ENERGY EFFICIENT SENSOR SELECTION IN VISUAL SENSOR NETWORKS BASED ON MULTI-OBJECTIVE OPTIMIZATION

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ABSTRACT

In this paper, we investigate the problem of visual coverage in visual sensor networks (VSNs). It is required to select a subset of sensor nodes to provide a visual coverage over the monitoring region at each point of time. In contrast with the pervious works which considered only single metric for sensor selection method, in this study we assumed the sensor selection as multi-criteria problem. For the purpose of maximizing the network lifetime, we consider three metrics a) visual coverage ratio, i.e., percentage of monitoring region which is fully covered by camera sensors, b) number of selected sensors, i.e., number of active sensors for covering the desired region, and c) overlapping coverage ratio, i.e., percentage of monitoring region which is covered by more than one camera sensor. Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is used to solve the problem. Besides, impact of steady state selection and generational selection method is studied on the network lifetime. Simulation results show the superiority of multi-objective optimization. NSGA-II results not only longer network lifetime but also fewer number of active sensor and lower overlapping ratio at each point of time.

KEYWORDS

Visual sensor network, coverage, multi-objective optimization, genetic algorithm, NSGA-II

1. INTRODUCTION

VSNs are a large number of cheap and small camera sensor nodes which are distributed over a region to provide visual coverage. VSNs are also known as Wireless Camera Sensor Networks (WCSNs). In contrast with wireless sensor networks (WSNs) which can only be used to collect numerical data from the sensing area, VSNs are capable of providing images or video from the monitoring region [1]. The most important applications of VSNs are area surveillance, tracking and environmental monitoring. In fact, camera sensors can be deployed on a sensing area to provide images or video from the monitoring environment. Each sensor node has limited energy power and battery replacement is an inconvenient and expensive task and usually is not possible. Thus, there is a huge interest to prolong the network lifetime.

The main difference between the VSNs and WSNs is the types of sensors which are used in each one. WSNs composed of sensors which are used for temperature sensing, humidity monitoring and etc. On the other hand, VSNs consist of wireless camera sensors which can bring visual data from their monitoring environment [2]. The coverage is an important issue in the networks. In VSNs, the sensing range of sensor nodes is replaced by the viewing volume of the camera called field of view (FoV). All cameras are static and there is no pan, tilt and zoom (PTZ) possibility for cameras. Cameras' FoVs can overlap, so that same parts of sensing area would be monitored by more than one camera sensor. Although overlap monitoring may increase the reliability but it consumes more energy for both area monitoring and data transmission.

Full coverage and partial coverage are two main types of coverage which can be discussed. In fact, full and partial coverage could be considered in both WSNs [3,4] and VSNs [5]. Full coverage is useful for applications where monitoring a target plane (monitoring area) completely as much longer as possible is desired. Conversely, partial coverage can be used in applications where network lifetime prolonging is more critical than providing full coverage or in applications where the data provided by a subset of the target plane is satisfactory. In this paper surveillance of a target plane with energy constrained camera sensors is considered. Our objective is to enhance the area coverage using minimum number of camera sensors in order to achieve maximum coverage with minimum overlapping at each time step.

The NP-completeness of sensor selection for coverage in VSNs and WSNs proved in [6,7]. Therefore, an evolutionary multi-objective optimization algorithm is employed to select the best subset of sensors at each point of time. In fact, multi-objective optimization used to achieve maximum coverage with minimum overlapping and minimum number of sensors. The rest of this paper is organized as follows: A brief overview of the state-of-the-art in visual coverage in VSNs is given is given in section 2. In Section 3, we gave a problem definition and statement in detail. Proposed method is presented in section 4. Performance evaluation and simulation results are shown in section 5. In section 6, the paper ends with a concluding epilogue along with a hint on future works conceivable in this area.

2. RELATED WORKS

Camera selection techniques are used when camera deployment is redundant. In such cases, by using camera selection methods, the visual network can prevent redundant monitoring of overlapped areas. There are many quality metrics which are employed in the evaluation of a sensor selection method, such as the energy-efficiency or the quality of the gathered image data. In fact, camera selection strategy depends on the application [8]. Surveillance and monitoring of large areas such as parking lots, public areas and large stores, require complete coverage of the area at each point of time. Dagher et al.[9] proposed an efficient strategy for monitoring parts of the desired region with cameras sensors while the battery lifetime of the camera nodes are maximized. The optimal fractions of regions covered by every camera are found in a centralized way at the base station. JPEG2000 [10] encoding used at the cameras to encode the allocated region such that the cost per bit transmission is reduced. However, energy efficiency is the only metrics used in [9], while in this study coverage ratio, energy efficiency, minimum overlapping are assumed as the efficiency metrics.

In [11], the authors investigated on distributed power management of camera nodes based on coordinated node wake-ups in order to reduce the energy consumption of camera sensors. They used a coordinated distributed power management (CDPM) policy which includes dynamic and adaptive timeout thresholds, two-hop broadcast information dissemination and remote wakeup. In fact, they assumed that each camera node is awake for a certain period of time. After a while each camera node decides whether it should enter the low-power state based on the timeout statuses of its neighbouring nodes. Similarly, camera nodes can decide whether to enter the low-power state according to their neighbour's votes. However, their proposed method cannot be applied to the application with large area monitoring environments. The most relevant study is that of [12] where camera sensor nodes are used for an airspace surveillance applications. They used heuristics and evolutionary methods to select a subset of sensors which brings maximum coverage with minimum number of sensor nodes. Actually, in the evolutionary methods coverage maximization and minimizing the number of sensor selection are not solved simultaneously. Besides, minimizing the overlapped coverage is not considered in their methods.

Soro and Heinzelman [5] investigated on two different camera selection strategies for prolonging the network lifetime. One scheme selects cameras that minimize the difference between captured images and the other scheme is based on choosing a VN by considering the energy constraints and the three-dimensional coverage. In [13] camera selection is performed based on the user defined applications. For each type of application, minimum number of cameras sensors is selected to satisfy the desired coverage. Similarly in [14] camera selection, frame rate and resolution assignment is performed based on the user defined QoS. However, most of camera sensor nodes have simple cameras which cannot be adjusted with different resolution and frame rates. In [15] problem is formulated as convex optimization problem. Using the lagrangian duality, the problem solved in distributed environment. However, the convergence of their optimization happens very slowly and consumes a lot of energy for transmitting the lagrangian variables between sensor nodes. In [16] authors investigated on collaboration routing and camera selection for removing the overlapping coverage. They formulated the problem as convex optimization. However, the assumed that each camera sensor node can select a part of camera field of view which is not always possible.

3. PROBLEM STATEMENT

In this paper we assumed camera sensors which scattered randomly in visual sensor nodes plane and employed for monitoring a parallel plane called target plane. Figure 1 shows an example of this situation for monitoring the floor by camera sensors mounted on the ceiling and directed toward the floor[17]. Another example of this scenario is airspace surveillance through a terrestrial VSN with randomly distributed camera sensors on the ground[12]. The same assumption is made in [13,18,19,20,21].

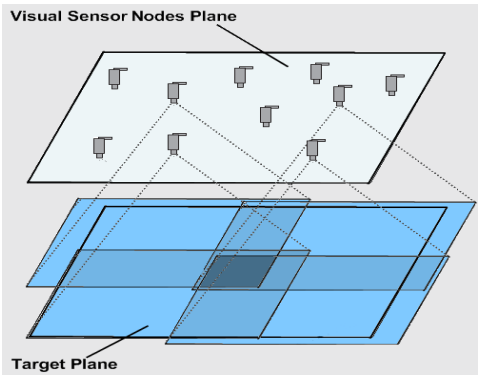

Figure 1. Visual coverage model

Our goal is to prolong the monitoring of the target plane as much as possible. We believe that monitoring the target plane with minimum number of camera sensors and minimum amount of overlapping would increase the network lifetime. The visual coverage of a camera sensor is defined as a set of points which lies in the intersection of a camera's FoV and the target plane.

Let S shows an arbitrary set of sensors, then $C(S)$ can be defined as visual coverage of S on the target plane. Let L show the set of alive of sensors at each time step and L_0 shows the set of alive sensors at the system initialization. Obviously, $C(L_0)$ is the maximum achievable visual coverage and $C(L)$ is the maximum achievable visual coverage at each point of time. We assumed that full visual coverage is achievable at the system startup.

As result, full visual coverage lifetime can be defined as period of time where $C(S) = C(L_0)$. In other words, full visual coverage lifetime is the duration of time that complete coverage of target plane is achievable by the selected sensors. Although maximizing the full visual coverage is the ultimate goal of surveillance cases, but after a while, by the death of some sensors, full visual coverage is not achievable. Meanwhile there exist a lot of visual sensors which can bring partial visual coverage. Accordingly, partial visual coverage can be defined as period of time where $C(S) \geq \gamma C(L)$ and $C(S) \geq 0.5C(L_0)$ while full coverage cannot be achieved any more. In other words, after a while, when full visual coverage cannot be achieved, the task is degraded to achieve γ of maximum achievable coverage. Meanwhile, the partial visual coverage solution should be able to monitor at least 50% of target plane at each point of time. Maximizing the full visual coverage lifetime is the first priority of our problem. However, when full visual coverage is not achievable, γ of maximum achievable coverage is acceptable.

4. PROPOSED APPROACH

Visual coverage problem is a multi-criteria problem in which coverage ratio, number of selected sensor and overlapped coverage ratio affects the network lifetime. Increasing the visual coverage ratio causes more working sensor and reducing the working sensors will lead to a lower coverage ratio. Meanwhile, visual overlapped coverage ratio is affected by number of selected sensors and coverage ratio. Obviously, these three metrics need to be considered simultaneously. Using the multi-objective optimization technics leads to solve multi-criteria problem and results the optimum answer. So, we assumed a three criteria problem where $f_1$shows the total amount of coverage ratio, $f_2$shows the number of selected sensors and $f_3$shows the total amount of overlapped coverage ratio. In that case, the multi objective optimization can be formulated as follows:

$$Min(-f_1(x), f_2(x), f_3(x))^T \qquad (1)$$

$$s.t\ x \in X$$

Where X is the feasible set of decision vectors. Obviously minimizing $-f_1(x)$ leads to maximize $f_1(x)$. Therefore, the problem can be modeled as multi-objective minimization problem. In multi-objective optimization, usually there no exists a feasible solution that minimizes all objective functions simultaneously. Therefore, attention is paid to Pareto optimal solutions, i.e., solutions that cannot be improved in any of the objectives without impairment in at least one of the other objectives. In mathematical terms, for a multi-criteria problem with K objectives ($Min(f_1(x), f_2(x), \dots, f_K(x))^T$), a feasible solution $x_1 \in X$ is said to dominate another solution $x_2 \in X$ strongly iff:

$$1 - f_i(x_1) < f_i(x_2) \qquad \forall i \in \{1,2,\dots,K\} \qquad (2)$$

In the same way, a feasible solution $x_1 \in X$ is said to dominate another solution $x_2 \in X$ weakly iff:

$$1 - f_i(x_1) \leq f_i(x_2) \qquad \forall i \in \{1,2,\dots,K\} \qquad (3)$$

$$2 - f_i(x_1) < f_i(x_2) \qquad \exists i \in \{1,2,\dots,K\} \qquad (4)$$

An example of non-dominated sorting for a two objective problem is illustrated in Figure 2. As it can be seen, F_1 dominates F_2,F_3 and F_4. F_2 dominates F_3 and F_4. F_3 dominates F_4.

A solution called Pareto optimal if there does not exist another solution that dominates it. The set of Pareto optimal outcomes is often called the Pareto front.

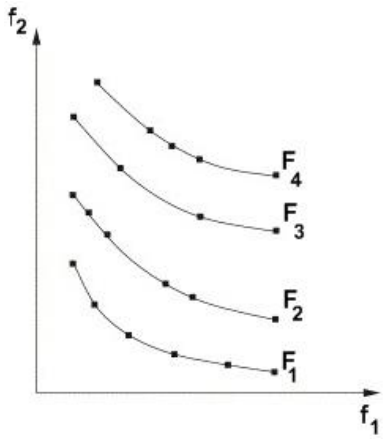

Figure 2. Non-dominated sorting

4.1. NSGA-II

There are several well-known MOGA such as [22-24]. NSGA-II [24] (elitism non-dominated sorting genetic algorithm) is one of the most popular algorithms proposed as an improvement of NSGA [23]. In this paper, we present an approach based on NSGAII to find Pareto optimal solutions for visual coverage problem in VSNs. In fact, the goal of NSGA-II is to find the non-dominated fronts using genetic algorithm approach. The overall complexity of the algorithm is $O(MN^2) + O(N^2)$, where M is the number of objectives and N is the population size. The whole operation of NSGA-II approach is shown in Figure 3.

Algorithm 1(NSGA-II algorithm)

Input: Given number of population size N, recombination probability P_r and mutation probability P_m

Output: The non-dominated front solution

01 Generate P_0 at random

02 Set t=0

03 While termination criteria has not been reached {

04 Generate offspring population Q_t from P_t by performing recombination and mutation according to P_r and P_m and save them in R_t

05 Set $F = \{F_1, F_2, \dots\} = non - dominated\ sort(R_t)$

06 Set $P_{t+1} = \emptyset, i = 1$

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07  While |P_{t+1}| + |F_i| < N{
08  Set P_{t+1} = P_{t+1} ∪ F_i
09  Set i = i + 1
10  }
11  Sort F_i according to the crowding distance
12  Set P_{t+1} = P_{t+1} ∪ F_i[1: (N − |P_{t+1}|)]
13  Set t = t + 1
14  }
15  Return F_1
```

Figure 3. NSGA-II pseudo code

In the above pseudo code, the initial population is generated randomly. In line 04, at each iteration a new child population is generated. In fact, based on the selection scheme, there exist two main types of GAs: generational and steady-state. In the generational model, after creating new population of individuals from an old population, both new and the old ones would be selected for next generation ($R_t = Q_t \cup P_t$) . On the other hand, a steady-state GA creates typically only one new member which is tested to be inserted in the population at each step of the algorithm. In this paper we study both generational and steady-state models which are shown by $NSGA - II_{gen}$ and $NSGA - II_{ss}$ respectively. In line 05, the non-dominated sorting, tries to divideR_t into $\{F_1, F_2, ...\}$ while for each F_i and $F_j (i < j)$, the following conditions should be satisfied:

1- x dominated by y $\quad \forall x \in F_i, \nexists y \in F_j$

2- x dominates y $\quad \exists x \in F_i, \forall y \in F_j$

In other word, for all $x \in F_i$ there should not exist $y \in F_j$ that dominates x and meanwhile for all $y \in F_j$ there should be at least one $x \in F_i$ that dominates y. After sorting the population, elitist sets are selected for the next population. When the size of elitist set F_i is found to be more than population size, subset of gens in F_i needs to be selected according to their crowding distance.

In fact, crowding distance is used to get an estimate of the density of solutions surrounding a particular solution in the population. Crowding distance is calculated by first sorting the set of solutions in ascending objective function values. The crowding distance value of a particular solution is the average distance of its two neighboring solutions. The boundary solutions which have the lowest and highest objective function values are given an infinite crowding distance values so that they are always selected. This process is done for each objective function. The final crowding distance value of a solution is computed by adding the entire individual crowding distance values in each objective function. However, this procedure would be repeated until the convergence of the optimum solution. Using the above method, we can find out the optimum set of sensors which has the maximum coverage, minimum number of sensors and minimum overlapping coverage. Using a discrete genetic representation, each chromosome shows whether a sensor is selected or not.

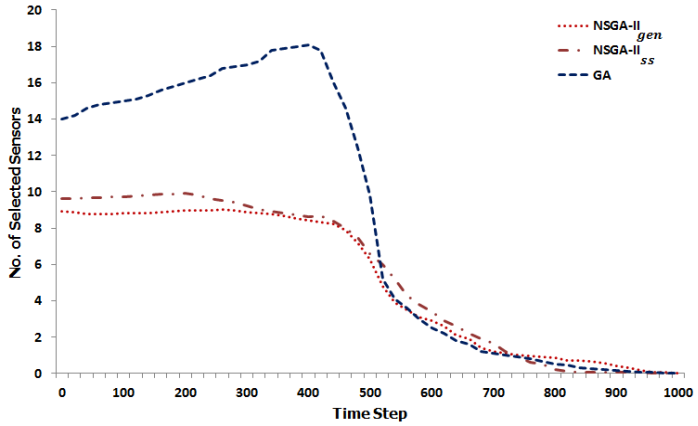
The output of the above method would be a non-dominated front solution which represents N various solution for a problem. Each solution has different values of f_1, f_2 and f_3. Since the coverage is the most important criteria, we choose a sub set of solutions which satisfies the coverage requirement. Among the chosen subset, another subset of solution will be selected which has minimum number of active sensors and after that, among the selected ones, a solution would be selected which has the minimum amount of overlapping coverage. Using the mentioned approach, a solution would be achieved that can satisfy coverage requirement by minimum number of sensor nodes while the overlapped coverage is minimized. The selected set of sensors would be used until at least one of the sensors dies and the visual coverage requirement cannot be satisfied. After that, another set of sensors would be selected based on the NSGA-II. This procedure continues until the solution of NSGA-II cannot satisfy the coverage requirement.By knowing the sensors locations, their camera FoV and their initial energy, the problem can be solved in an off-line phase in the sink node.

5. SIMULATION RESULTS

In this section, we evaluate the performance of proposed approach by solving both $NSGA-IIgen$ and $NSGA-IIss$ algorithms for visual coverage problem. Furthermore, to demonstrate the superiority of our methods, we compare it with GA heuristic introduced by [12] for different scenarios. In fact, in [12] authors proposed different heuristics and evolutionary approaches to solve the visual coverage problem. Their simulation results showed that a GA based heuristic can solve the problem in an efficient manner which results a trade of between coverage ratio, number of active sensors and overlapping. However, we believe that optimizing these three metric simultaneously would result a better solution for the problem.

A stationary network assumed while 50 camera sensors are deployed randomly in a 100m×100m plane for monitoring a 100m×100m target plane. The initial energy of each camera sensor selected randomly between [100,200]. Each scenario plotted on the figure is the average of 100 randomly generated networks. For partial coverage γ=0.93 (i.e. at each point of time $C(S) \geq 0.93C(L)$). OMNET++ [25] is used for simulation of each scenario. Figure 4 shows the coverage ratio of solutions achieve by using GA [12], $NSGA-II_{gen}$ and $NSGA-II_{ss}$ for visual coverage problem. Even though the results are shown until the entire sensors die but the comparisons are performed until at least 50% of coverage ratio could be achieved (based on the partial coverage definition). Obviously, after a while, some sensors runs out of energy and full coverage could not be achieved. The full visual coverage lifetime achieved by GA is about 100 seconds while $NSGA-II_{ss}$ and $NSGA-II_{gen}$ results 200 and 250 seconds respectively. After a while, when a typical number of sensors run out of energy, the partial coverage could not be achieved. GA can insure the partial coverage requirements for 400 seconds while $NSGA-II_{ss}$ and $NSGA-II_{gen}$ can insure the partial coverage requirements for 495 and 520 seconds respectively. Figure 5 compares the number of selected sensors in solutions resulted by using each method. It can be seen that both $NSGA-II_{gen}$ and $NSGA-II_{ss}$ select fewer number for sensors in cooperation to GA. Because of that, it can be seen in Figure 3 that GA results lower network lifetime for both full and partial visual coverage. In fact GA stops after finding a chromosome which has the required coverage. As result, after full coverage cannot be achieved by GA, it tries to select more sensors for the partial coverage.

Figure 4. Impact of sensor selection method on the network lifetime



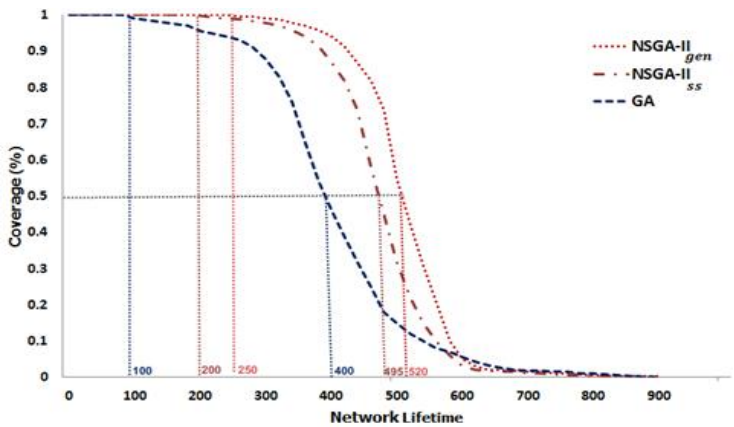


Figure 5. Impact of the sensor selection schema on the number of active sensors at each point of time

Figure 6 compares the overlapped coverage ratio of solutions resulted by each method. In fact, GA does not consider overlapping directly and tries to select minimum number of sensors for the visual coverage. It can be seen that $NSGA-II_{gen}$ and $NSGA-II_{ss}$ result solutions with very lower overlapping coverage in the network lifetime. Convergence speed is another important parameter which affects on the efficiency. We used improvement ratio as convergence metric. In fact, the improvement-ratio is the ratio of the number of previous population dominated by the new members. Figure 7 shows that, $NSGA-II_{ss}$ converges faster than $NSGA-II_{gen}$. Obviously, GA convergence is very faster than $NSGA-II_{gen}$ and $NSGA-II_{ss}$. The results confirm that $NSGA-II_{gen}$results more accurate solutions but with slower convergence.

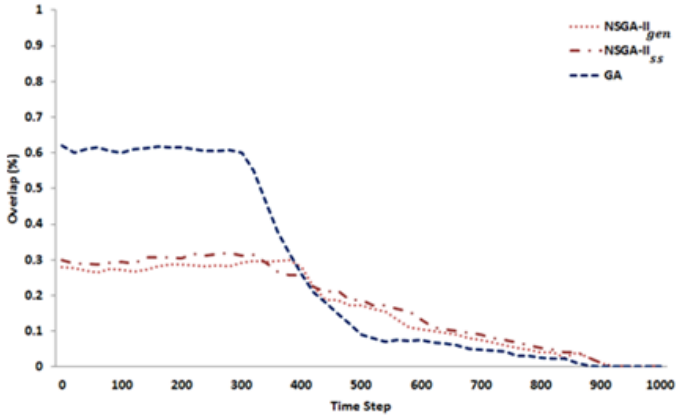


Figure 6. Overlapping coverage of different sensor selection schema

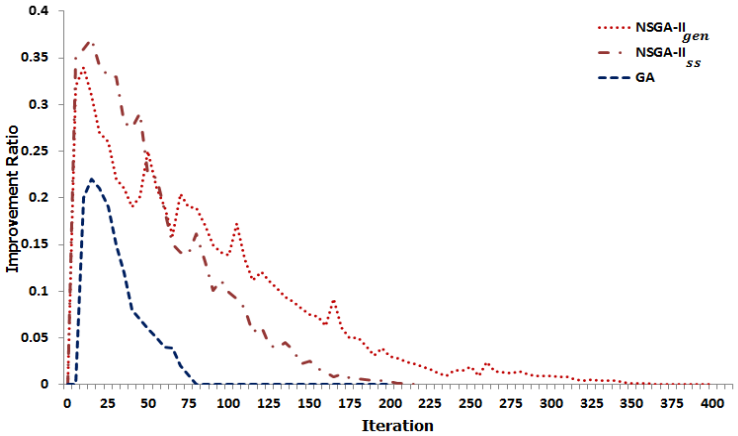


Figure 7. Impact of sensor selection method on the convergence speed

6. CONCLUSION

In this paper we studied on visual coverage using VSNs. Due to the restricted energy resource in sensors nodes, at each point of time a subset of sensors should be selected to cover the desired region. Since full coverage is not always possible, we investigate on both full and partial visual coverage. Coverage ratio, number of selected sensors and overlapping ratio considered as performance metrics for sensor selection approach. Based on that, we consider the coverage problem as multi-criteria problem which solved by NSGA-II. Besides, impact of both generational and steady-state selection schemas studied on the performance of NSGA-II. Simulation results indicated that a multi-objective optimization can result a much better solution in comparison to single-objective optimization. Moreover, simulation results showed that generational selection results more accurate solution but converges slower than the steady state selection method. We believe that by considering both routing and sensor selection, the impact of multi-objective optimization would be more significant. In fact, by selecting camera sensors with lower overlapping coverage, transmission energy consumption would be decreased and simpler source coding technics could be used.

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