NODE PLACEMENT FOR A WIRELESS SENSOR NETWORK USING A MULTIOBJECTIVE GENETIC ALGORITHM

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This paper examines the optimal placement of nodes for a wireless sensor network. The sensors are dropped from an aircraft, and they must be able to relay their data to a Long Range Communication Node (LRCN), which serves as a high-power data relay from the ground to the base (via satellites or high-altitude aircraft). The sensors are assumed to have a fixed communication and sensing radius, and the terrain is a flat square surface. This simple framework serves to benchmark an optimization strategy using Genetic algorithm (GA), which can then be applied to a more realistic environment. First a single objective GA is used to evaluate the algorithm, and then two competing objectives are considered – the sensor Coverage and the Endurance of the network. It is shown that a multi objective GA using Pareto ranking leads to diverse Pareto-optimal network designs, from which a user can select depending on his or her preference. A sensitivity analysis of the objectives to the number of sensors is also conducted, and finally a robustness metrics is introduced in order to account for the inaccuracy of the airborne drop.

I. INTRODUCTION

Motivation

Unmanned Aerial Vehicles (UAV) are increasingly used for a variety of missions, from defense to environmental observations. Although vehicles like the USAF Predator or the Global Hawk can perform useful surveillance mission from high altitudes, they are unable to provide accurate data in certain scenarios where only close up surveillance is possible (monitoring the inside of a building, under-the-canopy observations, etc.). This realization led military planners to plan to rely heavily on remote unattended sensors for detection, identification and tracking of targets, as in the Future Combat Systems 1.

Human personnel are usually the ones performing the placement of such sensors, which is at best dangerous for their lives, and at worst altogether impossible (because of enemy presence, biological or chemical hazard, or terrain inaccessibility). Recently the miniaturization of sensors has made it possible to drop them from a flying aircraft, using a guided drop vehicle. UAVs can be used to perform this task, therefore removing any human from the deployment phase.

The system considered in this paper consists of a UAV carrying sensors inside their respective drop vehicles. Once arrived at the mission site, the UAV launches these vehicles that deliver the sensors at predetermined locations. The sensors on the ground then perform their surveillance mission, while relaying their data to the flying UAV, which in turn transmits it to the home base. This system does not require any human presence and has therefore a wide range of application beyond the military realm – any situation where lives are endangered or where access is difficult.

The number of sensors that can be deployed from a UAV is constrained by the payload capacity of the aircraft. It is therefore important to carefully determine where to deploy these sensors, so as to maximize their efficiency – their layout will determine the performance of the network. An optimizer taking into account the sensors characteristics, the terrain and the desired objectives is needed in order to provide an optimal configuration.

This paper examines such an optimization technique that optimizes the sensor layout.

Sensor Network Description

The sensor network placed on the ground is composed of two different types of units (or nodes):
II. SENSOR PLACEMENT PROBLEM FORMULATION

Objectives

Two objectives were chosen in order to determine where to place the sensors. The first is the sensor Coverage; it is equal to the fraction of total area covered by the network.

\[
\text{Coverage} = \frac{\text{Area Covered}}{\text{Total Area}}
\]

The second objective is the lifetime, or Endurance of the network; it is equal to the ratio of the number of sensing cycles possible before the Coverage drops to 90% of its initial value (due to sensor failure caused by power shortage of sensors) over the maximum number of sensing cycle. A sensing cycle is defined as an event where all sensors transmit their observed data to the LRCN.

\[
\text{Endurance} = \frac{\# \text{ cycles}}{\text{total cycles}}
\]

These objectives are competing for the following reason. On the one hand the coverage objective will desire “spread out” network configurations, where sensors are as far apart from each other as possible. In order to reach the LRCN, data packets from peripheral sensors will therefore have to be “hopped” from one neighboring sensor to another. This implies a large number of relay transmissions for sensors communicating directly with the LRCN, so that their failure will happen sooner due to the consumption of all their power – the network endurance will then be small. On the other hand, in order to get an endurance of 1 all the sensors must communicate directly to the LRCN, so that their power is used only for their own data transmission. This implies a clustered configuration around the LRCN, yielding a poor coverage value.

Design Variables

The design variables are the XY coordinates of the sensors. They are homogenous variables and therefore do not need to be scaled. The design vector has the following form:

\[
X = [x_1, y_1, \ldots, x_n, y_n]
\]

Constraints

As mentioned before, every sensor must be able to relay its data to the LRCN – disconnected sensors are
worthless since their coverage data cannot be accessed. Data transmission to the LRCN can be done either directly if the LRCN is within the communication range of the sensor, or in several hops using other sensors as relay nodes.

Parameters

Certain parameters are fixed and cannot be changed during the optimization. The number of sensors was fixed to 5 because it makes it easier to check the results using intuition. The sensing and communication ranges of each sensor are also such constant parameters.

The total power capacity and power draw required for each data transmission are also fixed, respectively equal (for all sensors) to 100 and 1 (in arbitrary units).

III. MODEL IMPLEMENTATION

Simplifying assumptions

Several simplifying assumptions were made. Firstly, the communication and sensing range of each sensor is chosen constant and equal to 2.

\[ R_{\text{COMM}} = R_S = 2 \]

Secondly, the area is considered to be a flat square of side 10. No terrain effect is considered and two nodes communicate if and only if they are within their communication range \( R_{\text{COMM}} \). Likewise, a sensor covers a point if it is \( R_S \) or closer to it. This assumption is realistic for seismic sensors, which performance does not depend on the terrain. However for acoustic and visual sensors the surrounding environment should be taken into account in more realistic models. This is illustrated in Figure 2.

Objectives calculation

The Coverage is obtained by discretizing the area into a set of points, and then determining how many of these points are within \( R_S \) of at least one sensor. The ratio of this number to the total number of points gives a good estimate of the Coverage, provided the grid is refined enough.

The Endurance is more complex to obtain. The adopted technique was chosen for its relative simplicity. A Breadth First Search (BFS) is performed from the LRCN in order to obtain the paths linking it to each sensor. These paths are assumed to be the paths that a packet of information emitted by sensor \( i \) would take in order to reach the LRCN. This knowledge is used in order to determine which are the most frequently used sensors in terms of data relay.

A loop is then performed which simulates sampling cycles of the sensors, where each emits a packet of data. Since the path that each packet follows is known, for each sensor it is possible to determine how many relay transmission it has to make during each sampling cycle (in addition to its own data transmission). These transmissions have a cost in energy, and sensors that relay the most information will fail sooner. Once enough sensors have failed so as to reduce the coverage by 10% or more, the calculation ends and the resulting number of sampling cycles is obtained. This is finally divided by the maximum number of sampling cycles (determined by the initial energy contained in each sensor).

It should be noted at this point that there is no single global optimum to the sensor placement problem. Similar layout rotated about the origin will have similar objectives but different design vectors. It may therefore be legitimate to talk about a global optimal layout, but not about an optimal design vector of coordinates.

This model was implemented using MATLAB 6.1 on a Pentium 4 PC, running at 1.8GHz.

IV. OPTIMIZATION ALGORITHM DESCRIPTION

Design Space Study

Although the terrain considered is idealized, the design space remains highly non-linear. This is illustrated in Fig. 3 for a network of five sensors. The layout of the network is shown on the top figure, where the dashed top sensor is moved throughout the design.
space. The objectives are then mapped versus the sensor position.

![Graph](image)

(a) Initial network layout

(b) Coverage versus sensor position

(c) Endurance versus sensor position

Fig 3 – Design space analysis

The coverage plot looks like a football stadium with very steep outside walls. This is because there is a discontinuity in the coverage when the sensor is moved outside of the communication range of the rest of the network. Since it cannot relay its data anymore, its Coverage contribution is not taken into account – hence the abrupt loss of Coverage. On the other hand if the sensor is placed inside the network it has no effect on the nominal Coverage value (since the area where it is located is already covered by other sensors), but it increases the Endurance of the network by providing another relay point (Fig. 3c).

This non-linearity is amplified when the effects from all the sensors are put together, and it will be even greater for more realistic terrain conditions. This is one the main motivation for using Genetic Algorithm (GA) to optimize the network.

**Genetic Algorithm Description**

The nomenclature used is the following:
- NG: number of generations
- N: population size
- P<sub>m</sub>: mutation rate

Due to the homogeneity of the design variables there is no need for encoding as is usually done in GA. The design vector used is therefore composed of the physical coordinates of the sensors.

\[
\begin{bmatrix}
X_1 \\
y_1 \\
X_2 \\
y_2 \\
\vdots \\
X_n \\
y_n
\end{bmatrix}
\]

The crossover is performed between two individuals. Every individual mates with another to produce two Children. The crossover point is chosen randomly.

The Children are then mutated at a rate P<sub>m</sub>, so that each coordinate of \(X\) is modified with a probability P<sub>m</sub>. New coordinates are chosen at random between 0 and 10. The Coverage and Endurance of each Child is then evaluated.

Parents and mutated Children form the new pool out of which N individuals will be selected. The selection technique is based on elitist selection, which will be discussed separately for the single objective and the multi objective case.

The process is repeated until the maximum number of generation is reached.

**Single Objective GA (SOGA)**

The GA was first tested using a single objective (Coverage) in order to evaluate its efficiency. The selection is based on elitism, where the N individuals with highest Coverage are passed on to the new generation. Other schemes were tried such as Roulette Wheel or Binary Tournament, but this deterministic technique outperformed them. Its disadvantage is its
tendency to produce a homogenized population early, with often sub-optimal results. To counter this effect a mutation rate of 0.2 was chosen to maintain diversity.

The initial population is composed of N networks with a sensor placed next to the LRCN and the others distributed randomly.

The results presented in Fig. 4 were obtained after 100 generations, with a population of 60 individual and a mutation rate of 0.2, and it took about 45 minutes to complete. A steady improvement in Coverage can be noticed on Fig. 4a. As expected the Endurance is declining as the SOGA progresses, because networks with good coverage have poor endurance. The best network has a Coverage of 0.42 and its layout is shown in Fig. 4c. This final design can then be refined using a gradient based technique or a greedy algorithm. These techniques are possible in this case because the design space has been thoroughly explored and they can tune the solution to arrive to the maximum. Referring to Fig. 3b, these techniques can be seen as working within the continuous regions of the graph in order to reach a maximum. This is an area of interest for future work.

In order to compare the SOGA with results obtained for the multi objective case, the objectives graph showing Coverage versus Endurance is included in Fig. 4b. The Pareto Front (PF) can be seen to move towards the lower right, where Coverage is maximized and Endurance minimized. Since the objectives are competing and we are only optimizing for Coverage this is consistent. It can also be seen that the individuals are clustered on the right portion of the PF.

Multi Objective GA (MOGA)

SOGA yielded good results in terms of Coverage, but the objectives graph showed that there are not many Pareto optimal designs with differing Endurance. However it is attractive to offer Pareto optimal designs to a user willing to settle for a poorer Coverage in order to gain in Endurance, so that the sensor network lasts longer. This possibility is not offered by the SOGA. A MOGA was therefore implemented and its results are compared to those of the SOGA.

The GA itself is identical than the one used in the single objective case, with the exception of the selection, which must take into account both objectives. Since the goal of the MOGA is to provide a uniformly populated PF, the weighted sum approach was rejected since it assumes an a priori knowledge of the user’s preference of one objective over the other. Several schemes were devised to incorporate both objectives in the selection, and as in the case for the SOGA the deterministic elitist selection outperformed Binary Tournament and Roulette Wheel Selection. The fitness assignment was done using the Pareto dominance described by Fonseca and Fleming, where the fitness of an individual is inversely proportional to the number
of individuals that dominate it. The pool of individuals is then sorted from the best ranked (non-dominated individuals) to the worst ranked. Deterministic selection then keeps the N best individuals. This selection scheme insures that the current Pareto best networks are kept from generations to generations, irrespective of their objectives value. This makes it possible to keep a uniformly populated PF. One drawback again is the rapid sub-optimal convergence if the mutation rate is too low. To counter this a mutation rate of 0.2 was again chosen.

Fig. 5 displays the results of a MOGA run of 150 generations, with a population size of 60 and a mutation rate of 0.2. It took 3.5 hours to complete.

The PF (Fig. 5b) is uniformly populated, and it evolves towards the utopia point at the top right corner. This is to be compared to the SOGA where the PF evolved only towards the bottom right. The individual shape of the evolution of the objectives (Fig. 5a) is irregular and is due to the movements of the PF. The overall slopes are positive, which is expected since both objectives are improved (as shown by the PF progression to the upper right). At about the 75th generation the Coverage suddenly drops, while the Endurance increases. This is an indication that the PF evolved upwards, as a new configuration with more Endurance was found. From then the PF expands to the right, as is shown by the magenta and red points on the PF. Therefore the irregular behavior of the objectives is explained by looking at the PF.

The layout of the network with maximum coverage is similar to the one found with the SOGA, with three sensors linked directly to the LRCN (Fig. 5c). However
now that a well-populated PF is obtained, the user can choose which level of Endurance (s)he desires by looking at the PF. For example if the Endurance of the best network in terms of coverage is too low (0.13) for the user, another network can be chosen – for example the one which has a Coverage of 0.35 and an Endurance of 0.5 (displayed in Fig. 5d).

The MOGA therefore yielded satisfactory results in terms of design choices for the user. This basic framework can be used to optimize more complicated problems where terrain affects performance.

V. Sensitivity of the Objectives to the Number of Sensors

It has been said earlier that the number of sensors considered was fixed beforehand to 5. It might be interesting to relax this parameter and see what benefits there is in including more sensors.

Obviously the more sensors, the better the objectives. However the nodes are deployed from a UAV, which has a payload constraint, so that carrying more nodes is costly. It is therefore important to know the trade-off between number of sensors deployed and the expected values of the objectives. The user can then choose whether it is worth adding a sensor or not, considering the gain in performance.

Such a trade-off study was conducted assuming all sensors had ranges \( R_S \) and \( R_{COMM} \) equal to 2. This was done by running the MOGA for increasing values of number of sensors, up to 15. Figure 6 shows the plot of the Coverage and of the Endurance versus the number of sensors.

![Figure 6](image)

**Fig. 6 – Effect of an increase in the number of sensors on the objectives**

If the number of sensors is increased beyond 15, it should be expected that the Coverage converges to 1 and that the Endurance stops decreasing and instead increases, as more sensors serve as relays. For a number of sensors lower than 15 the Endurance decreases with the number of sensors because the more sensors there is, the more relay needs to be done by a few of them.

Using this graph the user can determine what value of Coverage and Endurance can be expected from the MOGA, and accordingly choose the number of sensors to be placed.

VI. Placement Inaccuracy Robustness Analysis

Another important aspect of the airborne sensor deployment is the inaccuracy of the drops. The nodes will not get positioned at the exact location where the optimizer had planned. It is therefore important to calculate the robustness of the design with respect to drop inaccuracy. Figure 3b showed that if a communication link exists between two sensors located near the edge of their communication range, there needs only to be a small deployment inaccuracy for the link to fail – the corresponding sensor can then be disconnected from the LRCN which renders its coverage useless. A probabilistic approach could be used to vary the position of each sensor according to a distribution with a specified standard deviation (depending on the accuracy of the deployment system). However the computational cost is high and a simpler approach based on a metric developed by Allen was used. This metric measures the robustness of a communication link between node i and j.

The Robustness of the network is then obtained by summing over all links.

\[
\text{Robustness} = \sum_{\text{all } \text{links}} [R_{COMM} - \text{dist}(i, j)]
\]

A network with a high Robustness will therefore be more likely to maintain a good performance (i.e. to have all its sensors connected) in the event of deployment inaccuracy.

This was tested on the two networks considered in Fig 5c and 5d. For the network with best coverage but poor Endurance, the Robustness is 0.13, while that of the network with a better Endurance is 0.23. This fits the intuitive results, that a network with good Coverage will have poorer Robustness (since the nodes are spread out). Endurance and Robustness to deployment inaccuracy tend to work in the same direction.
A MOGA was conducted with the Coverage and Robustness as objectives. Results are presented in Figure 7.

The PF has the same shape than the one obtained before, and the layout of a network situated towards the middle of the PF is similar to the one found in fig (d) (and they have similar Coverage). This confirms that Endurance and Robustness tend to similar network layout. This means there is no need to run a MOGA with both of them as objectives in addition to Coverage. One is sufficient to drive the layout towards satisfactory designs for both.

VII. CONCLUSIONS AND FUTURE WORK

This paper presented a MOGA with elitist selection, which yielded good results in terms of PF population. This framework can then be implemented in a more realistic model for the communication and sensing of the sensors.

Future work needs to be done on the GA itself. More effort should be put into improving the elitist selection, so as to make sure to include non-dominated points that span the PF uniformly, as well points with low domination. Also, mating two networks with similar but rotated layouts can produce very poor offspring since nothing of the qualities of the Parents are passed on. These destructive crossovers may be prevented if some “smart” mating restriction operator is implemented in the physical XY space.

Figure 3b indicates where additional nodes should be placed in order to maximize the coverage gain (high peaks). This knowledge could be useful in placing additional nodes.

Finally the output of the GA are rather “raw” and need to be refined. A technique involving gradient search or greedy algorithm should be developed to refine the GA optimal designs.

REFERENCES


