Routing Using Messengers in Sparse and Disconnected Mobile Sensor Networks

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***Abstract*—Sparse mobile sensor networks, such as those in the applications of ecology forest and modern battlefield, can frequently disconnect. Unfortunately, most existing routing protocols in mobile wireless networks mainly address connected networks, either sparse or dense. In this paper, we study the specific problem for dynamic routing in the sparse and disconnected mobile sensor networks utilizing messengers. We propose two routing discovery protocols: Genetic Fuzzy Straight Line Moving of Messengers (GFSLMM) and Genetic Fuzzy Flexible Sharing Policy of Messengers (GFFSPM). A preliminary simulation shows the efficacy of our protocols.**

***Index Terms*—Mobile Sensor Networks(MSN), Minimum Spanning Tree(MST), Dynamical Source Routing Protocol (DSR), Ad Hoc On Demand Distance Vector Routing (AODV), Genetic Algorithm(GA), Fuzzy Inference System, Disjoint Mobile Sensor Networks (DMSN), Straight Line Moving of Messengers (SLMM), Flexible Sharing Policy of Messengers (FSPM), Genetic Fuzzy Straight Line Moving of Messengers (GFSLMM) and Genetic Fuzzy Flexible Sharing Policy of Messengers (GFFSPM) .**

1 Introduction

Rapid progress of wireless communication and distributed embedded sensor and actuator technologies has lead to the thriving of the applications of mobile sensor networks (MSN) which range from natural ecosystem to security monitoring, especially in inaccessible terrains or disaster relief operations [1].

Mobile sensor network is a dynamic sensor network with a large number of static sensor nodes and mobile nodes and wireless communication between them. These mobile nodes can be mobile vehicles (cars or buses) which are loaded with sensors. In a habitat monitoring scenario, animals can perform the role of mobile vehicles [5]. The MSN possess the self-organizing and cooperative ability to detect record, collect, process, predict and estimate some events of interest [1].

The first application we consider here is to monitor basic forest ecology. UCLA used infrared imagers to track forest temperatures and heat patterns [8]. But it is not cost-effective to study the entire ecology environment change by deploying lots of sensor nodes in the entire forest to form a dense connected network and maintaining the entire network. So a feasible way is to attach sensors to the trained or observed animals.

The second application we present here is the modern BattleField which demands critical surveillance information system of the enemy site and the most rapid and precise decision support system. Mobile wireless sensors, scattered in targeted zones, form the MSN. They are able to quickly and secretly gather information about the location and environment and periodically relay this information back to the command, control, and communication center [6].

Since sensor nodes inherently have limited power, short-distance communication and prone to failure, in the above two applications, it is difficult to form a globally connected topology. For sparse/disconnected networks,[2][5][7] proposed mobility-based approaches. [2] assumes network topology is relatively stable and the information about network partitions are conveyed by out-of-band means. [5] assumes that the sensor networks in the bottom tier are fixed. All the assumptions allow ignoring the inherently and highly dynamic nature of the distributed dynamic environment. Our previous work [7] was mostly devoted to implementing the agents based simulator for the problem. We proposed two solutions, one based on straight line moving of messengers and the other based on flexible sharing policy of messengers. However, we did not give the problem formulation for it and show the feasibility topologically. These previous work will be described in details in section 2.

This paper deals with the distributed dynamic environment. We propose solution and show the feasibility. Because the uncertainty of dynamic environment and wireless communication, we propose to employ the genetic fuzzy system in the previous two solutions.

The problem and solution method are as follows. Because the use of a long range radio consumes excessive energy, we employ the mobile vehicle (cars, buses, people, or animals with sensors) as the messenger. Once network partitions are generated, the autonomous routing discovery and maintenance based on messenger will be invoked in delay-tolerant sparse/disconnected mobile sensor networks. Through SLMM and FSPM based on the messengers [7], the information of the available network partitions can be shared. And then, in our problem model, we set every one of network partitions to be a vertex and find the cut-edges in the minimum spanning tree (MST) which connects these partitions and meets the condition of the minimum distance weight. The minimum distance weight represents the minimum total energy consumption in the process of the moving. Furthermore, distributed and dynamic characters of the specific applications make the problem more challenging and interesting. With the advent or moving of targets, the network partitions, as vertices in the MST, are changing. On the consequence, new MST should be built and new cut-edges should be discovered. So the problem is focused on the discovery and rebuilding of the dynamic MST with the tradeoff between the delay and real-time availability of network partitions information. Additionally, after MST is constructed, the problem is simplified and the currently existed techniques can be applied [3]. Our goal is to design an energy efficient, decentralized, scalable and flexible approach to share the information of network partitions and rebuild the MST for the distributed dynamic application environment in the delay-tolerant range when network partitions change. Figure 1 shows Process of building topology in disconnected network partitions. It can be iteratively operated. And every network partition can be composed of the hierarchy of subnetwork partitions no matter whether there has been a MST in it. The iterative operation of the loop results in the decentralized rebuilding of MST for dynamic network partitions in energy efficient, scalable and flexible way for the distributed dynamic application environment.

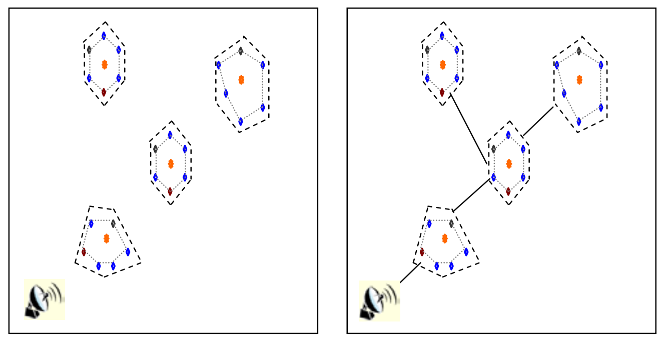
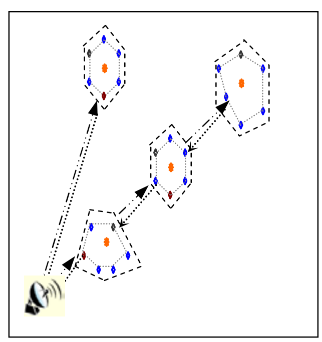


Figure 1.a. Form disconnected MSN with partitions (at T timestep)

Figure 1.c. Establish network topology via MST for T timestep



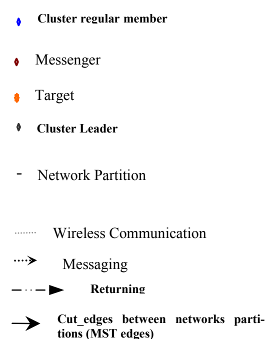


Figure 1.b. Share the information of network partitions by messengers (one of solutions)

Figure 1. Process of building topology in disconnected network partitions.

The remainder of the paper is organized as follows: Section 2 presents previous work. Section 3 introduces genetic fuzzy system routing discovery and maintenance. The autonomous agents' simulation and evaluations on energy consumption are presented in Section 4. Finally, we conclude the paper in Section 5.

2 Previous Work

A message ferrying approach is developed in [2] for sparse mobile ad hoc network. This method employs a set of special mobile nodes called ferries to provide communication service for regular nodes in the deployment area according to a specific route which is generated in out-of-band means so that they are responsible for data delivery in sparse networks. Because authors assume that network partitions are relatively stable and their information is conveyed in the out-of-band means, in [2], they ignore the route discovery and maintenance in the sparse or disjoint dynamic system. Additionally, as a result of the asymmetric roles between ferries and regular nodes, the system will more depend on the robustness of ferries and the consistent coordination between ferries.

R. Shah [5] proposed 3-tier architecture Mules for sparse sensor networks. In the middle tier, the mobile transport agents as messengers collect sensor data from the bottom tier and deliver the data to the top tier. They assumed that the sensor networks in the bottom tier are fixed. The assumption is not suitable for the distributed dynamic application environment.

In our previous work [7], we presented a novel autonomous messenger-based route discovery and routing protocol for disjoint clusters-based MSN. The proposed protocol does not depend upon centralized control or prior global knowledge. It does not depend upon ferries or sensors with special hardware capabilities. The protocol can establish communication in disjoint network of clusters that has not been addressed previously. We provided the framework for the route discovery and routing protocol. And we designed and implemented two route discovery protocols, one based on straight line moving of messengers (SLMM) and the other based on flexible sharing policy of messengers (FSPM). Furthermore, we designed the agent-based modeling and simulator in the application and implemented the prototype. However, our previous work [7] also ignores to describe the highly dynamic problem model and to show the feasibility of the solutions. Additionally, we treated all uncertain elements such as signal strength and the preciseness of direction and distance as crisp elements in the previous version.

3 Genetic Fuzzy System Routing Discovery and Maintenance

3.1 Framework

Based on the framework in previous work, we add a higher tier genetic fuzzy system to SLMM and FSPM in Routing Discovery and Maintenance Component. The whole framework is shown as figure 2.

In routing discovery and maintenance component, we provide three sub components and implement the four routing discovery protocols, one based on straight line moving of messengers (SLMM), one based on flexible sharing policy of messengers, one base on genetic fuzzy flexible share policy of messengers (GFFSPM), and the other based on genetic fuzzy straight line movement of messengers (GFSLMM).

3.2 Genetic Fuzzy System

The genetic fuzzy system prototype is shown as figure 3.The prototype is composed of TSK fuzzy system and genetic algorithm. The TSK fuzzy inference system generates the crisp output which is input into the genetic algorithm as fitness function value. The training feature of genetic algorithm optimizes the TSK fuzzy system. The system input parameters is the distance and angle between the messenger and the sensor which belongs to a full cluster.

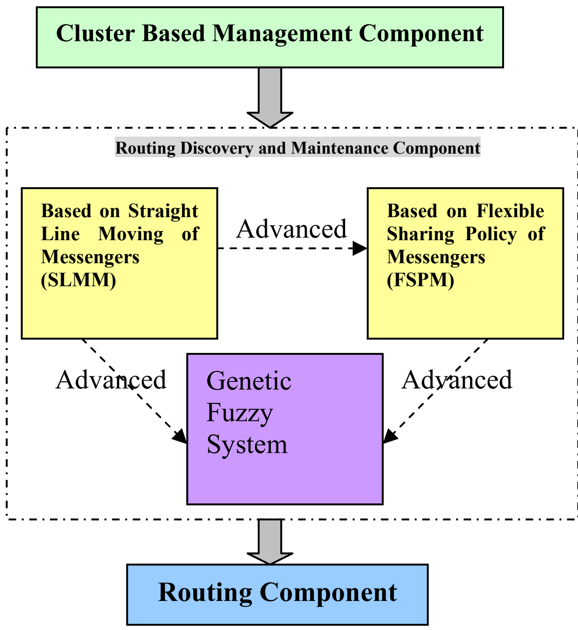


Figure 2. The Framework

3.2.1 The TSK Fuzzy System

Regular fuzzy inference system consists of fuzzy sets, fuzzy if-then rules, and aggregation and defuzzification parts. According to the direction of path planning, we define eight linguistic variables related to direction shown in figure 4: Front Zero (FZ), Front Left (FL), Front Right (FR), Rear Zero (RZ), Rear Left (RL), Rear Right (RR), Left (L), and Right(R). Additionally, we define Signal Strength linguistic variable (SS). The term set for Signal Strength (SS) = {Strong, Medium, Weak}.

Individually the linguistic variables have the membership function as figure 5 and figure 6.

According to a thorough understanding of the system, we design 24 fuzzy rules as the following format:

If direction is FZ and signal is strong, move to FZ;

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If direction is FZ and signal is medium, move to the average of FZ and Base Station; ……

If direction is FZ and signal is weak, move to Base Station; ……

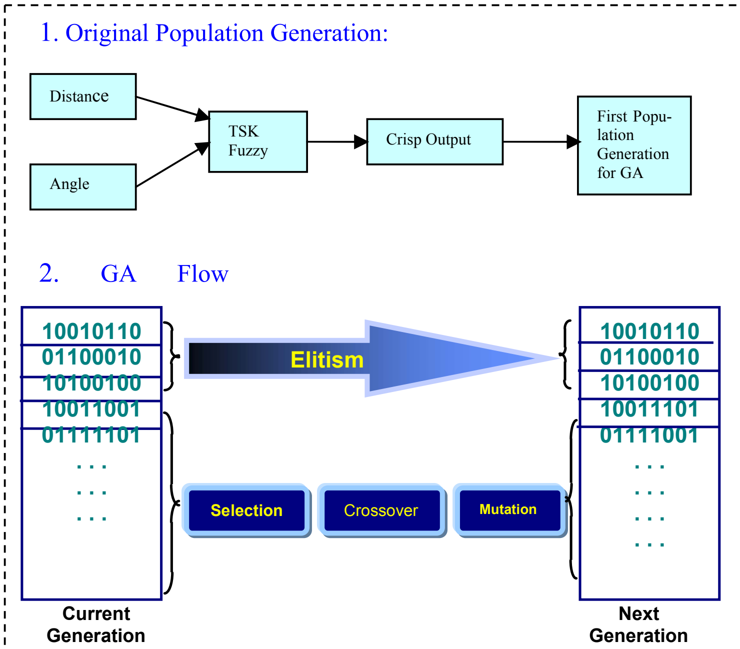


Figure 3. Framework of the Genetic Fuzzy System Based on SLMM and FSPM

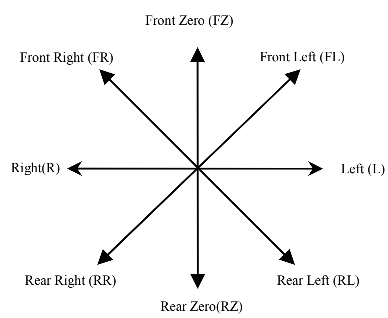


Figure 4. Direction Define

And in the design of the fuzzy rules, we consider the convergence of all messengers' movement towards the nearer available neighbors and the base station.

Based on the distance and angle inputs and the fuzzy rules, we define the angles with the larger certainty as the crisp output.

3.3 Genetic Algorithm (GA)

The second part of figure 3 presents one cycle of the iterative steps of genetic algorithm for generating the offspring generations.

In our GA, chromosomes are stored as floating point numbers. The outputs of the fuzzy inference system are input as the discrete data set and are retrieved as fitness function value.

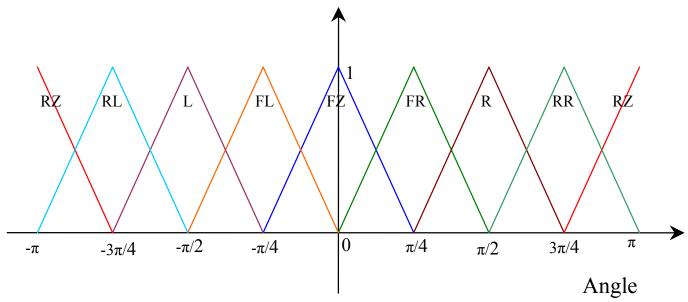


Figure 5. Membership Functions of Path Direction

The same color curve lines represent the membership function of the same linguistic variables

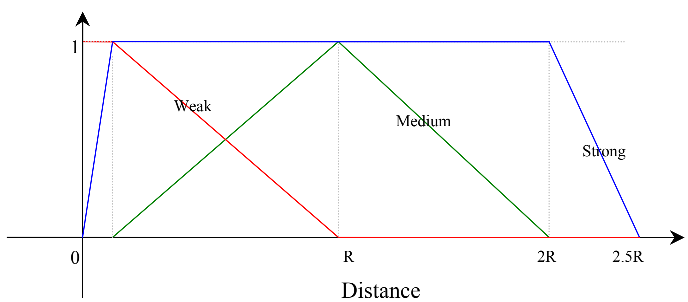


Figure 6. Membership Functions of Signal Strength (R= Sensor Transmission Radius)

The same color curve lines represent the membership function of the same linguistic variables

In the simulation experiment mentioned in section 6, we set the following GA parameters:

Chromosome Dimension (number of genes) = 10;
Population of Chromosomes = 100;
Crossover Probability = 0.7;
Random Selection Chance % (regardless of fitness) = 6
Max Offspring Generations = 30;
Number Prelim Runs (to build good breeding stock for final--full run) = 10;
Max Prelim Generations = 20;
Chromosome Mutation Probing = 0.1;
Crossover Type = Two Points Crossover;

After messengers move for one time step, they broadcast probing signal and receive the response from nearby sensor nodes. First, the distance and angle from the nodes are input to the TSK fuzzy system. Secondly, the crisp outputs are input as fitness function value to GA. After the specified offspring generation, the best fitness value is used as the current optimal direction.

4 Agents Simulation and Evaluation

4.1 Simulation

Due to the dynamic and non-predetermined connection and disconnection among sensor nodes in DMSN, we still use the Autonomous Agents Simulator MSensorSim designed in our previous work [7]. The result will be addressed in the following sub section.

4.2 Evaluation

Based on the agents based modeling and simulation in the application of route discovery and routing protocol in DMSN, we conducted experiments to evaluate and compare the energy consumption of the protocols: genetic fuzzy routing discovery based on SLMM, genetic fuzzy routing discovery based on FSPM, and route discovery based on flexible sharing policy of messengers.

As we know, mobile nodes in MANET have limited battery capacity. So the saving of battery power is a vital issue when determining the network route [4]. We denote the battery power consumption for the entire network as BPC. Because the battery power consumption of a node is caused by the following activities:

1. The roaming of sensor nodes;
2. The moving of messengers;
3. Uploading data or message to cluster head;
4. Messenger assigning of cluster head(because of the routing consumption in the cluster);
5. Data exchanging with messengers;

We define BPC as a linear function shown below:

$$BPC = W_{Roaming} \times M_{Roaming} + W_{Moving} \times M_{Moving} + W_{UploadData} \times M_{UploadData}$$
$$+ W_{AssignMessenger} \times M_{AssignMessenger} + W_{ExchangeData} \times M_{ExchangeData}$$

where the $W_{Roaming}$, W_{Moving}, $W_{UploadData}$, $W_{AssignMessenger}$ and $W_{ExchangeData}$ are the battery power consumed by the network interface when a node does the above mentioned five activities; $M_{Roaming}$, M_{Moving}, $M_{UploadData}$, $M_{AssignMessenger}$ and $M_{ExchangeData}$ are the amount of five types of activities respectively. Therefore, BPC is obtained by averaging the total amount of the power consumption for every T time steps.

In the prototype, we initially define the following constant of energy consumption on different activities: ENERGY_SENSOR__MSGER_EXCHANGE_DATA = 1; SENSOR_FULL_ENERGY = 100000; ENERGY_SENSOR_ROAMING = 10; ENERGY_SENSOR_MEM_UPLOAD_MSG = 1; ENERGY_SENSOR_HEAD_SELECT_MSGER = 1; ENERGY_SENSOR__MSGER_MOVE = 10; SENSOR_NO_ENERGY = 10;

For retrieving the energy consumption trend in the environment of emulating the random event of interest, we employ the average value method. First we do the same experiment ten times using the same parameter set and then calculate the average value. These experiments ran in the Windows XP system of my Pentium ® 4 CPU 2.66 GHz HP laptop. We have 100 sensor nodes and 20 targets. Two hundred mobile nodes were deployed within a 640 m *800 m area. Each node had a radio propagation range of 20m and channel capacity was 0.1Mb/s. Also, 20 targets appear in randomly distributed places that are far enough away from each other to form network partitions. The experiment results are provided in the table and Chart 1. The user interface is shown in figure 7.

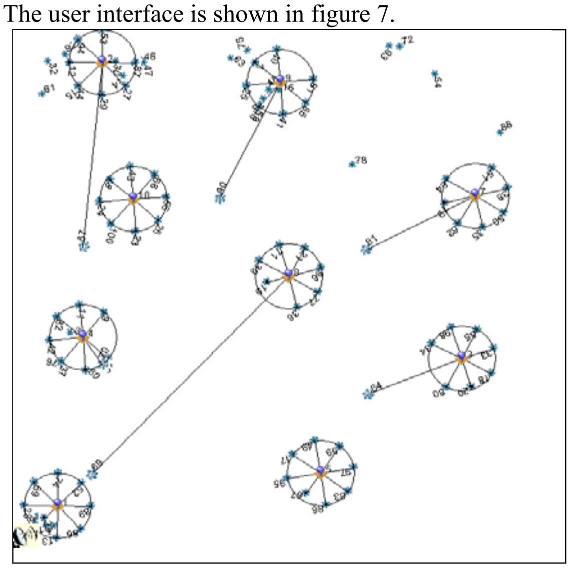
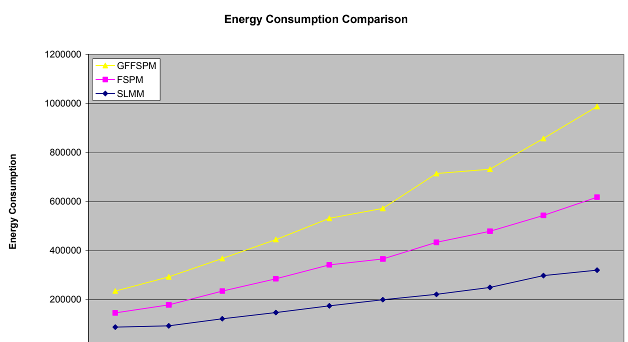


Figure 7. Simulation of route discovery and routing in DMSN



	600	700	800	900	1000	1100	1200	1300	1400	1500
GFFSPM	89117	114219	133260	159995	189920	206242	280322	252739	313909	369655
FSPM	57756	85462	112534	137742	167203	165747	212196	229415	245422	297972
SLMM	88261	93183	122345	147453	174749	199994	221538	249665	298191	320054

Time Steps

From the above stacked line chart and table, we observe that FSPM route discovery protocol is consistently more energy efficient than SLMM and GFFSPM. As the simulation time increases we can see that FSPM becomes more and more energy efficient.

From the theoretic point of view, genetic fuzzy system based on the routing discovery protocols should show better energy consumption. But in my experiment, due to the limited clusters, the population space is not big enough to make efficient use of genetic algorithm. In out next parallel simulation version for the large scale mobile sensor networks, we will see the results of genetic fuzzy system applied to the novel routing discovery protocols.

5 Conclusion

In this paper, according to the highly dynamic property of the distributed dynamic environment, we present the specific problem and the corresponding solution model and show the feasibility from network partitions topology graph's perspective. And due to the uncertainty of dynamic environment and wireless communication, we employ the genetic fuzzy system in the previous two solutions, one based on straight line moving of messengers and the other based on flexible sharing policy of messengers. With varied repetitive experiments based on the simulator MSensorSim , we draw a conclusion that the flexible sharing policy route discovery and routing protocol (FSPM) provides more energy savings than the genetic fuzzy solution based on the straight line moving one (SLMM). Additionally, due to the limited clusters, the population space is not big enough to make efficient use of genetic algorithm. On the other hand, our protocol not only increases network life time but also enables sensor data and cluster knowledge sharing for co-operative efforts of the autonomous agents to perform autonomous monitoring of the terrain and communicating with the base station for prolonged duration in an energy-efficient manner. Our future work will focus on improving the efficiency of routing discovery planning in disjoint network and finishing the routing component.

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