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Adaptive Based Multiobjective Optimization Based Node Placement and Target Detection in Bistatic Radar Network

M. Amala Christy, Ms. N.Anushya
M.E-CS, Dept of ECE, Arunachala College of Engineering for Women. amalachristy3@gmail.com
Dept of ECE, Arunachala College of Engineering for Women.anu_star1987@yahoo.com

Abstract
A bistatic radar network that consists of multiple separated radar transmitters (TXs) and receivers (RXs), aiming to detect a target on a set of points of interest (PoIs) is considered. The detection range of a bistatic radar depends on both locations of the TX and RX. The design of the bistatic radar network is investigated by studying the problem of optimally placing a number of radar transmitters and receivers by minimizing the maximum distance product between a PoI and its closest transmitter-receiver pair. In our proposed Voronoi based multi-objective algorithm we optimally place the number of transmitters and receivers and also the efficient power distribution scheme is analyzed. Experimental results show that, the proposed scheme is a way forward from the previous schemes in terms of optimal placement and power distribution.

Index Terms- Multiobjective optimization, node placement, Point of Interest (PoI).

I. INTRODUCTION

RADAR has become an essential component of surveillance and defensive systems. Target detection is one of the main applications of radar. In contrast to passive sensing employed by traditional sensors, one salient feature of radar sensing is that the radar transmitter actively transmits radar signals and then the radar receiver collects the reflected energy from the target. Thus, radar has an ability to monitor wide areas rapidly during the day or at night and in different weather conditions. Traditionally, radars are classified into three categories [1]: a mono-static radar is a single device where the transmitter and receiver are co-located; in a bistatic radar, the transmitter and receiver are placed at different sites; a multi-static radar consists of multiple separated transmitters and receivers. Although physical layer issues in radar have been extensively studied [2], very limited attention has been paid to the radar network design. Notably, Baker *et al.* [3] considered a network of mono-static radars. In [4], [5], the coverage area of a multi-static radar with one transmitter and multiple receivers was analyzed. We are thus motivated to study radar networks from a networking point of view. Specifically, we consider a bistatic radar network consisting of multiple transmitters and receivers, where any pair of transmitter and receiver operating the same frequency can form a bistatic radar. A potential attacker may choose to attack any point among a set of points of interest (PoIs). The bistatic radar network is deployed to detect the attacks and set an alert. To better defend the PoIs, the bistatic radar network should be carefully designed.

One important issue in the design of the bistatic radar network is the placement of transmitters and receivers in the surveillance area. Mini-max-based placement is of great importance in the facility location problem, which is concerned with finding p facility locations that minimize the maximum distance between a demand point and its closest facility. This problem is also known as the P-center problem [6], and it is equivalent to Covering all the demand points by p circles with the smallest possible radius (the facilities are located at the centers of these circles). The problem of mini-maxed based bistatic radar placement is clearly quite different because the coverage area of a bistatic radar depends on the locations of both the transmitter and receiver, and is characterized by the Cassini oval, which is the locus of points with constant distance product to two fixed points [7].

We assume that the transmitters use orthogonal frequencies to illuminate signals for interference avoidance, and each receiver chooses one of the frequencies to receive the corresponding radar signals reflected by the target. For a given frequency selection scheme, the bistatic radar network can cover a subset of the PoIs. Since the attacker adaptively changes the PoI to attack, the receivers should also dynamically adapt their frequencies to cover different subsets of the PoIs. Accordingly, the scenario can be modeled as a repeated security game between the bistatic radar network and the attacker.

Optimally placing the number of radar transmitters and receivers in the sense of minimizing the maximum distance product between a PoI and its closest transmitter receiver pair causes high power consumption, low accurate as it doesn't consider channel constraints. To overcome this the optimization is based on the encoding and objective function, for this Non dominant sortic genetic algorithm is proposed for the multi-objective optimization.

II. PAST WORK

In the evolutionary algorithms, various techniques have been used to overcome the problem of being trapped in local optimums, e.g., hill climbing and simulated annealing algorithms. These random techniques increase the probability of finding the global optimum. Inspired by this, we next show how to borrow the idea from the simulated annealing to the
Voronoi algorithm in order to search for the global optimum, the randomized voronoi algorithm is proposed but it is less accurate in detection.

A. *Detection Range and PoI Coverage Vector*

For a given bistatic radar, the maximum-range equation can be written as [1]

$$D = (dt\ dr)max = \left(\frac{c}{(4\pi)^2 SNRmin}\right)^{1/2} \quad \_(1)$$

where dt and dr are transmitter-target and receiver-target distances, respectively; SNRmin is the minimum required signal to-noise ratio for detection; and *C* is the bistatic radar constant reflecting physical-layer parameters such as transmitter power, antenna gains of the transmitter-receiver pair, and radar cross section of the target. For ease of exposition, we assume that the bistatic radar constant *C* is the same for all transmitter-receiver pairs.

B. *Randomized Voronoi Algorithm*

Let I be a subset of P, and F(I) be the optimal value of the objective function for the 1-center problem regarding PoIs I. F(I) is
given by

$$F(I)=\min_r\{\max_{pi\in i}\{wid(pi,r)\}\} \quad \_(2)$$

where r is the receiver to be located. Let r∗ (I) be the optimal receiver location of problem (5), which is also the center with respect to the PoIs in I. For the 1-center problem regarding all PoIs within the set I, there exists a subset, denoted by B(I), of no more than three PoIs with the following properties [6]

F(B(I)) = F(I);

r*(B(I)) = r*(I).

PoI pi is called the critical point if and only if pi ∈ B(Imax), ∀pi ∈ P. The critical point will be closer to cn than to its original center, and thus it removed from B(Imax) and F(Imax) may decrease.

Randomized Voronoi Algorithm for Receiver

Placement

Input: P PoIs P, *M* transmitters T, and N starting receiver's locations Rs.
Output: N final receiver's locations R.

1. Compute the weight for each PoI based on fixed transmitter's locations.
2. Construct the Voronoi partitions based on the *N* receiver's locations.
3. Calculate the center cn for partition In, n=1, . . .,N; identify the critical points in partition Imax.
4. Compute Δdn, and move cn toward one of the critical points with a random amount gn∈[0,Δdn], n =1, . . .,N. Relocate the *N* receivers to the newly moved centers of their corresponding Voronoi partitions.
5. If receivers move from iteration to iteration by less than ε, stop. Otherwise, go to Step 2.

Randomized Voronoi Algorithm for Transmitter-Receiver Placement

Let *x* be the iteration number, *x* = 0.
1. Choose the starting locations T [0] and R [0] for the transmitters and receivers, respectively.
2. R[x+1] ← RRP (P, T [x],R[x],R);
T [x+1] ← RTP (P,R[x+1], T [x], T);
x = x + 1.
3. If the objective function value changes from iteration to iteration by less than a given threshold ε,stop. Otherwise, go to Step 2.

C. *The Radar Network*

We propose two learning algorithms for the radar network to choose the coverage vector. One is model based, and the other is model-free.

Model-based Learning

In the model-based learning algorithm, the radar network models the attacker's strategy with the information about with the information about the attacker's actual actions.
It first forms a belief about the attacker's strategy, and then uses the best response based on the formed belief. Since the radar network
has incomplete information about the attacker's actions, it uses the estimated empirical frequency of the attacker's actions as the belief instead. Let â(t) = {â1(t)…âp(t)}
be the estimated empirical frequency of the attacker's actions until round *t*, where âi(t) is the estimated empirical frequency of point pi being chosen by the attacker until round t.

Modified-regret-matching Learning

In the model-free learning algorithm, the radar network uses the information about its own actions and realized utilities. In particular,a regret-matching procedure is proposed, where the play probabilities are determined by the "regrets" for not having chosen other actions.

D. ***The Attacker***

In this subsection, two model-free learning algorithms are proposed for the attacker based on the history of its own actions and realized utilities. Note that the attacker can not use a model-based algorithm, because it has no information about the radar network's actions.

Modified-regret-matching Learning

Similarly, the attacker can also follow a modified-regret-matching procedure without its actual regret R_a^t (Pi ,Pj).

Let the attacker's utility at each round be bounded in $\cup_a(l) \cup_a(h)$. If the attacker chose *pi* at round *t*, then it will choose *pj* at round $t + 1$.

No-external-regret Learning

The external-regret is proposed to quantify the performance, which is defined in the following. If the attacker follows an algorithm, which chooses sequence of points P(1),… P(t), the attacker's total utility until round t is Ua(t).
The attacker's average external-regret after *t* rounds is defined by the attacker's total utility until round *t*.

Since the attacker can determine the number of attacks to launch, we assume that the attacker would like to play total *T* rounds. At the beginning of each round, the attacker runs Algorithm 6 to choose a point according to the distribution as shown in Step 1. Note that this algorithm is different from the Exponential-weight algorithm by using a different computation method for estimated utility (Step 2). For the actual chosen point *p*(*t*), Algorithm 6 sets the estimated utility to be

Initialization: V(i) = 1
While $t \in [1, T]$ do

1. Choose PoI *pi* according to the following distribution: ai(t).
2. After choosing point *p*(*t*), the attacker can obtain the utility *Ua(t)* compute
   the estimated utility.
3. Update the weights by $\forall i \in \{1, , \dots, p\}$
   end while

E. ***CORRELATED EQUILIBRIUM***

Before describing the convergence property of the repeated security game, we first introduce the following two definitions.

EMPIRICAL DISTRIBUTIONS

The empirical distribution of play up to round *t*, i.e., Z*t*, is a distribution on the space of both the radar network's and the attacker's joint actions

*S= C*P*

Is the relative frequency that the 2-tuple of actions s has been played in the past *t* rounds, where s*x* is the realization of the2-tuple of actions at round *x*. The correlated equilibrium is a well-studied notion of rationality that generalizes the Nash equilibrium. Specifically, we define the correlated equilibrium in the repeated security game as follows:

CORRELATED EQULIBRIUM

A probability distribution of a correlated equilibrium of the repeated security game if, for every Ci,Cj. From the in-equality. We can see that when the recommendation for the radar network is to choose c*i*, choosing c*j* instead of c*i* cannot obtain a higher expected utility. Similarly, for the attacker, when the recommendation for it is to choose *pi*, choosing *pj* instead of *pi* cannot obtain a higher expected utility. The following theorem gives the convergence result of the repeated security game.

III. PROPOSED SCHEME

The significant contribution in the proposed work is to increase the detection accuracy and coverage area using the non dominant sortic genetic algorithm for multiple objective optimization.

A.*Voronoi based multiobjective optimization*

A stochastic model will be generated from a database. If the database does not exist, initial data will be generated randomly and evaluated. Based on the stochastic model, new promising individuals will be generated and evaluated. With the fast ranking method, the rank of the individuals will be calculated. Using the crowded tournament selection, individuals will be selected and stored in the database. The non-selected individuals will be stored in a different database as"bad examples". Note that when new data are added to the database, the stored rank information can become incorrect and thus should be updated. If a given termination condition is met, the VEDA will stop, and otherwise the same procedure will be repeated. In the database, design parameters, fitness values and ranks are stored. To construct stochastic models, a clustering method is used. In each cluster, principal component analysis (PCA) is carried out to reduce the dimensionality and to build up a stochastic model efficiently. The data points will be projected to a new coordinate system of a lower dimensionality determined by PCA. The minimum and maximum value for each axis will be calculated. Since PCA was carried out, linear dependency among the design parameters should be minimal. In the new coordinate system, a Voronoi diagram will be generated as the stochastic model. Based on the rank of each mesh the probability for generating off spring will be calculated for each mesh. To generate a new individual, a mesh will be selected based on the assigned probability and a new individual will be generated within the selected mesh with a uniform probability. Finally, the new individual will be projected back to the real coordinate system.

B. *Non Dominant Sortic Genetic Algorithm*

A genetic algorithm (GA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization andsear. Genetic algorithms belong to the larger clach problems of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection and crossover.

In a genetic algorithm, a population of strings which encode candidate solutions to an optimization problem, evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population and modified to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

A typical genetic algorithm requires:

1. A genetic representation of the solution domain.
2. A fitness function to evaluate the solution domain.

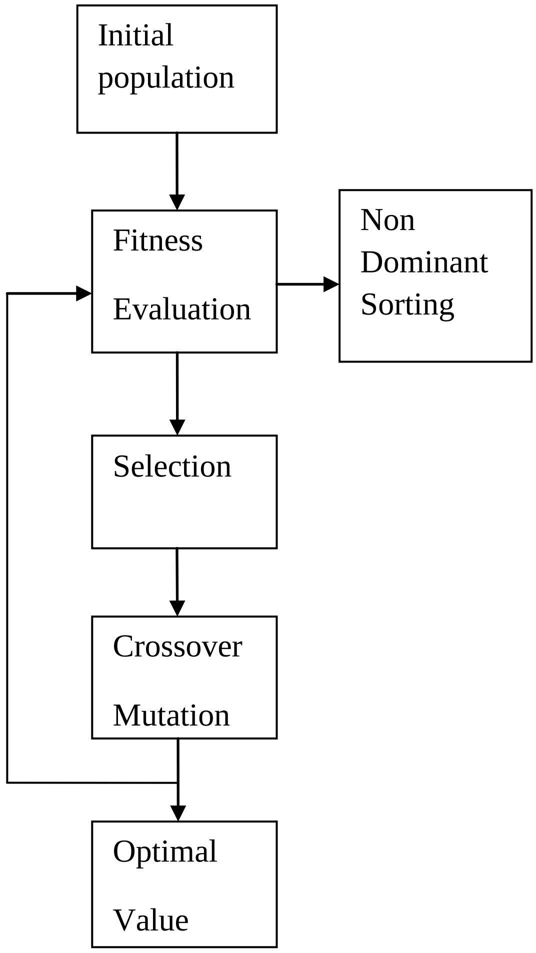

Fig 1.NGSA flow diagram

Initialization

Initially many individual solutions are randomly generated to form an initial population. The population size depends on the nature of the problem. The population is generated randomly, covering the entire range of possible solutions. Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

Selection

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions are typically more likely to be selected. Other methods rate only a random sample of the population, as this process may be very time-consuming.

Crossover Mutation

The next step is to generate a second generation population of solutions from those selected through genetic operators: crossover and mutation. Although Crossover and Mutation are known as the main genetic operators, it is possible to use other operators such as regrouping, colonization-extinction, or migration in genetic algorithms.

Optimal Value

The accurate value is selected using this process and the iteration procedure is repeated.

Algorithm

Step:1.Choose the initial population of individuals

Step:2.Evaluate the fitness of each individual in that population

Step:3.Repeat on this generation until termination (time limit, sufficient fitness achieved, etc.)

1. Select the best-fit individuals for reproduction
2. Breed new individuals through crossover and mutation operations to give birth to offspring
3. Evaluate the individual fitness of new individuals
   4.Replace least-fit population with new individuals.

IV. NUMERICAL RESULT

In this section, we present numerical results to illustrate the performance of proposed algorithms. We can observe that the performance is improved as the number of transmitters or receivers increases. Moreover, if the number of placed receivers is small, it will improve the performance greatly to add one more receiver. Using the Nondominated sortic genetic algorithm the coverage area and detection increases,the performance is evaluated.

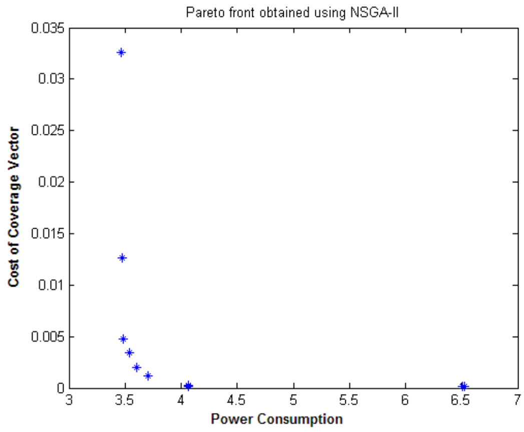

Fig 2. The coverage vector of an radar obtained using NSGA

The result shows the detection range and coverage area increases compared to the previous method.

V. CONCLUSION

In this paper we studied the bistatic radar network that consists of multiple separated radar transmitters (TXs) and receivers (RXs), aiming to detect a target on a set of points of interest (PoIs) is. The design of the bistatic radar network is investigated by studying the problem of optimally placing a number of radar transmitters and receivers by minimizing the maximum distance product between a PoI and its closest transmitter-receiver pair. In our proposed Voronoi based multi-objective algorithm we optimally place the number of transmitters and receivers and also the efficient power distribution scheme is analyzed. Experimental results show that, the proposed scheme is a way forward from the previous schemes in terms of optimal placement and power distribution.

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