Improving Energy-Efficient Target Coverage in Visual Sensor Networks

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Abstract

Target coverage is one of the important problems in visual sensor networks. The coverage should be accompanied with an efficient use of energy in order to increase the network lifetime. In this paper, we address the maximum lifetime for visual sensor networks (MLV) problem by maximizing the network lifetime while covering all the targets. For this purpose, we develop a simulated annealing (SA) algorithm that divides the sensors' Field-of-View (FoV) to a number of cover sets and then applies a sleep-wake schedule for cover sets. We also identify the best possible FoV of sensors according to the targets' location using rotating cameras, to reduce the solution space and approaching to a near-optimal solution. Our proposed energy and neighbor generating functions of the SA result in a balanced distribution of energy consumption as well as escaping from local optima. We conduct some simulation experiments to evaluate the performance of our proposed method by comparing with some well-known solutions in the literature.

Keywords: *target coverage; network lifetime; scheduling; simulated annealing; visual sensor networks.*

1. Introduction

A wireless sensor network (WSN) is composed of a large number of sensor nodes deployed over a geographic area for monitoring physical phenomena [1]. A power source supplies the energy needed by the sensors to perform their tasks. This power source is usually a small battery with a limited capacity. In traditional WSNs, sensors collect the scalar data such as humidity, temperature, pressure, etc. But the advent of inexpensive CMOS cameras has created the opportunity to build Visual Sensor Network (VSN) which enables us to gather, process and transmit the visual data [2]. VSNs are significantly different from the traditional WSNs. For example, unlike scalar sensors in traditional WSNs, the sensing region of a camera sensor node is limited to its Field of View (FoV). In a two-dimensional space, the FoV of a camera looks like a sector of a disk with its own specific viewing angle. Consequently, in addition to the sensing range (radius), there is an important property (angle of view), which should be considered. One of the issues addressed in literature is the coverage problem that the different solutions are proposed to solve it [3-9]. Coverage answers this question; how well the sensing field (or targets) is monitored (tracked) by camera sensors? Thus, coverage is a quality of service (QoS) problem. Based

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on what is to be covered, three types of coverage are defined: area coverage, barrier coverage, and target coverage to monitor a number of fixed or moving targets. In this paper, we concentrate on the target coverage problem and assume that visual sensors are randomly deployed for monitoring a set of targets with known locations. To guarantee the coverage of all the targets, a sufficiently high density of sensors along with redundancy is necessary. On the one hand, as mentioned earlier, a battery that gets depleted over time usually handles the power supply of sensors. Sensors are often deployed in such environments as forests, under water or glaciers and replacing the batteries is nearly impossible. On the other hand, it is necessary to increase the network lifetime in order to satisfy the requirements of such applications as long-term coverage. Consequently, we intend to solve a problem with two conflicting goals: coverage of all targets requires the activation of more camera sensors, but the energy saving requires turning the most sensors off.

As implied in [3] and [10], one of the common approach to increase the network lifetime is to schedule sensors in sleep-wake cycles. In this paper, we will deal with the issue of “Maximum Lifetime for VSN” (MLV) in visual sensor networks. We aim to find sensor-FoV cover sets (CS) and to determine the appropriate camera viewing angles so that all intended targets could be covered. Then, we intend to properly schedule consecutive waking of CSs and the other sensors to sleep to conserve energy and hence to prolong the network lifetime. Here, the lifetime of the network is the period of time during which each target is monitored by at least one active sensor. This issue is very similar to the Maximum Coverage with Minimum Sensors (MCMS) problem [3] that has been proven to belong to the class NP-complete (NPC).

In the literature, many solutions have been proposed to solve the target coverage problem in visual or directional sensor networks [3, 4, 10-13]. Although the proposed solutions achieved substantial improvement in the network lifetime, most of them assumed the fixed, predetermined and non-overlapping directions for cameras [3, 10]. These limitations and lack of attention on the location of targets lead to inappropriate selection of camera direction and consequently loss of maximum coverage of targets. A few works, which assumed the overlapping sensors, is possible either did not take energy consumption into consideration [9, 13] or they did not pay attention to the position of targets and encompass all possible camera directions, that resulted in scaling up the variables of the problem and consequently increasing the execution time and the complexity of the problem [12].

Our main contributions in this paper can be summed up as follows:

1) We use the method proposed in [14] to detect the camera directions in maximal subsets of targets and then employ them as an input for the scheduling algorithm. In other words, the cover sets are included of the FoVs with at least one target on its extreme edge (right or left). This reduces the solution space and complexity of algorithm.

2) We model and solve the MLV problem using SA algorithm. The simulation results show an improvement in network lifetime along with the complete coverage of targets.

3) We define the new energy and neighborhood generation function in SA. Our proposed energy function increases the number of cover sets, and takes into consideration the balanced distribution of energy consumption among sensors as an influential parameter in increasing the lifetime in future. Also, our new neighbor generating function examines the various moves in the neighborhood of current solution to escape local optima.

The rest of this paper is organized as follows: section 2 reviews some researches in this field. Section 3 defines and formulates the Maximal Lifetime with Coverage Scheduling problem. Section

4 describes our proposed algorithm to solve MLV problem. In section 5, the performance of the proposed algorithm will be demonstrated using simulation and different experiments. Section 6, finally, is devoted to the conclusion and the future works.

2. Related Work

The concept of coverage is a fundamental standard for Quality of Service (QoS) and has been received a lot of attention in recent years. The goal is to have at least one sensor for each target to sense it in the camera's FoV. This issue was initially discussed by Cardei et al. [15, 16] for omni-directional sensors. They proved the problem under the title of Maximum Set Cover (MSC) is NP-Complete. Two heuristic algorithms were proposed to solve it: Linear Programming (LP) and greedy algorithm. The authors show that the computational complexity and run-time are less, and network lifetime is more in greedy algorithm than LP method. They solved the problem using disjoint sensor sets [16] but in [15] could increase the network lifetime with incorporating sensors in non-disjoint cover sets.

The algorithms introduced in [15, 16] are centralized and the position of targets and sensors are assumed to be determined. The first distributed algorithm with a polynomial time complexity was introduced by Kasbekar et al. [11] to maximize the network lifetime. In [11], the sensors are, aware of its telecommunication and sensing distance to its neighbors. The operating time of the network is divided into several time slots, and in each time slot a subset of sensors is activated to cover k targets. In order to balance the energy distribution on all the sensors, in each time slot, the sensors with higher residual energy will be chosen. The authors proved that the lifetime is at least $1/_{O(\log n \times \log nB)}$ of the optimal solution, where n refers to the number of sensors and B is the initial energy of each sensor. In this way, using distributed-approximation algorithm, they provided a testable guarantee for network lifetime that did not need the exact localization of sensors.

The target coverage problem in directional sensor networks (DSN) was firstly introduced by Ai et al. [3]. The authors formulated this problem under the title of Maximum Coverage with Minimum Sensors (MCMS) and proved that the problem is NPC. The main idea of [3] is to choose sensor-FoVs which cover the most possible targets. This is done iteratively and the selected sensors are turned on one after another until their energy will be discharged and the remaining sensors cannot cover the targets. This algorithm was implemented utilizing the three methods of centralized and distributed greedy and incorporating sensors' residual energy into distributed method.

Gil in [10] has proposed two solutions for the MSCD problem: heuristic greedy algorithm and meta-heuristic genetic algorithm. Greedy algorithms usually find the solution more rapidly, but because of the locality the answers may occur in local optima. Consequently, the authors employed a genetic algorithm to find the optimal solution. In [10], the authors take a constant number of the possible directions for each sensor into consideration, indeed overlapping is not allowed. This assumption made obtaining the global optimal solution doubtful.

In all of methods mentioned so far, the network topology is assumed fixed, but Hosseini et al. [12] assumed that targets are mobile. They offered two approaches to solve the sensors selection problem. The first approach deals with the sensors selection in each time slot independently so that the total of energy consumed by the sensors will be minimized, but the second approach in addition to the optimization of energy consumption in each time slot; take into consideration the uniform energy consumption for the next time slots. The authors simulated their proposed algorithms and showed that uniform consumption of energy throughout the network and during the time slots will cause a remarkable improvement in the network lifetime.

In the most studies devoted to the target coverage in rota table directional sensor networks, the best sector for supplying the maximum coverage is chosen from a constant and predefined set of sectors. For example, if the viewing angle of the sensor is 90 degrees, it can be divided into four sectors [13]. Removes this limitation and adjusts sensor directions based on the targets location. Thus, each sensor choosing the appropriate sector can cover more targets and as a result, fewer sensors are needed to cover targets completely. This reduces the amount of energy consumed.

3. The Problem Definition

3.1. Directional Model

Before the MLV problem definition, it is needed to describe the model of directional camera sensors. The model used in this paper is similar to what introduced in [10], except that firstly, cameras can turn towards the target and secondly, there is the possibility of overlapping between neighboring FoVs. Fig. 1 demonstrates the model of rotatable camera sensors with two random targets located in the FoV.

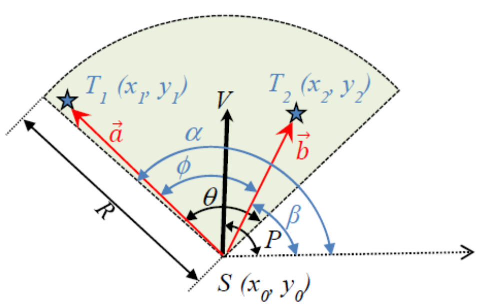


Fig. 1. FoV of a camera sensor and two targets located in.

In this picture, S is camera and (x, y) is its Cartesian coordinates. T1 and T2 are the intended targets with (x1, y1) and (x2, y2) as their coordinates on a two-dimensional plane, respectively. P is the camera orientation relative to the horizontal axis, θ is the Angle of View (AoV) and R refers to the sensing radius of camera. V is the unit vector in the direction of the bisector θ that is the index of camera direction. The AoV and sensing radius define the FoV.

In order to detect the FoVs covering all maximal subsets of targets (MaxFoV), the method suggested in [14] will be used. Based on [14], The FoV with at least one target on its extreme edge (right or left) will be given a chance to be included in MaxFoV. For example, based on Fig. 1, if T1 is on the left edge and $\|\vec{a}\|_2 \leq R$, we can adjust the P angle based on the following equation:

$$P = \alpha - \theta/2 \qquad (1)$$

In which α is the polar angle of T1. If another target (e.g. T_2) satisfies the three below conditions, then it will be included in the FoV, as well:

$$\|\vec{b}\|_2 \leq R \qquad (2)$$

$$\varphi = \cos^{-1}\left(\frac{\vec{a}.\vec{b}}{\|a\|.\|b\|}\right) \leq \theta, \quad 0 \leq \varphi \leq \pi \qquad (3)$$

$$\beta \leq \alpha \qquad (4)$$

Which in (3)φ is the angle between and $\vec{a}$ and $\vec{b}$:

$$\vec{a}.\vec{b} = (x_1 - x_0)(x_2 - x_0) + (y_1 - y_0)(y_2 - y_0) \qquad (5)$$

$$\|a\| = \|\vec{a}\|_2 = \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2} \qquad (6)$$

$$\|b\| = \|\vec{b}\|_2 = \sqrt{(x_2 - x_0)^2 + (y_2 - y_0)^2} \qquad (7)$$

and in the (4) β is the polar angle of T2.

In this way, the set of covered targets by FoV will be detected. Now, if the current set is not a proper subset of another FoV, it will be added to MaxFoV.

3.2. Defining MLV Problem

We consider a VSN network with N camera sensors deployed in a totally random manner. We intend to monitor M targets using these sensors. The set S={s1, s2, ..., sn} is a set of N sensors and the set T={t1, t2, ..., tm} is a set of M targets. The cameras used in the network are pan-tilt-zoom (PTZ) type, i.e. they were able to rotate horizontally (pan), vertically (tilt), and magnify (zoom). Since our problem is two-dimensional, only the horizontal rotation of cameras is intended.

The MLV aims to maximize the lifetime of a VSN network utilizing the proper sleep-wake schedule for sensors while covering all targets. Our assumptions are as follows:

- VSN is a homogeneous network. That is, all sensors have equal initial energy, sensing radius, and AoV and energy consumption ratio.
- The location of sensors and targets are fixed and known. There is only one non-overlapping sensor (or target) in each point.
- The network connectivity is guaranteed assuming that the transmission radius is long enough.

Other symbols used in this article are as follows:

- P_i: Maximal cover set included the sectors of sensor s_i that is defined based on the coverable targets.
- $F_{i,p}$: the *p*th sector of sensor s_i (i:1, 2, ..., N, p:1, 2, ..., $|P_i|$).
- F: the set of $F_{i,p}$ of sensors.
- $F(t_j)$: the set of sensor-FoVs with the potential of covering target t_j (j:1, 2, ..., M)
- $CS_k(\subseteq F)$: the kth cover set from sensor-FoVs that cover all of targets (T), under the following condition:
  1) Every target is covered by at least one sensor-FoV.
  2) There is at most one sensor-FoV for each sensor in CS_k.
  3) The sum of the consumed energy by each sensor cannot be more than its initial energy
- CS: the collection of CS_k resulted in scheduling
- E_i: the initial energy of sensor s_i (i:1, 2, ..., N). (By homogeneity assumption of VSN: $E_i = E, \forall s_i \in S$)
- r_k: the ratio of energy consumed to initial energy of each sensor in the kth cover set ($0 \le r_k \le 1$)
- Cost: the energy consumed per unit of time (Joule/s)
- CE_k: the energy consumed in the *k*th cover set ($CE_k = \min\{r_k * E, \min_{F_{i,p} \in CS_k}(RE_i)\}$)
- RE_i: the residual energy of the *i*th sensor (the initial residual energy is: $RE_i = E_i = E, \forall s_i \in S$)

a_k: the active time of the *k*th cover set ($a_k = {CE_k}/{Cost}$)

To maximize the lifetime, we form CSs using the sensors with residual energy. Each CS includes sectors of sensors to cover all of the targets. By a scheduling algorithm, these CSs in turn will be activated and the sensors consume a pre-specific of their energy. It is clear that if we find more CSs, the network lifetime will be increased. We divide collection F in k cover sets. Each sensor-FoV can belong to several cover sets if its residual energy is not fully consumed (non-disjoint cover set). Our goal is to find the greatest value of k based on three conditions mentioned before. As evident in [15], the upper bound of k is shown by L and equal to d/r where d is the number of sensor-FoVs that cover a critical target (a target with minimum potential sensor-FoVs to cover it) and r is the ratio of energy consumption.

In order to precisely define the problem, we introduce a variable called $M_{i,p}^k$:

$$M_{i,p}^k = \begin{cases} 1 & , if\ F_{i,p} \in CS_k \\ 0 & , \ otherwise \end{cases} \tag{8}$$

If a sensor-FoV in CSk is selected, that is if we turn on the sensor si and adjust its FoV in sector p, the value of $M_{i,p}^k$ equals 1, and otherwise 0. After defining this variable, the MLV will be defined as follows:

$$\text{Max} \sum_{k=1}^{L} a_k \tag{9}$$

$$\text{s.t.} \sum_{F_{i,p} \in F(t_j)} M_{i,p}^k \ge 1, \forall t_j \in T, k = 1,2,\dots,L \tag{10}$$

$$\sum_{p=1}^{|P_i|} M_{i,p}^k \le 1, \forall s_i \in S, k = 1,2,\dots L. \tag{11}$$

$$\sum_{k=1}^{L} \sum_{p=1}^{|P_i|} a_k\,.\,cost.\,M_{i,p}^k \le E_i, \forall s_i \in S. \tag{12}$$

where $M_{i,p}^k \in \{0,1\}$.

Equation (10) guarantees that each target is covered by at least one sensor-FoV. Equation (11) shows that each sensor in each CS can have at most one active direction and (12) explains that the sum of consumed energy by each sensor over all the CSs should not exceed its initial energy.

This problem is known as an NP-Complete problem [3], and this paper proposes an evolutionary algorithm to solve it.

4. Proposed Algorithm for MLV Problem

Here, we describe the details of proposed algorithm to solve the MLV problem. Fig. 2 shows an algorithm to solve the MLV problem. Then we present a meta-heuristic SA method. To the best of our knowledge, it presented for the first time to solve the target coverage problem in visual sensor networks.

4.1. Solving the MLV Using the Simulated Annealing

In SA, an arbitrary point (s: initial state) is chosen from the search space and its energy (E(s)) will be calculated. Then, we choose an initial temperature (τ0). Then, a state from the neighboring states will be chosen for the next step. The neighbors are obtained based on variation of the current state. To decide about moving towards a new state we follow this instruction: If the energy of new state is smaller than current state move to new state, if not move to it with the possibility of P. To escape from local optima, although the algorithm favors better solutions, accepts some of the worse neighbors with a possibility (P). One of the most customary functions as acceptance probability function is defined as follows [17]:

$$P(e, e', \tau) = \begin{cases} \exp\{-\Delta e / B\tau\}, \Delta e > 0 \\ 1, \Delta e \le 0 \end{cases} \quad (13)$$

where e is the energy of current state, e' is the energy of new state, $\Delta e = e' - e$, τ is the temperature and B is the Boltzmann constant [18]. The function is defined so that with a high temperature, the acceptance probability of a worse state will increase. Another effective parameter on P is the amount of energy variation (Δe). If that becomes greater, then the probability of P will decrease and vice versa. When the temperature is high, the solution space is searched to find the range of global optimum. When there is a temperature drop, the goal is to make the solution as close to the global optimum as possible. Consequently, a mild decrease in temperature is important to provide a more comprehensive search in the solution space. Two common methods are introduced in literature in order to reduce the temperature: exponential and linear. In exponential method, when the temperature is high, less time will be spent to search the solution space, but with a decrease in temperature, a more time is spent to refine the quality of prior solution. In the linear decrease of temperature, the search time will be uniform.

In our proposed algorithm, each states show a candidate solution to solve the problem and it is shown as a two dimensional matrixes with M rows (number of targets) and L columns (upper bound of the cover sets) as in Fig. 3.

	cs_1	cs_2	…	cs_k	…	cs_L
T_1	8,25	4,55		5,170		14,28
T_2	2,110	21,30		12,22		-
T_3	15,10	4,55		3,193		8,196
…						
T_M	2,110	2,320		3,193		-

Fig. 2. A sample of State representation in proposed SA algorithm.

In this figure, each $A_{i,k}$, which means *i*th row and *k*th column (i=1, 2, ..., M and k=1, 2, ..., L) of the matrix possess the following value: $A_{i,k} = (SensorID, ctionDire)$

The Sensor ID refers to the identity of the sensor, which covers target ti with the adjusted Direction based on its polar angle in CSk. Each column of matrix will make up a CS, if the following criteria are met:

1) There is no sensor with inconsistent directions in a column.
2) For each target (row), there is at least one sensor with specified direction.
3) The covered targets of no sensor-FoV are a subset of another one in each column.

If we assume that the network is homogeneous and the ratio of consumed energy in all of cover sets is equal (r_k=r), the network lifetime will be calculated as follows:

$$Network\ Lifetime = |CS| * (r * E / cost) \quad (14)$$

Where |CS| is the number of CSs and E is the initial energy of sensors and Cost is the rate of consumed energy per unit of time.

Algorithm for MLV Problem (S, T, r, E, Cost)

```
k = 1; Sensors = S; Targets = T
Set RE_i of each sensor to E
Coverage_time = 0
F = ∅
foreach sensor s_i ∈ Sensors do
  P_i = MaxFov(s_i, Targets)
  for p = 1 to |P_i| do
    F = F ∪ {F_i,p} // F_i,p ∈ P_i
  end for
end for
while each target is covered by at least one FoV in F do
  CS_k = ∅
  while Targets ≠ ∅ do
    for each FoV F_i,p ∈ F do
      C_Fi,p = ∅
      for each target t_j ∈ Targets do
        if t_j is covered by F_i,p then
          C_Fi,p = C_Fi,p ∪ {t_j}
        end if
      end for
    end for
    for each target t_j ∈ Targets do
      F_tj = ∅
      for each FoV F_i,p ∈ F do
        if t_j is covered by F_i,p then
          F_tj = F_tj ∪ {F_i,p}
        end if
      end for
    end for
    find a t_c ∈ Targets with lowest |F_tc|
    MaxCF = ∅
    find all F_i,p ∈ F that cover t_c with highest |C_Fi,p| and insert
  them into MaxCF
    select a FoV F_s,q ∈ MaxCF with highest RE_s
    CS_k = CS_k ∪ {F_s,q}
    for each FoV F_i,p ∈ F do
      if i = s then
        F = F - {F_i,p}
      end if
    end for

    for each target t_j ∈ Targets do
      if t_j is covered by FoV F_s,q then
        Targets = Targets – {t_j}
      end if
    end for
  end while
  Min_RE = find minimum of RE_i so that F_i,p ∈ CS_k
  if (r * E < Min_RE) then
    CE_k = r * E
  else
    CE_k = Min_RE
  end if
  for each FoV F_i,p ∈ CS_k do
    RE_i = RE_i - CE_k
    if RE_i = 0 then
      Sensors = Sensors – {s_i}
    end if
  end for
  F = ∪_{p=1}^{|P_i|} {F_i,p} for each s_i ∈ Sensors
  Coverage_time = Coverage_time + (CE_k / Cost)
  k = k + 1
  Targets = T
end while
return Coverage_time and K-number of cover set and the
  cover sets CS_1, CS_2, … , CS_k
```

Fig. 3. Pseudocode of algorithm MLV

In order to assess the states (e.g. matrix in Fig. 3), an energy function is used. The energy function must be defined so that firstly, its value is increased with an increase in the number of CSs, and secondly, the balanced distribution of energy among network sensors is taken into consideration. The high number of remaining sensors and their residual energy are important, since in the case of new network configuration (e.g. addition of one or several sensors) the possibility of discovering new cover sets will increase.

With the above introduction, we define the energy function as follows:

$$E_s = \alpha.\left\{\frac{|CS|}{d/r}\right\} + (1-\alpha).\left\{avg\left[\frac{Q}{N}, \frac{\sum_{i=1}^{N} RE_i}{N*E}, \frac{\cos^{-1}(\sigma/E)}{\pi/2}\right]\right\} \quad (15)$$

In this equation, d/r is the upper bound of number of CSs. N is the number of useful sensors (a sensor with at least one target in its sensing range) and Q refers to the number of sensors with residual energy at the end. E is the initial energy of sensors and $\sum_{i=1}^{N} RE_i$ is the total residual sensor energy. σ shows the standard deviation of residual energy in sensors and indicates the energy consumption distribution. The lower standard deviation implies more balanced energy distribution between sensors of the network. Consequently, the energy function has an inverse relation with σ. Thus, the descending function $\cos^{-1}(\sigma/E)$ is used. All parameters of the above function are normalized between zero and one, and as a result $\cos^{-1}(\sigma/E)$ is divided to $\pi/2$ and then along with Q/N and $\sum_{i=1}^{N} RE_i / N*E$ is averaged to limit its range between 0 and 1. α is the importance coefficient in the range 0-1.

We will continue with a step-by-step description of proposed SA algorithm:

Step 1: Initialization- at this stage the initial values for temperature (τ_0), temperature threshold (τ_{th}) and cooling coefficient of annealing process (η) are set. Temperature threshold is set as: τ_{th}=0.01*τ_0 to provide sufficient opportunity to perform comprehensive search at the search space, and then, with a much reduction of final temperature the probability of accepting the worse solutions will be minimized.

Step 2: Production of solution matrix (S(A, k))- for each target, from potential sensor-FoVs covering that target one will be randomly chosen if each column forms a CS, based on the triple conditions mentioned. The completion of next columns of matrix will continue until remaining sensor-FoV sets cannot create a new cover set. k is the number of resultant columns (CSs).

Step 3: Producing neighborhood solution matrix- by relocating the S matrix components the new matrix S_{new} is rebuilt. Choosing the candidate components to be substituted and the criteria of such a choice are based on rules indicated in Table 1. In each row of the table, there is a choice and its possible rules. All rules have equal chance to be chosen (There are three rules and therefore the probability of choosing each rule is 0.33). For each row, a random number will be chosen: $u \in [0,1]$, if $0 \leq u \leq 0.33$, then rule one, if $0.33 < u \leq 0.66$ rule two and if $0.66 < u \leq 1$ rule three will be selected for that row. This procedure is run as follows:

1) Selection of candidate CS (column) for substitution of component in S based on the first row of the table. The candidate cover set can be the first or last column or chosen randomly.

2) From the column selected in the previous step, a sensor-FoV (row) should be candidate for substitution with new options that are randomly substituted or a sensor-FoV with the least or most number of columns (CSs).

3) Now, a substitute of sensor-FoVs should be replaced. This substitution can be random or a choice can be made based on the least overlap with other sensor-FoVs or a sensor with the most residual energy will be selected.

4) Ultimately, we come to adjusting next cover sets (columns). The options include random, sensor-FoVs with the least overlap and sensors with most remaining energy.

The random selection rule in all rows of the table is needed to escape of local optima.

Step 4: The comparison between energy of S and S_{new}– in this step the energy matrix of the new (S_{new}) and old (S) matrix will be calculated based on (6) and then will be compared. If S_{new} results better than S, the new matrix will replace the old one and will be registered as S_{best} and we proceed to the 6th step, otherwise we will continue with the 5th step.

Step 5: Calculation of acceptance probability- a worse matrix is accepted with the acceptance possibility P as will be defined later:

$$P = e^{-\Delta E(S,S_{new})/B\tau} \tag{16}$$

where B is the Boltzmann constant and τ is the temperature. Then a random number between zero and one will be generated. If P is smaller, the new matrix will be accepted.

Step 6: Annealing or cooling the temperature- In the proposed SA, the linear cooling function is used as follows:

$$\tau_{i+1} = \eta * \tau_i \tag{17}$$

η is the annealing coefficient between 0 and 1. τ_i and τ_{i+1} are current and new temperatures, respectively.

Table. 1. Sensor-FoV selection rules for substitution by neighborhood function generator matrix

Category	Rule 1	Rule 2	Rule 3
Cover Set Selection (Column)	Random	First Col	Last Col
Sensor-FoV Selection (Row)	Random	At least CSs	At most CSs
Sensor-FoV Replacement	Random	At least overlapping	At most residual energy
Next Columns Configuration	Random	At least overlapping	At most residual energy

5. Performance Evaluation

In this section, the performance of the proposed SA algorithm will be evaluated using simulation and then will be compared with four common methods in the literature.

5.1. Simulation Environment

We implement a simulation environment using C++ to evaluate the performance of our algorithm. A 500×500 m2 area is considered for simulation, in which a different number of camera sensors (N=50, 100, 150, 200 and 250) and targets (M=20 and 40) randomly scattered in a region with the uniform distribution. Various sensing ranges from 50 m to 120 m and angle of view (45◦, 60◦, 90◦) are used. The initial energy of all camera sensors (Ei for i = 1,..,N) is set to 1000 Joule, and the energy consumed per second is set to 20 Joule/sec. The values for different simulation parameters are presented in Table 2.

Fig. 4-a depicts a sample of initial deployment of sensors and targets in our simulation environment. In this picture, the number of sensors is assumed 20 that covered 10 targets with the sensing range of 100m and the angle of view of 90◦. All possible maximal FoV for each camera based on the location of nearby targets. It is clear that at most one sector of a sensor is activated for covering all of the targets (Fig. 4-b). All simulated algorithms are centralized and it is assumed that in the base station will be run once. Then, the obtained scheduling will be announced to the sensors deployed in the network. Each experiment will be repeated 10 times and the reported results have been average over 10 runs.

Table. 2. Simulation parameters and their values

Parameters	Values
Number of Camera Sensors (N)	50, 100, 150, 200, 250
Number of Targets (M)	20, 40
Sensing Radius (R)	50 m, 100 m, 120 m
Angle of View (AoV)	45°, 60°, 90°
Initial Energy (E)	1000 Joule
Consumed Energy per Second (Cost)	20 J/s
Initial Temperature (τ_0)	200
Annealing Coefficient (η) (Eq. 17)	0.9
α (Eq. 15)	0.9

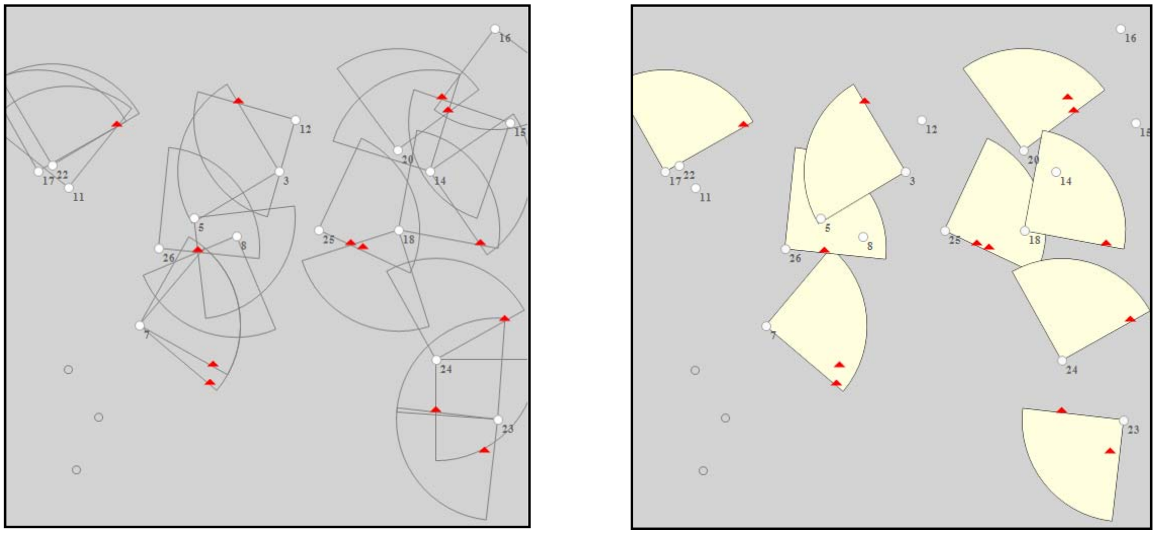
5.2. The Comparison of Proposed Method with Greedy Algorithms

We compared the SA method with four greedy heuristic algorithms mentioned more often in the literature. Greedy algorithms can be divided into two categories:

1) Greedy algorithms to find Disjoint Cover Sets (DCS): in these algorithms, each cover set will be active until all of its sensors are discharged. Consequently, with the complete discharge of sensors of the current cover set; they cannot participate in other cover sets [3].

2) Algorithms with non-disjoint cover sets: a cover set is active for a constant duty period and consumes a portion of its initial energy (with the rate of r, e.g. r=20%), consequently, if the residual energy of a sensor is not zero, it can participate in the next cover sets. Then these sensors go to sleep mode, and the next cover set will be activated to perform the sensing coverage. Based on the above, there are three possible criteria for choosing sensor-FoVs:

2.1) Maximum Coverage First (MCF): sensor-FoVs with most target coverage have a high priority to be added to the cover set [3].



(a) (b)

Fig. 4. A scenario of cameras and targets deployment (a) Max FoV based on target's location (b) Activated sensors in their maximal FoV.

2.2) Maximum Residual Energy First (MREF): sensors with maximum residual energy will be added to the cover set with a high priority [10].

2.3) Most Critical Sensor First (MCSF): sensor-FoVs with the least overlapping coverage will be chosen to participate in the CSs with high priority [19].

5.3. The Impact of the Number of Camera Sensors

In order to investigate the impact of the number of sensors, their sensing range and angle of view are set on 100m and 90◦, respectively. Camera sensors from 50 to 250 are used to cover 20 targets.

Fig. 5 shows the network lifetime to cover 20 targets (M=20). As evident in the figure, by increasing the number of camera sensors, the network lifetime will increase, since with more camera sensors to cover constant number of targets, more cover sets can be formed.

As depicted in figure, the network lifetime in the proposed SA algorithm will be more than other methods independent from the number of camera sensors. This demonstrates a significant improvement in proposed algorithm for coverage of targets.

5.4. The Impact of Sensing Range (Radius)

In order to investigate the impact of sensing range of camera sensors on the efficiency of proposed method experiments were conducted. There are 150 sensors and 20 targets. We increase the sensing range of cameras from 30m to 120m. The AoV for all cameras is set on 60◦ in these experiments.

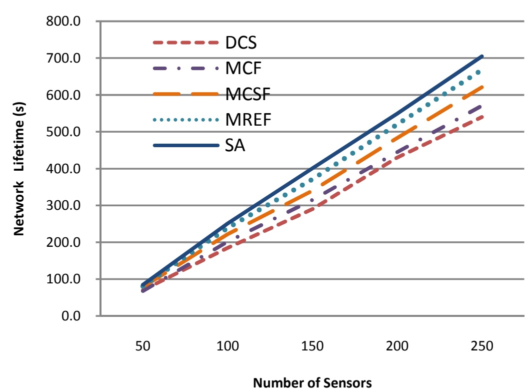


Fig. 5. Comparison of the Network Lifetime with respect to the Number of Sensors

Fig. 6 shows the impact of sensing radius on the network lifetime. Network lifetime in higher ranges is higher and on the contrary in lower ranges is lower, because with a drop in sensing range of cameras we need more sensor-FoVs to cover all targets. Consequently, cover sets are formed with the participation of more sensors. Therefore, the usable sensors exhaust their energy rapidly, resulting in decreasing of the network lifetime.

In Fig. 6, we can see that the network lifetime for radius less than 50m in different methods do not make significant difference but with an increase in sensing radius, the SA method shows a higher efficiency in choosing appropriate sensor-FoVs and with approaching to upper bound of number of cover sets, the network lifetime will increase.

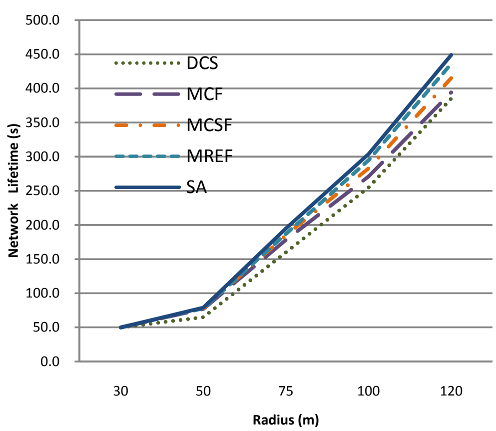


Fig. 6. Comparison of the Network Lifetime according to change in Sensing Radius

5.5. The Impact of Camera Angle of View

We conduct the experiments with the investigation of impact of camera AoV on the network lifetime. There are 150 sensors and 20 targets. The sensing radius is fixed on 100m and the AoV varies from 45◦ to 120°.

Fig. 7 shows the results of experiment after 10 rounds of execution in each scenario and averaging. As evident in the figure, the average network lifetime in different AoV is not so different. Of course, the average of network lifetime in proposed SA algorithm is more than other greedy methods but the network lifetime is independent from the cameras' AoV. In other words, the increase in the AoV has no impact upon the operating time of network to cover the targets.

In fact, angle of view in contrast to the sensing radius does not have a significant impact on increasing the number of targets covered by sensors; consequently, the number of active sensors in each cover set for different angle of views is nearly equal. Thus, the resultant number of CSs is constant. Since the consumed energy in the network has a close tie with the number of CSs, the network lifetime will not undergo a significant change.

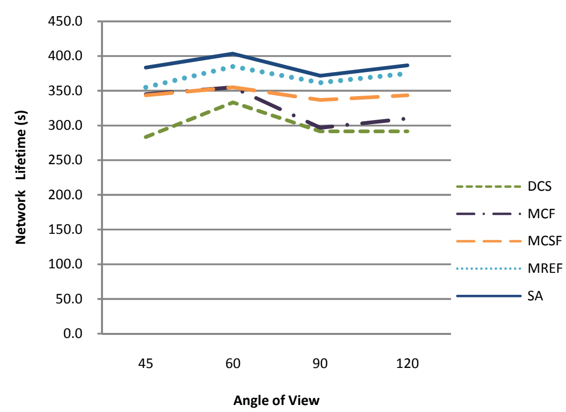


Fig. 7. Comparison of Network Lifetime according to change in Angle of View

5.6. Manner of Distributing the Consumed Energy Between Sensors

In order to investigate the distribution of the energy consumed by sensors in different algorithms, we set 150 sensors to cover 20 targets. The AoV and sensing ranges of camera sensors were considered as 60◦ and 100m, respectively. The initial energy of sensors varies from 500J to 2000J and for each case the average standard deviation in 10 rounds of execution was calculated. The results are depicted in Fig. 8. As expected, the greedy method based on MREF show the best performance in balanced distribution of energy, because the sensors with least participation in the sensing operation (highest residual energy) are more likely to be chosen. The energy distribution by the proposed SA method is very close to best schema

(MREF). This means SA performs well in energy efficient use as well as improving other parameters such as the network lifetime.

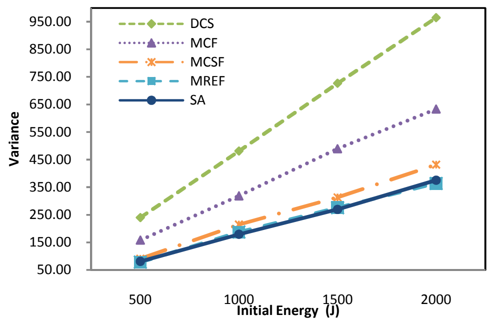


Fig. 8.The Standard Deviation of Residual Energy

6. Conclusion

In this paper, we proposed a solution approach based on simulated annealing to solve the target coverage problem in visual sensor networks. The rotating cameras were used to find maximum number of cover sets in our SA algorithm. To prolong the network lifetime, we assumed the sensors of each cover set monitor all the targets in a pre-specified time slot and then go to the sleep mode. The results from simulations indicate that our proposed algorithm is more efficient than other methods including genetic algorithms and greedy approaches. This is mainly due to incorporating the residual energy in our SA algorithm balancing the load on all the camera sensors. We also obtained a longer network lifetime by some improvements in SA method at the expense of some execution time overhead.

As our future work we will focus on addressing the some problems in the dynamic surveillance environments with moving targets. We will also incorporate other coverage quality parameters including the target's facing direction.

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