Team Optimization of Cooperating Systems: Application to Maximal Area Coverage

Jae-Byung Jung [†], Mohamed A. El-Sharkawi [†], G.M. Anderson [‡], Robert T. Miyamoto [‡],

R. J. Marks II [†], Warren L. J. Fox [‡ †], C.J. Eggen [‡].

University of Washington
Department of Electrical Engineering [†]
Box 352500
Seattle, WA 98125-2500, USA

Applied Physics Laboratory [‡]
1013 NE 40th Street
Seattle, WA 98105-6698, USA

Abstract

When a plurality of cooperating solutions are aggregated into a single performance criterion, the set of the best component solutions is not necessarily the best set of component solutions [1], *i.e.* the best team does not necessarily consist of the best players. The composite effort of the system team, rather, is significantly more important than a single player's individual performance. We consider the case wherein each player's performance is tuned to result in maximal team performance for the specific case of maximal area coverage (MAC). The approach is first illustrated through solution of MAC by a fixed number of deformable shapes. An application to sonar is then presented. Here, sonar control parameters determine a range-depth area of coverage. The coverage is also affected by known but uncontrollable environmental parameters. The problem is to determine K sets of sonar ping parameters that result in MAC. The forward problem of determining coverage given control and environmental parameters is computationally intensive. To facilitate real time cooperative optimization among a number of such systems, the sonar input-output is captured in a feed-forward layered perceptron neural network.

Key Words: maximal area coverage, neural network bank.

1 Preliminaries

A generic model for the *team optimization of cooperating systems* (TOCS) is illustrated in Figure 1. A total of K identical systems are replicated. The k^{th} system has control input parameters listed in the vector $\vec{c}_k$ and corresponding output response $\vec{a}_k$. The outputs are aggregated (e.g. combined). The aggregation is interpreted by a fitness evaluation. The fitness function is used to change $\{\vec{c}_k \mid 1 \le k \le K\}$ in a manner that increases and ultimately maximizes the fitness measure. We use evolutionary computing for optimizing although any one of numerous optimization algorithms can also be used [2]. Although numerous combinatorial optimization problems, such as the packing problem and set-covering problem [3], can be couched in the TOCS architecture of Figure 1, we investigate its application only to MAC. Such problems appear in many areas. Consider, for example, the placement of cellular antennas each having area coverage controlled by tunable parameters. When locations are fixed, finding the antenna parameters to find MAC is a TOCS problem. Alternately, for antenna deployment, antenna locations can be included in the set of adjustable parameters in the TOCS. In this paper, a related problem of MAC from a sequence of sonar pings is considered.

The architecture in Figure 1 has the property of distributed modularity important when the component systems require computational intensity. The procedure also has the advantage of straightforward implementation in object-oriented languages.

0-7803-7044-9/01/$10.00 ©2001 IEEE

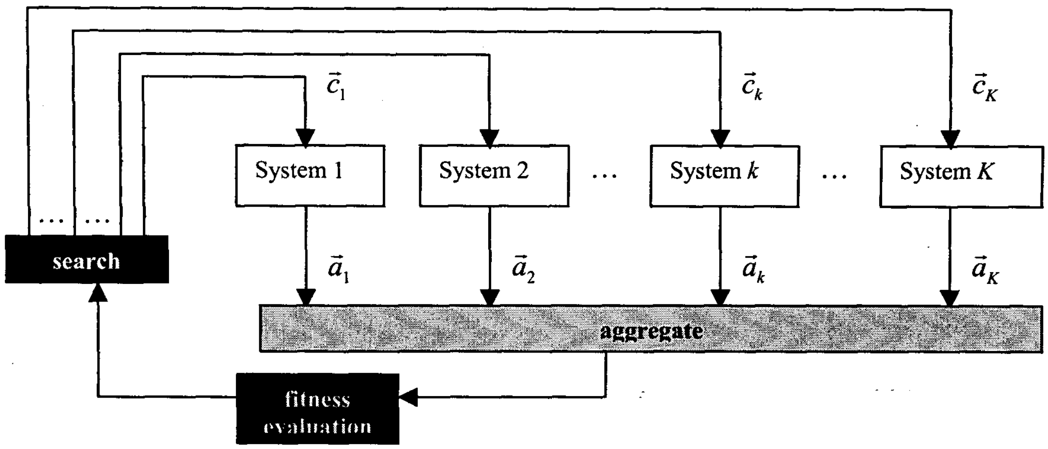


Figure 1: Team optimization of cooperating systems (TOCS) for maximal area coverage (MAC). The K systems, in response to stimuli generate respective area coverages of $\{\vec{a}_k\}$. These coverages are combined and a fitness function is evaluated. The fitness provides input to the control which, in turn, generates changes in the control vectors, $\{\vec{c}_k\}$.

2 Area Coverage With Deformable Shapes

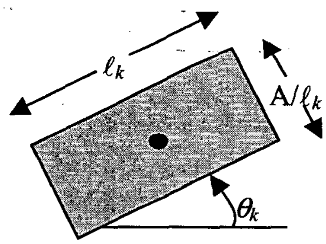


Figure 3: Illustration of a translatable, rotatable rectangle with adaptive aspect ratio

The MAC by TOCS procedure is applicable to area coverage with deformable shapes. To illustrate, consider the following instructive problem. K rectangular shapes of the type shown in Figure 3 each have fixed area, A, but can vary in accordance to aspect ratio (parameterized by length ℓ_k), rotation angle θ_k, and central of mass coordinates $\vec{\mu}_k = [\mu_{x_k}, \mu_{y_k}]^T$. As is illustrated in Figure 4, the problem for a given shape is to situate K rectangles in such as a manner as to maximally cover the shape.

This problem is straightforwardly implemented using the architecture in Figure 1. The k^{th} control vector is

$$\vec{c}_k = \begin{bmatrix} \theta_k \\ \ell_k \\ \mu_{xk} \\ \mu_{y_k} \end{bmatrix}$$

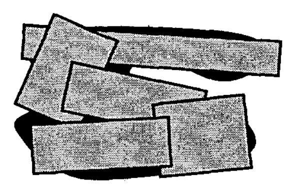


Figure 4: Coverage of an irregular shape with K=five rectangles of equal area.

The system outputs are representations of the areas covered by the rectangles. Aggregation is the union of these areas. The fitness value is the total area corresponding to the intersection of the aggregation with the target shape.

Examples of the evolution for MAC using TOCS is shown in Figures 5 and 6 for the cases of three and six rectangles, respectively, covering a circle. In both cases, due to the circle's symmetry, the number of solutions in the continuous version of the problem is infinite. A generic genetic algorithm was used in both cases for optimization.

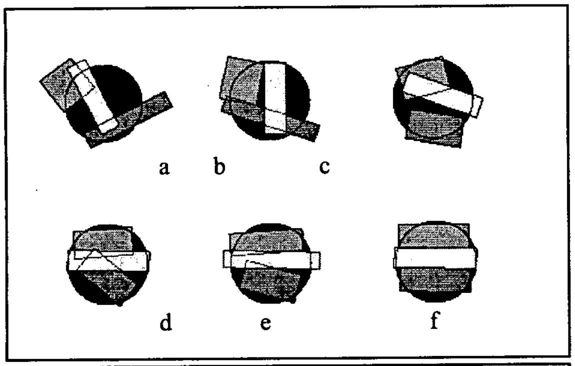
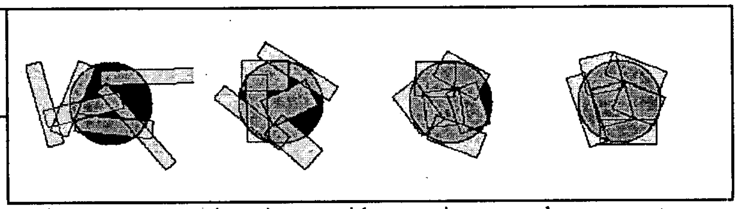


Figure 5: Snapshots of the process of coverage of a circle with K=3 equal area rectangles. The entire circle cannot be covered.

3 Maximizing Sonar Area Coverage

A more interesting problem of MAC using TOCS is in area coverage maximization by a plurality of sonar pings. Consider a sonar target area defined as a planar region under water of depth and range. The degree to which a single sonar ping covers a desired target area is a function of both environment and sonar control parameters. Given these parameters, computationally intensive emulations evaluate acoustic beam trajectories to evaluate acoustic signal strength at a plurality of depths and ranges. Relevant environmental parameters include wind speed and bottom type[1], bathymetry[2] and sound speed profile[3]. The positions of the submerged sonar transmitter and receiver also affect the ensonification. These two depths, in addition to the sonar ping parameters, constitute the control parameters of the problem. The sonar parameters can be controlled. The environmental parameters can't.

Figure 6: Snapshots of MAC using TOCS for six boxes covering a circle. Time increases from left to right. ⇒



The sonar problem under consideration is this. For a given environment, we desire, with K pings of the sonar, to observe as large an area in range and depth as possible. This is equivalent to design of the K ping parameters, $\{\vec{c}_k \mid 1 \le k \le K\}$, in Figure 1. The systems in Figure 1 are the emulators that, for given environmental conditions, compute coverage of the sonar. In range and depth, the output of each system in Figure 1 is the *signal excess* (SE) corresponding to the imposed control parameters. The SE is akin to a signal to noise ratio and measures the ability to detect a target. When the SE exceeds a prescribed threshold, coverage is assumed. Otherwise, it is not. The individual outputs can be thus characterized as binary maps – one for where coverage is made and zero otherwise.

As in the case of the previous example, aggregation is the union of the binary maps emerging from each of the systems. The fitness of the control parameters is equal to the total area covered by the K pings.

The forward problem for each of the K system modules in Figure 1 is performed using *Applied Physics Laboratory acoustic simulation software* (APLASS) [4]. The APLASS software is computationally intensive and several minutes are required to analyze the forward problem: the signal excess in range and depth as a function of the input environmental and control parameters. In order to speed the optimization, APLASS data was used to train a layered perceptron[4] [2]. The result is that the perceptron, after proper training, emulates the same results as APLASS – but much more quickly. K identical neural networks trained to emulate APLASS are then used in the architecture in Figure 1.

The resulting optimal control parameters in conjunction with environmental parameters will maximize the combined coverage and individual coverage maps and corresponding cumulative maps as is illustrated in Figure 6. The outputs from each bank can be characterized as binary maps – one for where coverage is made and zero otherwise. As in the case of the previous example, aggregation can be the union of the binary maps emerging from each of the systems. The fitness of the control parameters is equal to the total area covered by the K pings. The neural networks denoted as 1 to K in Figure 6 are identical but placed in parallel to distinguish different outcomes. The fitness function is determined by appropriate aggregation procedure from the K output SE maps ($\vec{O}_1, \vec{O}_2, \ldots, \vec{O}_K$), which are acquired from a set of K input vectors whose elements include a sonar control parameter and fixed environmental parameters. The aggregation procedure translates K output SE maps into a value that corresponds to the sonar ping coverage to be compared with desired coverage performance.

[1] both of which effects reflectivity
[2] the shape of the ocean's floor
[3] the changing speed of sound as a function of water depth.

[4] Details of the training of the neural network using ALPASS data is given by Jensen *et al.* [3].

The MAC procedure consists of three steps of operations. The maximum SE map, $\vec{O}_{\max}$, is calculated by taking maximum value in each element of K output SE maps respectively.

$$O_{\max,j} = \max_{k=1}^{K} O_{k,j}$$

where $O_{k,j}$ is the j^{th} element of k^{th} output SE map, $\vec{O}_k$, and $O_{\max,j}$ is the j^{th} element of maximum SE map $\vec{O}_{\max}$. This maximum SE map is fed into the nonlinear squashing function. Hence, in lieu of a strict binary representation, every element in the maximum SE map lies between 0 and 1 based on the specific threshold value implying whether the SE values are large enough to be considered covered or not.[5] The j^{th} element of the maximum SE map, $\vec{O}'_{\max}$, is denoted as

$$O'_{\max,j} = \frac{1}{1+\exp^{-\alpha(O_{\max,j}-\theta)}}$$

where α is a sensitivity parameter of sigmoid slope, and θ is a prespecified soft threshold value.[6] All elements in the composite maps are summed to give a global coverage

$$A = \sum_{j=1}^{N} O'_{\max,j} .$$

Accordingly, the fitness is calculated by normalizing the resulting aggregation with the desired aggregation, $A_{desired}$, which is N.

$$Fitness = \frac{A}{A_{desired}} .$$

For example, assuming 4 sonar ping problem (K=4), a single sonar control parameter, sonar depth, is implemented by bit stream with required precision of places after the decimal point. Thus, the required number of bits for each depth is 17 (See Figure 7).

Several genetic algorithm emulations using different probabilities are performed and their fitness functions converged in all cases to the same values. The algorithm, for this problem, was remarkably insensitive to initialization and algorithm parameters. Convergence for a number of cases is shown in Figure 8 as a function of generation.

The resulting optimal sonar control parameters in conjunction with environmental parameter maximize the combined global sonar ping coverage. Physical limitations imposed by the fixed environment prohibits 100% of target surveillance area no matter how many pings are used.

Figure 13 illustrates coverage maps of best 4 sonar pings and their contributions (cumulative coverage) as each sonar ping coverage map is added.

4 Generalizations

There exist numerous generalizations of the fundamental architecture in Figure 1 that allow application to a larger scope of problems.

- The systems need not be replications of each other but can, for example, specialize in different aspects of appeasing the fitness function.
- The search can be constrained [4]. In Figure 1, for example, a constraint imposing module can be inserted between the search box and the inputs to the systems. A simple example of constraint imposition is requirement that each element of each $\vec{c}_k$ lie within specified operating limits.

5 Acknowledgements

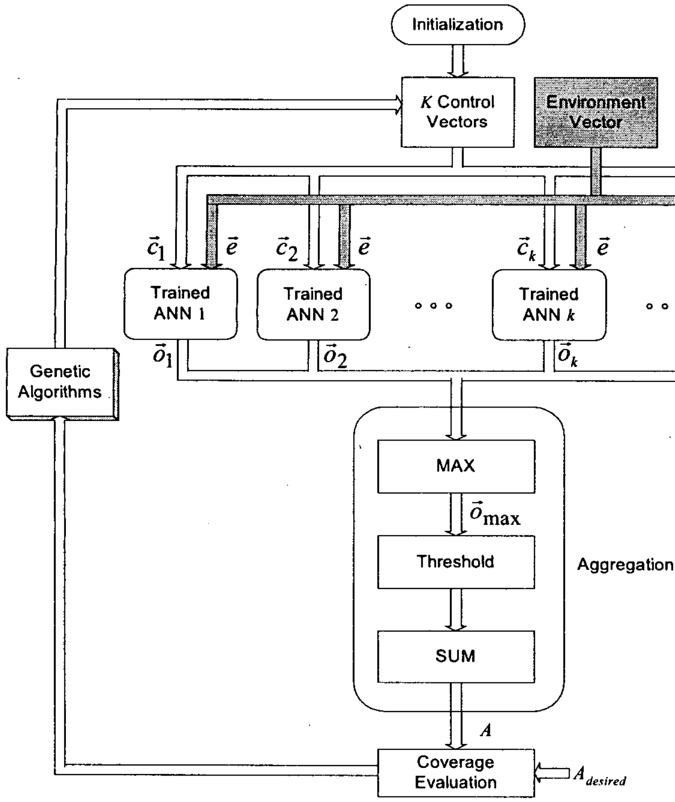
This work is supported by the Office of Naval Research.

6 References

1. T.M. Cover, "The best two independent measurements are not the two best", **IEEE Transactions on Systems, Man and Cybernetics**, vol. SMC-4, pp.116-117, January 1974.
2. Russell D. Reed and R.J. Marks II, **Neural Smithing: Supervised Learning in Feedforward Artificial Neural Networks,** (MIT Press, Cambridge, MA, 1999.)
3. Mitsuo Gen and Runwei Cheng, ***Genetic Algorithms & Engineering Optimization***, John Wiley & Sons, 2000.
4. Jensen, C.A.; Reed, R.D.; Marks, R.J., II; El-Sharkawi, M.A.; Jae-Byung Jung; Miyamoto, R.T.; Anderson, G.M.; Eggen, C.J., "Inversion of feedforward neural networks: algorithms and applications", **Proceedings of the IEEE,** Volume: 87 9, Sept. 1999 , Page(s): 1536 -1549

[5] Such representation also allows use of gradient based search techniques.

[6] Alternately, if strictly binary maps are desired, a hard limiter can be used.



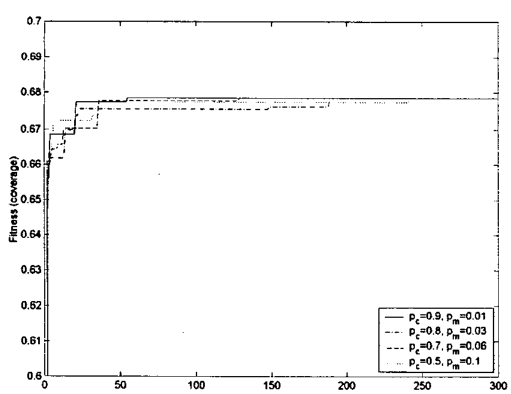
⇐ **Figure 6:** MAC by TOCS as applied to sonar. The vector of environmental parameters, $\vec{e}$, is fixed. For the given environmental parameters, the combination of control vectors,

$$\{\vec{c}_k \mid 1 \le k \le K\},$$

giving a combination maximal area of ensonification are desired. The control vector contains the parameters to be varied. The overall fitness value is equal to the area covered by the ensonification. A generic genetic algorithm is used to perform the search over the K vectors.

	depth 1	depth 2	depth 3	depth 4
Chromosome 1 :	17 bits	17 bits	17 bits	17 bits
Chromosome 2 :	17 bits	17 bits	17 bits	17 bits
	⋮	⋮	⋮	⋮
Chromosome P :	17 bits	17 bits	17 bits	17 bits

⇑ **Figure 7:** Population of genetic algorithm for sonar ping coverage optimization



⇐ **Figure 8:** Fitness function convergence using different probabilities of crossover and mutation.

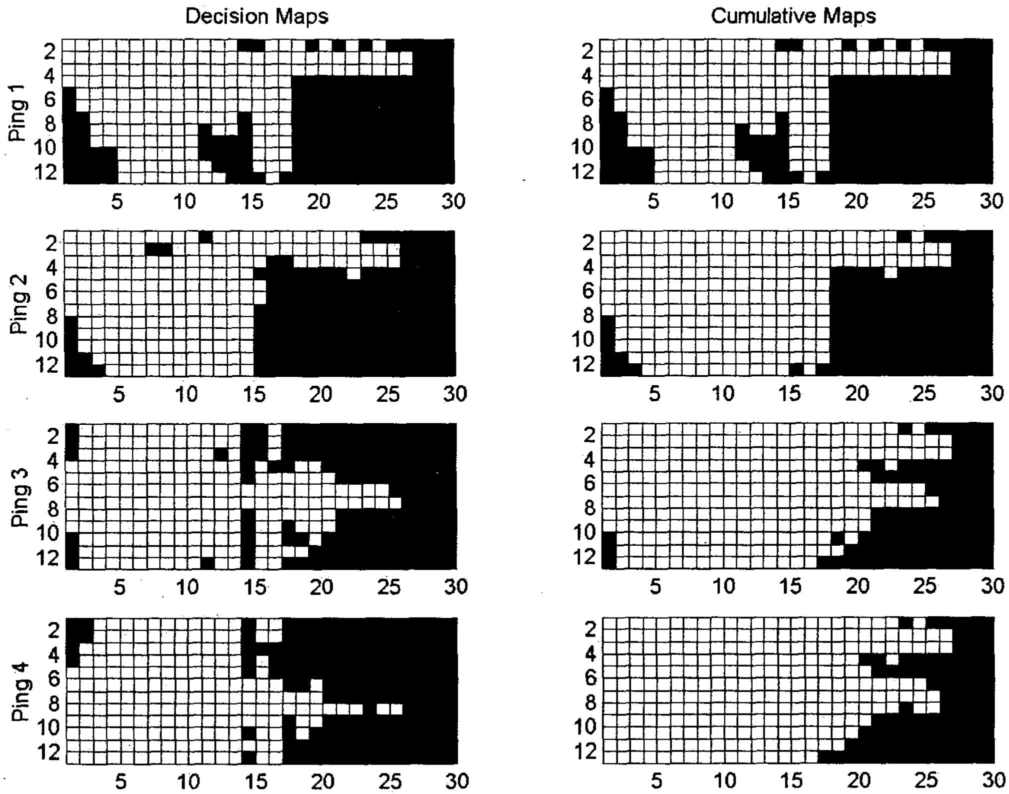


Figure 19. Modular maximal area coverage using a neural network bank for the multiple sonar ping problem (There are the best 4 different sonar pings that contribute to the maximal coverage after the convergence of the GA)