Mobility Control to Improve Nanosensor Network Lifetime based on Particle Swarm Optimization

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ABSTRACT
Mobility control is a very challenging issue in Wireless nanosensor networks (WNSNs). Motion and exploiting movement to improve the performance of WNSNs has significant impacts on the deployment of WNSNs. In this paper, we propose a new mobility control algorithm to maximize the wireless nano sensor node lifetime and improve the network performance. The algorithm is based on Particle Swarm Optimization (PSO). Simulation results show that the proposed optimization algorithm improves the network coverage by better utilization of neighbor nodes. The results also demonstrate that the algorithm increases nano sensor lifetime.

Keywords
Nanosensor, Lifetime, Coverage, PSO Algorithm, Mobility, Energy Consumption

1. INTRODUCTION
Wireless Nanosensor Network (WNSN) has newly drawn lots of attention due to its application in the medical, environment, military and industry. Nanosensors are any biological, chemical, or surgical sensory points used to convey information about nanomaterial to the macroscopic world [1]. Nanosensor device is a molecular scale is not necessarily to reduce in size to nano-scale, but a nano device can use as unique properties of nanomaterial to identify a novel event in the nanoscale.

Nanosensor network included of the number of nanosensor and vehicles that are deployed to carry out cooperative monitoring and medication over target area [2]. Most of the nanosensors are mobile, and nanonetwork topology change dynamically with the body condition and the nanonetworks simply going to failure. The spatially distributed nanosensor node claims useful data about the target environment by motion via the human body [3]. A group of nanosensors, which work as a team to collect information will produce Nanosensor Network.

Medical uses of nanosensor involve possible of accurately identifying specific cell or area in the human body. Nanosensors first injected in the body and then go to the exact organ and material mass [4]. They may be communicating with other nanodevice within the body. The target environment has chemical concentration that allows the nanosensor to detect and admit this concentration [5]. The medical needs the nanoscale device for investigation in the human body. The development of the intelligent device to perform the biomedical task is most important issue [6]. The behaviors of nanosensor based on natural species introduce great adaptability with a useful algorithm as well as very low energy consumption. Particle swarm optimization (PSO) is relatives of calculative models outstanding by evolution [7]. The purpose of PSO is to responsibility the best compound for problem under the presumption a set of the role. An adjustment problem included of a fitness function delineating in problem. This study presents the fault tolerance of mobility for nanosensor to improve the network lifetime based on PSO algorithm. This model today is the important issue, where in medical application to investigate in the human body for sensing the area and collect information from the target area and moving in the human body through the fluid.

Due to a maximum lifetime, nanosensor node has mobility for improving the network lifetime in the wireless nanosensor network. Mobility of nanosensor is based on connectivity and optimizes the performance of a lifetime on whole target area. The main problem in the wireless sensor network is coverage; however, the coverage problem depends on a coverage model in the wireless nanosensor network [8]. Coverage model can be guaranteeing the quality of service, fault tolerance and lifetime of sensing area and due to the large variety of application. Sensor node has different quality in different geographical location [9]. Wireless nanosensor node use unit disk model to coverage the area, in unit disk, each nanosensor use identified with unit radius r in the area and each node has connectivity to other nanosensor nodes in corresponding radius. One aspect to improve the nanosensor lifetime is movement of the nanosensor nodes. This research question is classified as a NP-Hard (non-deterministic polynomial-time in computational complexity theory) problem and lifetime performance problem algorithm.

The remaining parts of this paper are organized as follows. Some related works about finding the best position of the sensor and nanosensor nodes and improve a network lifetime is reviewed in Section 2. The WNSN lifetime approach is introduced in Section 3. In addition, in section 3 we analyze the network type and fitness function and PSO model to prolong the lifetime. Experimental results for a performance of the lifetime algorithm based on PSO and the effects of the parameters are described in Section 4. Conclusions are stated in Section 5.

2. REVIEW OF RELATED WORKS

Wireless nanosensor node able for exploring in unreachable location with extraordinary resolution. However, they are very responsive in front of surface force or obstacle. The nanosensor node arbitrary deployed in a specific area and moved away by body fluid in medical research, for doing some especially task [2]. Deployment of multiple nanosensor surevilling nodes in target area in exact time can improve the sensing coverage and increase the lifetime [3]. The Mobile strategy of nanosensor in WNSN that can help network prolonging lifetime, reduce the size of complexity and increase the quality of service (QoS) especially for WNSNs applications in the medical environment where sensors have to be placed in exact positions, or be programmed before starting a specific critical mission. One of the major deployments of the sensor nodes is an energy source. The energy resource in sensor node is a very limited and high failure rate could be affected in quality of service in the sensor network. In [10] began, a study of deploying sensors over star networks to meet the coverage, the lifetime, and the minimum-cost requirements instantaneously, where the network lifetime is assumed as a parameter. It is common practice to assume that, according to power analysis [11], Sensors have two modes: a sleep mode and an active mode. Sensors consume energy in active mode and do not consume energy in sleep mode. Sensors in wireless sensor networks have two modes in their lifetime: active and sleep. At any given time within the sensor lifetime, a sensor must be set to cither sleep mode for conserving energy or active mode for acquiring, processing, and transmitting data. A scheduling in the sensor arrangement is a timetable for switching the modes between active and sleep for each sensor in the wireless sensor network [12]. Rechargeable and replacing the battery of sensor is difficult and infeasible, causing breakdown and limitation in communication and process time between all sensors in the network. The only solution for coverage area that needs longer time is deploying multiple sensors for each target. That is the only way sensor node can monitor target area and gather information for long time [10]. The most important motive that mobility can prolong a network lifetime is that mobility increased the dimension of the problem [13]. This principle of high dimension space help finds the best result in this dimension in front of subspace with minimum space.

3. WNSN LIFETIME MODEL

3.1 Network Model

For a WNSN, we use set {N}:|N|=n to shows us the number of sensor node in network. For cost duty c:v*v →R+, such as link(i,j), if 1)i $\in$ N,2) j $\in$ N, and 3)the transmission energy e_i^T of sensor node *i* is not below *c(i,j)*. All of this provide for us graph model $\mathcal{G}=(\mathcal{V},)$. For energy reserve E_i for any sensor node $i \in N$ the network will be going die if some of sensor node run out battery [14]. Furthermore, the network lifetime *T* defines as time when sensor node runs out the battery or dies. Taking to account the sensor node changing their position time to time, we shows as *epoch* as duration of time the sensor node change the position. Thus *T* can be sum of time period of each *epoch* t_i. The detailed of network notation can be found in Table 1.

Table 1. Notation of Network and Sensor Node

Network Notation	
N	The set of sensor node in WNSN.
n	=|N|, the number of nanosensor node in set of all link.
v	$\subset$ N The potential location of node.
E	The set of all link.
C	Cost of feasible sensor link.
T	Network lifetime.
$\hat{T}$	Maximum network lifetime.
t_k	Period of each epoch.
Node Notation	
E_i	The energy initial for sensor node.
e_i^T	Consumption of energy for node i to transmit of data.
e^R	Consumption of energy for node i to transmit of data.
λ_i	Information rate of sensor node i.
r_{ij}^k	Rate of data from node i to node j.
r_i^k	Data rate demand of the WNSN from node i in kth epoch.
q_{ij}^k	Quantity of data from node i to node j during kth epoch.
p_i^k	The set of path going through the node I in kth epoch.

3.2 PSO Model

Particle swarm optimization (PSO) is relatives of calculative models outstanding by evolution. The purpose of PSO is to responsibility the best compound for problem under the presumption a set of the role. An adjustment problem included of a fitness function delineating in problem. PSO by Kennedy and Eberhart and was first intended for simulating the social behavior. A difficulty optimized with the PSO which having a population of candidate solution, here tagged particles and active these particles nearby in the search-space similar to be common arithmetical formulate. The pursuits of the particle are aimed by establishing best positions in the search-space which are bettered as best positions that establish by the particles [7].The particle Swarm Optimization presented for the *d*th dimension of position and velocity of *i*th particle with following:

$$v(t+1) = \omega * v(t) + c_1 * R_1 * (P_b - x_{id}) + c_2 * R_2 * (g_b - x_{id}) \quad (1)$$

Where the parameters are describe as below.

1. *v(t+1):*the velocity of the *i*th particle in the next population;
2. *v(t)*: The velocity of the *i*th particle in current population;
3. p_b: the current best local position of *i*th particle in d-th dimension;

4. g_b: the current best global position of the *i*th particle in *d*th dimension;
5. x_{id}: the best position of particle *i*th in search space;
6. c_i: the acceleration coefficient for particle to move the best local position;
7. c_2:the acceleration coefficient for particle to move the best global position;
8. R_1,R_2:random number between {0,1};
9. ω: The inertia weight controls the motion of the particle. In nanosensor application used Reynolds number for inertia weight to simulate of body environment [6]. The Reynolds number, defined as following equation:

$$R = \delta\vartheta_f/\eta \tag{2}$$

Where velocity, represented by ϑ_f density, represent by δ and viscosity represented by η. The *R* is low for nanodevice operating in fluid of common viscosities.

The new best position of particle can be obtained after new velocity according the following formula:

$$x_{id}=x_{id}+v(t+1) \tag{3}$$

Particle moving around searching space, tending to find optimal solutions until, the termination is met. After a lot of populations, an approximate best solution is expected to be found.

3.3 Fitness Function

Fitness function is a specific type of aim function that measures the optimality of a solution in PSO. Depend on the goals of the research, fitness function could be designed differently, however all of them consist of objective to evaluate the solution in a particle swarm optimization. In this section, a heuristic algorithm as fitness function based on PSO to solve the sensor node lifetime problem under public limitations is proposed [15].According Table 1 sensor node initialize with E_i energy for each node and T is network lifetime as when first sensor node dies [16]. The purpose of fitness function model is faithfully associated to the specific of problem, should be measured numerous factors. The sensor node fitness function must meet the following requirements: first, to consider the initial energy for sensor node. Second, the energy consumption for sensor nod to transfer and receive a unit data according to the distance between two nodes. finally, to consider the relation between these important factor, including the initial energy for node and consumption of energy and so on [14].According the influence of the above mentioned the new fitness function is constructed as in Equation 5 to make realistic model [18].

$$T_{min} = \frac{G(\omega)}{P(\omega)} \tag{4}$$

Where G(ω) is the combination of energy reservation E_i of all node with λ coefficient and P(ω)is minimum cost among the sensor node based sensing range distance as in equation 6:

$$G(\omega) = \sum E_i\lambda_i \tag{5}$$

$$E_i = \sum_{i,j\epsilon gj\ ,i\epsilon g} r_{ij}^k \,.\, e^T + r_{ij}^k . e^R \tag{6}$$

$$P(\omega) = \sum_{i\epsilon g} r_i^k \,(e^R + e^T d_s) \tag{7}$$

$$T_{min} = \frac{\sum_i \lambda_i [\sum_{i.j\epsilon gj\ ,i\epsilon g} r_{ij}^k . e^T + r_{ji}^k . e^R]}{\sum_i \lambda_i [\sum_{i\epsilon g} r_i^k \,(e^R + e^T d_s)]} \tag{8}$$

According the equation 8, we assume that the data rate between any two sensor nodes *i* and *j*, r_{ij}^k, is achievable under the matching link capacity. In this paper, we also assume that all sensor nodes use a unit transmitting energy e^T, whereas the receiving energy e^R is set by a sensor node *i*. That is, the fitness function of the *i*th sensor node is its minimum lifetime among the sensor node. A best fitness value is corresponding of sensor node location for minimize the energy consumption for sending and receiving unit data and improve coverage sensing rate. The best position of each particle compared with that of its best position. If the value of *i*> P_{best} then P_{best} is changed the position with *i*th particle. The best of P_{best} is selected as the global position g_{best}. All particle moves around search space, when the final g_{best} as the best position of the sensor node the termination condition are archived.

3.4 The PSO Algorithm for lifetime problem

For using PSO to find solution for best covering set, a fitness function which contains the status for all sensors in the field is used. The information of the geographical position and sensing radius are global and local.

Input: A set of sensor node, each sensor with location of (x_i,y_j), initial energy E_i, consumption of energy for transmitting and receiving e^T,e^R respectively.

Output: A sensor node location with control of mobility will provide a maximum coverage for performance and prolong lifetime.

Step 1: Initialize the fitness function value of all local best location and global best location to adjust zero.

Step 2: population of n particle randomly generate, end each particle position in 2-dimension represent of sensor node position.

Step 3: Initialize the velocity and coefficient of each particle.

Step 4: Calculate the T lifetime of the network for the *i*th nanosensor node by below formula:

$$T_{min} = \frac{\sum_i \lambda_i [\sum_{i.j\epsilon gj\ ,i\epsilon g} r_{ij}^k . e^T + r_{ji}^k . e^R]}{\sum_i \lambda_i [\sum_{i\epsilon g} r_i^k \,(e^R + e^T d_s)]} \tag{9}$$

Where r_{ij}^k is data rate from nod *i* to *j*, r_{ji}^k is a data rate from nod *j* to *i*,e^T is a energy consumption for transmission, e^R is a energy consumption for receiver, r_j^k is a data rate during in node *i* and d_s is the Euclidean distance [17] between nanosensor node as following equation:

$$d(s_i, s_j) = \sqrt{|x_i - x_j|^2 + |y_{i-}y_j|^2} \quad (10)$$

Step 5: Find minimum lifetime among the entire nanosensor network for the *i*th sensor node as following equation:

$$fitness(i) = Min_n^i\{T\} \quad (11)$$

Step 6: Set p_{best_i} as the current *i*th particle if the value of *fitness(i)*> current p_{best_i}

Step 7: Set g_{best} as the local best position p_{best} among all sensor node. With following:

$$fitness\ of\ p_{best} = (max_i^n) fitness\ of\ (p_{best}) \quad (12)$$

and then set g_{best} as p_{best} .

Step 8: Update the velocity of each particle as the following equation:

$$v(t+1) = \omega * v(t) + c_1 * R_1 * (P_b - x_{id}) + c_2 * R_2 * (g_b - x_{id}) \quad (13)$$

Where v(t+1) is the velocity of i sensor node at 2 dimension(t) is current velocity of sensor node ate 2 dimension, ω is inertial force calculate as equation 2, c_1, c_2 are acceleration of moving sensor to the best local and global position respectively, R_1 and R_2 are two random number among 0 to 1, x_{id} is current position of *i* sensor node and p_b is the value of local position at the d-th dimension, and g_b is the value of global position at the d-th dimension.

Step 9: Update the best position of sensor node as:

$$x_{id}^{new} = x_{id}^{old} + v(t+1) \quad (1)$$

Where x_{id}^{new} +and x_{id}^{old} +are respectively the best position and new position of *i* sensor node.

Step 10: Repeat Step 4 to 9 until the consideration condition are meet.

4. SIMULATION RESULT

Initialize the fitness function To start experimenting WNSN environment and develop PSO algorithms, the implementation of this algorithm we chose some parameter value, they are the initial energy for node E_i, the total number of sensor n, the energy consume for transmit and receive e^T, e^R respectively, λ_i data generation rate, data transmit from node i to node j,r_{ij}^k r_{ji}^k is data rate from node j to i and d_s distance among sensor node. We chose to perform our work with heuristic and PSO algorithm Table 2 shows the parameters of each parameter value. We implemented our algorithm, mention above, in Java, and carried out our experiments on a HP PC with Pentium 4dual processors and 1 GB memory in a Windows environment. Assumed the topology of the regions is 20*20 micron. Sensor nodes were deployment randomly in the sensing area and deployed outside of the sensing area. However in each instance the global best position was allowed sited in the sensing area. The center of sensing area is considered as central point (0, 0) of 2 dimensional.

Table 2. The Parameter value

Element	Condition
Sensor Range	7
Communication Range	15
Number of Sensor	16
Delay	0.5
Sensing range	50*50
Number of iteration	300
ϑ_f	100
δ	1
η	10^{-2}
E_i	1000
e_i^T	200
e^R	200
λ_i	100
r_{ij}^k	3
r_i^k	3

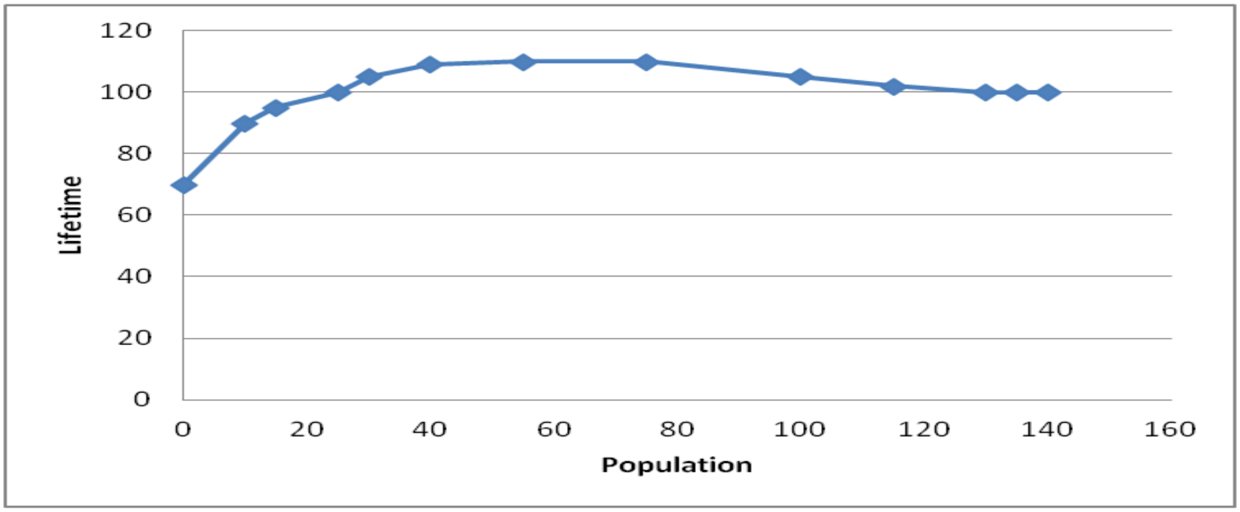

Fig 1: Lifetime in different population

The result to show the proposed PSO algorithm when the acceleration constant c_1 for sensor node change position p_{best} was set as 1 and c_2 set as 1 and the inertial weight ω compute as in Equation 3.The results are shown for the network coverage and lifetime Figure 1 along with different generations for 16 sensor node in each generation.

In Figure 1, result shows lifetime among different inertial forces for 16 sensor node in each population. It is clear that the PSO algorithm easily can convergence in 20 populations. It can be observed that the lifetime first increased and then remain in same number for next population.

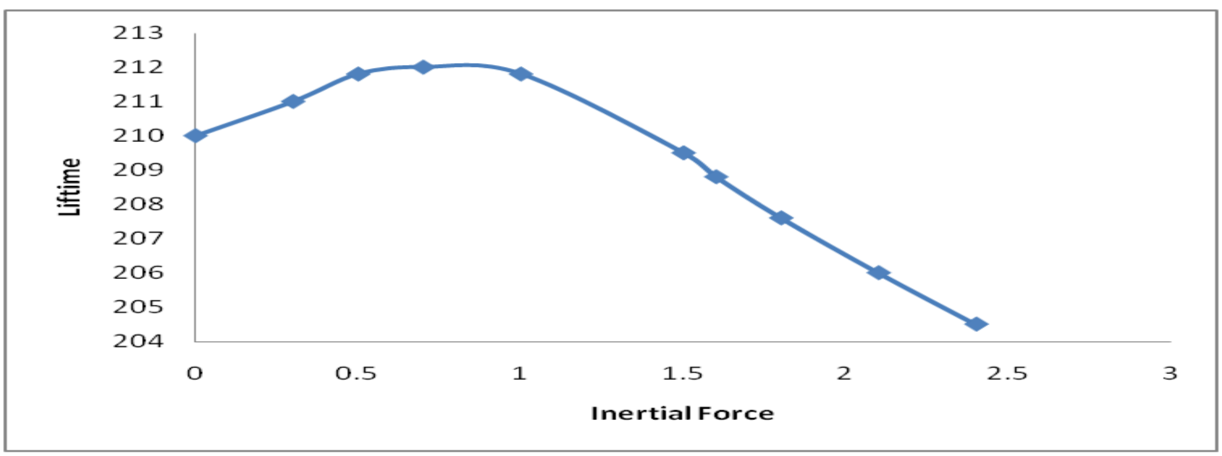

Fig 2: Movement in different inertial force

Figure 2 shows the PSO algorithm have the good lifetime when inertial force is around 0.5 to 1 the lifetime will be decreased when the inertial force increase. However, it's clear that the inertial force depended on the viscosity and density of a body and its most of the time will be constant but in some time the body condition may be the change dynamically than inertial force will be the change. When the inertial force increase the movement will be going fast due to the old velocity of particle. Figure 3 show the impact of mobility in the nanosensor lifetime. It can be observed from Figure 3 that the mobility has significantly affect in network performance, especially in lifetime and coverage to collect data from the specific area inside the body and stability of network for long time. The sensors node are able to change the position to find the best position in a domain and use less energy for transfer and receive unit data from another sensor node or sink.

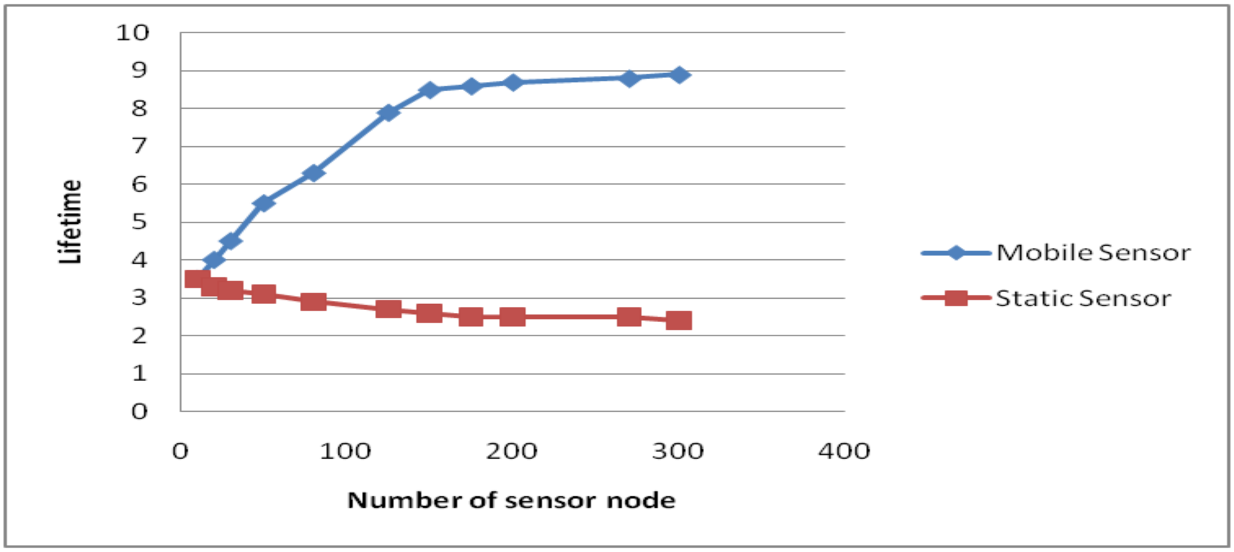

Fig 3: Lifetime in static and mobile nanosensor node

5. CONCLUSION

The very important challenge in a wireless nanosensor network is energy consumption to prolong the network lifetime. In this paper, we extend our previous approach to solve the network lifetime problem that can improve the sensor coverage. For solving this problem, we use PSO algorithm for finding the best position of a sensor node to reduce the power consumption and increase the network lifetime and coverage. In our proposed approach, the lifetime problem in a heterogeneous nanosensor network, when the data transmission rates are different in parameter and energy. The PSO has a great effect to solve the lifetime problem. From the result, we can conclude that the PSO algorithm has fast convergence.

6. ACKNOWLEDGMENT

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