Decision Making In a Building Access System Using Swarm Intelligence & POSETS

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Abstract - The need for a new decision making approach for **s**electing communication routes in a biometric sensor network supporting a building access application[1] inspired this research. This paper uses swarm intelligence[2] to choose the optimal route in a distributed, time-varying, wireless building sensor network and partially ordered sets called POSets[3] to properly weight the performance parameters based on the time varying access needs.

I. Introduction

The building consists of a sensor network with a multitude of heterogeneous communication links and sensors interconnected by means of RF communication links. The state of the sensors may change from active to idle to disconnected. Typical issues related to a wireless network are energy conservation, stability, scalability, QoS [Quality of Service], real time adaptation, location awareness, seamless handovers, reliability, and mobility[4, 5]. The routing algorithm must optimize these performance parameters while monitoring the state of the communication links among sensors and possibly change the communication links if the dynamic situation changes through the Poset weights**.**

The functionality of the nodes in this application is to sense, collect, process, and communicate or any combination of those functions to secure access of the room using biometric technology. Conceptually, smart cards, the size of a credit card, are carried by the users and contain the biometric data. The biometric data is collected by sensors surrounding the doors. Within the room, people are routinely monitored and identified just to maintain safety and security**.**

Energy usage is a key issue as the biometric sensors are typically tiny and wireless and the smart cards are also wireless. Each tiny sensors ha**s** a limited memory and functional

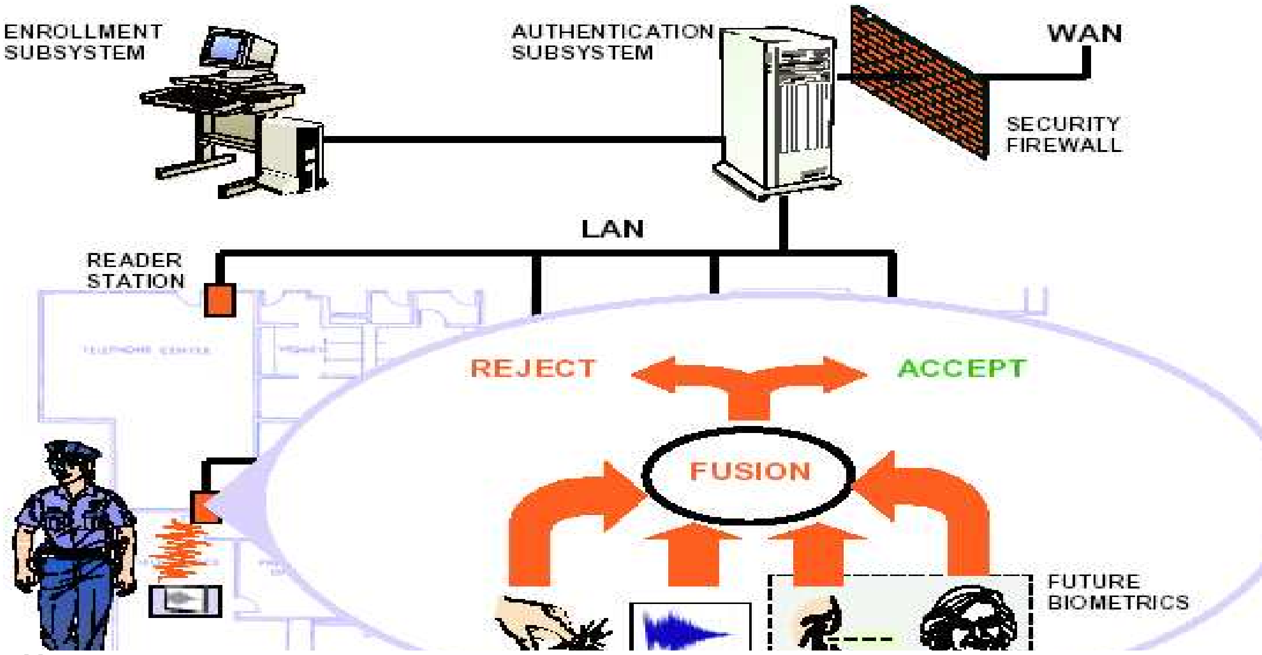

Fig. 1.Building Access System

-ity given the fact that the batteries(y) have a limited power supply hence difficulties arise during computation[6]. Energy usage becomes an important performance parameter under the above constraint. The sensor network must manage energy consumption and optimize this factor with the proper POSet weight in the swarm algorithm.

Another optimization issue is the communication delay. If a node, which may or may not include a sensor, fails, this swarm routing, unlike some other types of routing, automatically reroutes messages around this node. The only data lost is data that was last prepared by the node or collected and processed by the node. The new route is determined by applying the POSet factors to the performance parameters that include energy and delay. The delay needs to be considered in two forms: the number of hops and the physical distance. The number of hops takes into account the energy required to receive and transmit messages. The distance accounts for the energy loss in the transmission of data through the wireless RF communication link.

This paper presents a swarm algorithm that solves this complex optimization problem involving many complex and unique nodes. This evolutionary algorithm adapts as the network and environment changes. The effect POSets has on the resulting optimal solution is demonstrated for a few scenarios in this paper [7]. These effects are obtained by applying weights to the computed energy, distance and number of hops on each sensor node to compute network performance. In the third section, the justification for using swarm intelligence and its impact on sensor network (i.e. performance) is discussed. The fourth section gives an introduction to POSets and how it is applied to this system. The paper concludes with the fifth section discussing the results obtained and future work.

II. Building Access System

Figure 1 shows a Building Access System, where a smart card transmits encrypted biometric feature information via a wireless smart card reader. The reader receives and processes the features to authenticate the person and ensure access privileges. Once inside, the user is monitored for safety as well as security purposes. The access privileges to the building resources may vary significantly based on the user's need or role. This can be reflected in the accuracy of the biometric identity verification. The system can take more complex and longer biometric verifications or shorter and simpler identity verifications. The system can be easily programmed to vary this depending on the person and the region of the building being accessed.

Also, user identity and movement may raise a safety and health concern. For instance, a sudden fall can indicate a possible heart attack so monitoring movement in a building may be valuable to the employees as well as employer. Thus, a accept/reject decision depends on the user movements and routing becoming critical for monitoring and notifying information.

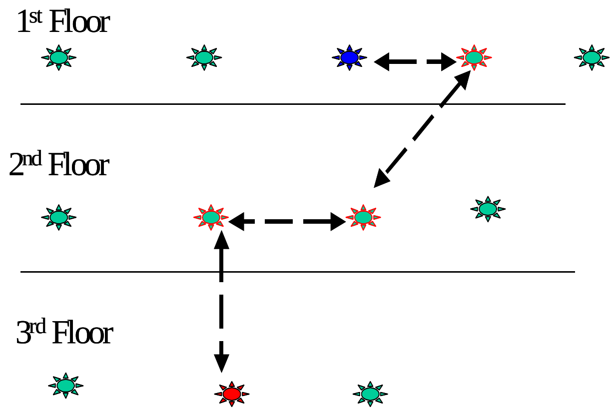

Fig. 2. Illustration of Sensor Network - Using Swarm Routing.

In Figure 2, a sensor network is illustrated with the route taken by the agents shown in dashed lines. The sensor node in blue denotes where the communication starts, (1,3), the sensor node in red denotes the end of communication, (3,2). The other sensor nodes between are green with red outlines. The sensor nodes in an idle state with energy are green. If the node turns red, the sensor node has been depleted of energy and can no longer function without being somehow recharged.

The chosen route is selected using nodes with the necessary transmission energy, desired number of hops, and shortest communication distance. The desired number of hops for the example in Figure 2 is 4 from start to stop. The route with the least number of hops leads to trade-off between energy and time. In the next section, the swarm algorithm for communication routing is described in detail.

III. Swarm Intelligence

There are many algorithms available for routing optimization such as genetic, simulated annealing [11, 12], travelling salesman [13], asymmetric travelling salesman, swarm intelligence [14, 15, 16, 17, 18, 19] and others. Each approach possesses advantages and disadvantages, the main issue in choosing an algorithm is the time and probability of obtaining an optimal solution. For example, an evolutionary algorithm might not always provide the global solution. Optimality, finding the solution that finds the best performance, and reachability, the global optimal is found instead of the local optimal, are the two important factors in choosing an appropriate algorithm.

Table I compares the issues related of the algorithms. The optimal solution is attained using PSO and Ant System, but the former more often obtains local optima whereas the latter attains the global optima with less computation time.

TABLE I. COMPARISON OF ROUTING ALGORITHMS

Algorithms	Time	Prob. Local Optima	Prob. Global Optima
Travelling Salesman Problem [TSP]	4	5	2
Asymmetric Travelling Salesman Problem [ATSP]	5	5	2
Simulated Annealing [SA]	3	2	5
Genetic Algorithm [GA]	2	1	6
Particle Swarm Optimization [PSO]	1	3	4
Ant System [AS]	1	4	3

1-Best [High - Probability of Local and Global Optima /Fast - Computation Time] 6- Worst [Low - Prob. Local and Global Optima /Slow - Computation Time]

Swarm intelligence, is an algorithm that models the collective behavior of social insects, namely the ants, bees, birds, etc. Each independent agent follows a trail left by the other members of the society. In our algorithm, the ant agents communicate interactively in a distributed problem-solving manner to achieve an optimal solution. The agents move towards the optimal solution and communicate directly by sharing knowledge with their neighbors. The initial set of agents traverse through the nodes in a random manner, and once they reach their destinations, they deposit pheromone trails as a means of communicating indirectly with the other ants.

The pheromone accumulation is proportional to the number of agents traveling between two nodes during one complete iteration. The amount of pheromone left by the previous ant agents increases the probability that the same route is taking during the current iteration. Other performance factors discussed also affect the probability of selecting a specific path or solution. Pheromone evaporation over time plays an important role in preventing suboptimum solutions from dominating in the beginning.

There are three different kinds of ant agents, which performs functions such as allocating, sensing and de-allocating the sensed values. Thus, no values are fed into the system other than the initial values. This allows the system to be more flexible, robust, decentralized and intelligent by learning features.

In the system, the agents minimize energy and keep track of network requirements. The allocator agents monitor the allocation process on active links and allocate resources required by the network. The sensing agent's function is to traverse the network and communicate with its neighbors to reach the destination using an optimal route. The deallocator agents are responsible for deallocating trails identified by the sensing agents with the sensed values. These agents ensure the optimal route to the destination using limited resources and also learning the network environment. Initially, the computational cost and time is high but this drops drastically once the agents learn the network and environment. Other performance parameters are incorporated using POSets.

IV. POSETS

One of the major challenges in sensor management is providing a mathematical framework that can consistently represent the complex, multidimensional optimization problem present in this building access system. Partially ordered sets (POSets) has been used in queuing theory, networking, and lately sensor management [24, 25] . POSets provides a graphical mathematical framework for representing relationships between a finite number of elements [26, 27] . In the last 3 decades, POSets have been applied in a variety of computer science, engineering, and social science areas [26, 27] . POSets began in the early nineteenth century with De Morgan.

POSets formulate weights at each graphical level to flow down the importance of a communication goal to the performance parameter measuring the success of achieving that goal. In this system, the primary goal is maintaining surveillance of the room by identifying everyone inside the room and everyone attempting to access the room. Two areas of concern are downtime and speed of alert. Downtime is the percentage of time the system is not functional because a sensor node ran out of energy. In Figure 3, the three levels to the mission POSet are illustrated. The current primary mission, which may be providing access to a building, is broken down into two performance concerns such as speed of alert, and downtime. These get weighted in importance. The weights are graphically entered on the POSet as shown in Figure 3. The nodes are the items described in the boxes of Figure 3. The flowdown weights, the lower case variables on the arrows, should sum to zero from their source. The entire POSet begins with a value of 1 at the top. Then the arrows exiting that node should sum to 1 or

$$\sum_{k=1}^{2} x_k = 1 . \quad \textbf{(1)}$$

The values of the next row of nodes is computed by multiplying the arrow's value by the preceding node or

$$X_1 x_k = Y_k, k = 1, 2 \; . \quad \textbf{(2)}$$

The computation of the remaining POSet proceeds in the same manner.

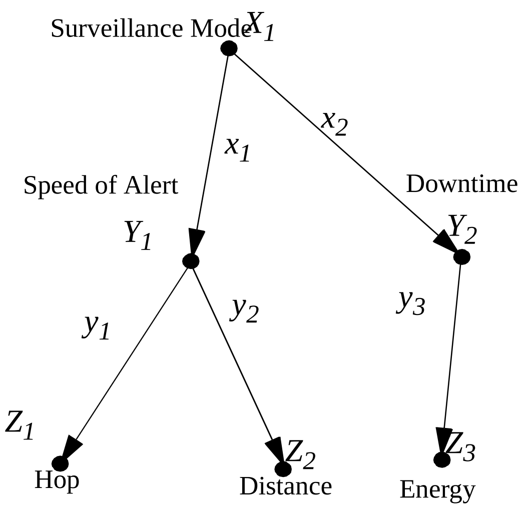

Fig. 3.Illustration to Support POSet Computation

The POSet provides a weighting scheme to guide the creation of a single global performance parameter so that sensor parameter decisions can be made by the sensor manager agents. For example, distance and the number of hops need to be emphasized if the sensor network needs to quickly send messages if intruders are expected. Saving energy to prolong the life of the sensors is less important at that particular point in the system's lifetime. The weights are then computed from

$$W_k = Y_i y_k,\ k = 1, 2, 3,\ i = 1, 2\,. \tag{3}$$

The total performance is recomputed by

$$P_{global} = \sum_{i=1}^{N} W_i \left[\frac{\left(\psi_{actual_i} - \psi_{required_i}\right)}{\psi_{required_i}} \right] \tag{4}$$

where ψ_i are global performance parameters (hops, distance, and energy) and W_i is the weighting from the POSets structure in (4). The operator may make new decisions at this point as to the weighting applied in the POSet.

V. Approach - Decision Making In A sensor network

In the wireless sensor network, the ant agents are spread at random across the network to speed up the search process. Monte Carlo simulations were performed for an euclidean distant sensor nodes as in (5)

$$D_{xy} = \sqrt{(X1 - X2)^2 + (Y1 - Y2)^2} \tag{5}$$

The ant agents accumulate pheromones as they traverse through the nodes, hence the distance travelled by the agents is one of the critical parameter's that needs to be considered while depositing the trails. The pheromone is updated upon completing a tour by every agent and is given by

$$\psi_{ij}(t) = \rho(\psi_{ij}(t-1)) + \frac{Q}{D_t \cdot E_t \cdot H_t} \tag{6}$$

where D_t,H_t,E_t is the total distance, hop and energy performance of the current agent in a tour.

Another key factor involved is the energy, which is weighted in the global performance by the POSets. Using pheromones in (7), the transition probability is calculated from

$$P_{xy} = \frac{(\Psi_{xy})^{\alpha} \cdot (\eta_{xy})^{\beta}}{\sum_k (\Psi_{xk})^{\alpha} \cdot (\eta_{xk})^{\beta}} \tag{7}$$

where Q is an arbitrary parameter, ρ controls the memory, α is the power and weights the pheromone in probability function versus the global performance, β is the power applied to the global performance in the probability function and η is the global performance from the swarm agents.

As discussed in section I, energy, distance and the number of hops determines the performance of the network. Hence, the factors need to be normalized and weighted, the global performance is

$$\eta_{xy} = \left[(W_3) \cdot \left(\frac{E_{actual} - E_{required}}{E_{actual}}\right)\right] \tag{8}$$

$$\left[(W_2) \cdot \left(\frac{D_{actual} - D_{required}}{D_{actual}}\right)\right] + \left[(W_1) \cdot \left(\frac{H_{actual} - H_{required}}{H_{actual}}\right)\right]$$

The energy dissipation from a sensor is the inverse of the distance traveled by the ant agents in the tabu list (history of nodes visited by the agents) of the ant system in (9).

$$E_{xy} = \frac{1}{(D_{xy})} \ldots [T_{xy}] \tag{9}$$

where D_{xy} is the total distance of the current tour of the agent.

The sensor node's whose energy falls below a set threshold is considered down. Thus, these nodes are neglected and an alternate route is taken. This keeps the network functional even during individual node failure.

VI. Simulation Results & Conclusion

A sensor network with 8 sensor nodes is considered in this simulation run with agents randomly placed on the nodes. After converging, the ant agents adapted itself to the network using the knowledge acquired from neighbors.

In the following figures, the route taken by the agents based on hops is shown.

In Figure 4, there are four subplots with start node, (1,5) and end node, (2,3). The route of the first subplot is (1,5),(1,4),(1,3)and (2,3) with a total of three hops. The second agent takes the route (1,5),(1,3),(1,2),(2,2)and (2,3) using four hops in total. Whereas, the third agent with the

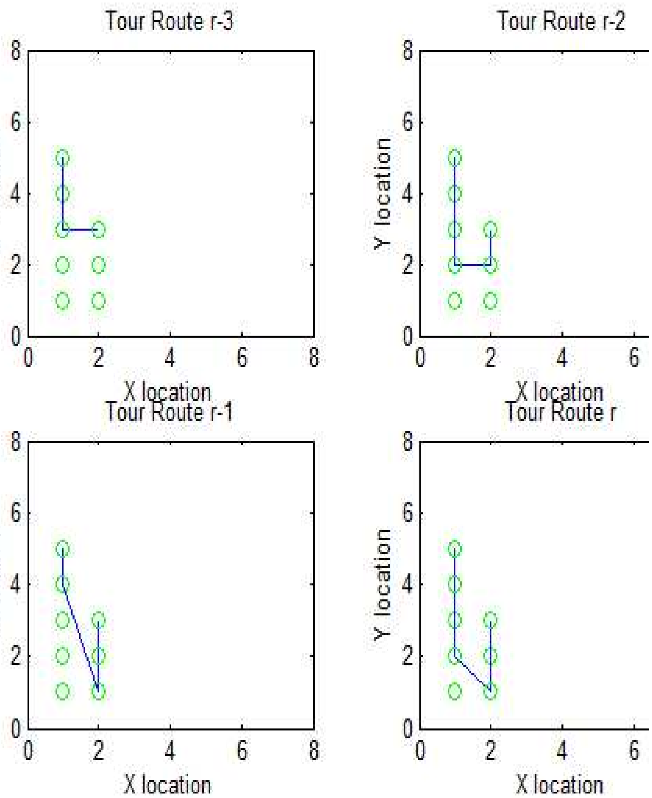

Fig. 4.Routes Taken by Swarm agents in Sensor Network - w.r.t. Hops

same number of hops as the second, takes the route (1,5),(1,4),(2,1),(2,2)and (2,3). The fourth agent with five hops, takes the route (1,5),(1,3),(1,2),(2,1),(2,2) and (2,3). Thus there could be many alternative routes for an agent to reach the destination node. Issues such as energy, distance and hops form constraints that restrict the movements to a specific domain space.

A trade-off between the number of hops, distance and energy is taken as the main arguable factors. The weights given on each of the factor influences the performance of the network.

Table II and Table III, provides the numerical details by calculating the total performance of the network. The dependency of energy consumed, distance taken in reaching the destination with respect to the number of hops (three factors or 3F), and the weights proposed by POSets play an important role. There needs to be a compromise between 3F under varied situation.

In the simulation, required number of hops is considered as 1, the distance required is 1 unit, and the energy dissipation being the inverse of distance is 1 unit. The normalized value of the energy, distance and the hops is used to compute the total minimal performance value of the problem using the weights implied by the POSet

TABLE II. PERFORMANCE OF SENSOR NETWORK

Situation	Weights (H,D & E)	E_{Actual}	E_{Reqd}	D_{Actual}
Case I	0.3,0.2,0.5	9.4391	1	9.4787
	0.5,0.2,0.3	6.5950	1	11.7734
	0.5,0.3,0.2	9.1157	1	14.1876
	0.3,0.5,0.2	7.2146	1	11.2361
Case II	0.5,0.5,0	6.0837	1	11.1224
	0.5,0,0.5	6.6404	1	12.4787
	0,0.5,0.5	6.5724	1	12.4721
Case III	0,0,1	12.0179	1	13.6344
	0,1,0	12.0014	1	12.9515
	1,0,0	11.4142	1	8.2850

TABLE III.PERFORMANCE OF SENSOR NETWORK - CONT

Weights (H,D & E)	D_{Reqd}	H_{Actual}	H_{Reqd})	Performance
0.3,0.2,0.5	1	1	1	0.6259
0.5,0.2,0.3	1	2	1	0.6875
0.5,0.3,0.2	1	3	1	0.7902
0.3,0.5,0.2	1	4	1	0.8528
0.5,0.5,0	1	5	1	0.8550
0.5,0,0.5	1	6	1	0.8414
0,0.5,0.5	1	7	1	0.8838
0,0,1	1	8	1	0.9168
0,1,0	1	8	1	0.9228
1,0,0	1	8	1	0.8750

Three different cases are analyzed. In the first case, the POSet weight for energy is 0.5, distance 0.2 and hops 0.3, the computed performance is 0.6259. Similarly, when the hop is 0.5, performance obtained is 0.6875. So is the case with distance where performace is 0.8528. Under case I, to obtain a minimal performance the weights on the energy is increased when compared to the other two factors.

In the second case, weights are equally distributed between two factors. When the distance and hops are weighed 0.5 each, the performance is 0.8550. Similarly, when energy and hops is 0.5 each, performance obtained is 0.8414. Lastly, when the energy and distance are considered, the performance is increased to 0.8838. In this case II, its shown that by neglecting one of the factors its difficult to attain minimal performance.

In the third case, only one factor is applied with weights equal to 1. When the energy was only considered and the other two factors 0, the performance is 0.9168. In case of considering distance only, the performance is increased to 0.9228. Lastly, in case of number of hops only, the performance is 0.8750. The results show that by giving preference to only one or two factors only, a minimal performance is never obtained. Thus the three factors need to be always balanced. The minimal performance is better obtained by increasing the weights of energy than the distance and number of hops. Energy greatly influences the performance in routing a network.

Under the above cases, the swarm agents did not exhibit any stagnation behavior, resulting in a global minimal. Thus the decision making approach in selecting communication routes using swarm agents and POSets accounts towards an efficient solution. In the future, time taken for communicating between nodes will be incorporated as one of the factors for achieving global performance.

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