Pareto set. In this work we report our work to implement a radar waveform simulator. As a first approach, we used simulated annealing to automatically find effective PRI profiles for a stagger emission system.

II. Multi-objective optimization problem

We consider a multiple-PRI stagger emission profile of level 2. The PRI was in the range [0.0002, 0.003] [s], pulse width of 100[us], and frequency 1300 [MHz]. To measure the performance of the radar waveform, we used 3 objective functions: unambiguous range, unambiguous Doppler, and dwell time [2]. The unambiguous range of a multiple-PRI radar is the least common multiple (LCM) of the unambiguous range of the individual PRI:

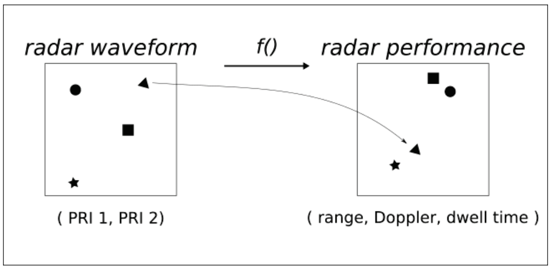

Fig. 1. Radar waveform design as a multi-objective optimization problem.

$$r_{max} = \frac{c(PRI - PW)}{2} \tag{1}$$

The unambiguous Doppler for the same system is the LCM of the unambiguous Doppler of the individual PRI:

$$v_{max} = \frac{c}{2PRI * frec} \tag{2}$$

Finally, the dwell time, or the time the radar is illuminating the target is:

$$d = \sum_{i=1}^{n} PRI_i \tag{3}$$

The optimization problem involves jointly maximizing (1) and (2), while minimizing (3), and thus the previous 3 objective functions are conflicting functions. Increasing PRI increases range and dwell time while decreasing Doppler, and vice versa. The optimization process aims to find the PRI solutions (Pareto set) that offer the best performance possible considering the trade-offs defined by these functions (Pareto front). Figure 1 depicts the overall optimization problem to be addressed. We used simulated annealing to address the aforementioned problem [3].

III. Results

The simulated annealing algorithm uses the Boltzmann distribution to assign an acceptance probability for each candidate solution, allocating exponentially decaying probability to solutions with a large energy difference. The energy evaluation rule, however, requires special attention as it may force the algorithm to assign low probability to solutions that are

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desirable. We experimented with several energy evaluations approaches and found that adjusting for percentage of energy difference was the only energy rule that generated the appropriate behavior for this problem. Other energy evaluation rules would make the algorithm to assign low probability to most solutions, thus hindering the exploration capabilities of the algorithm and the scalability of a radar waveform simulator. We also experimented with different initial value policies. Initial values had no effect on the optimization process, suggesting the absence of lottery tickets for this particular case.

The objective space of the optimization problem is shown in Figure 2. We calculated one million solutions, but a representative subset of ten thousand is shown for simplicity. Solutions belonging to the Pareto front(red) and dominated solutions(black) are organized sparsely in the space, forming well-defined contour lines, thus justifying the use of evolutionary algorithms to address this family of problems.

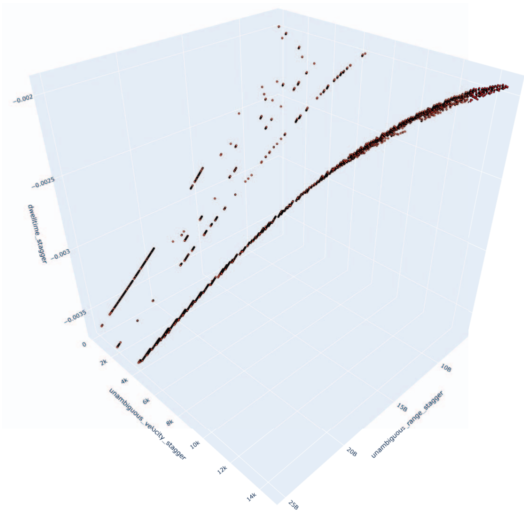

Fig. 2. Radar objective space.

IV. Discussion

In this paper we reported our first work to develop a radar waveform design simulator. We addressed a reduced problem containing the three most important objective functions to be optimized. The computation time and convergence of the algorithm can be improved by selectively adjusting its parameters, such as acceptance probability calculation, for optimal performance for this particular problem. Considering the structure of the Pareto front of radar performance, neural hyper-networks may be a possible solution to learn the Pareto front and thus accelerate the radar waveform design process [4]. Future work will assess this opportunity to scale the production of radar waveforms.

V. Conclusion

Here we reported the optimization of a radar waveform using simulated annealing; a metaheuristic algorithm to solve multi-objective optimization problems. We envision these evolutionary algorithms, coupled with machine learning techniques to learn the Pareto front, as the fundamental support for massive, scalable radar waveform design.

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