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Research on the Model Design of Self-Organizing Management for Wireless Sensor Networks Based on Microeconomics

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Abstract: This paper designed a self-organizing microeconomics system in which the application tasks were scheduled onto nodes by mobile agents while distribute their resource consumption across network. Further, it proposed the market-based resource allocation policy named MRA which satisfied the optimal division of the single capacity for multiple tasks. For harmonizing the resource allocation and task scheduling, it also proposed a market-based task scheduling policy named MTS which scheduled tasks to the set of optimal nodes. In addition, combining with the points and methods of microeconomic, this paper aimed to solve key technology for mutual optimization of resources and tasks and distribution and collection of data in self-organizing management for wireless sensor networks. *Copyright © 2013 IFSA.*

Keywords: Wireless Sensor Networks; Microeconomics; Mobile Agent; Market Mechanism.

1. Introduction

With wide use of microeconomics in traditional distributed problems, applying the viewpoints and methods of microeconomics can provide beneficial way for the model design of self-organizing management for wireless sensor networks. Economics studies how to make configuration optimally and how to make full use of scarce social resources, with which the market mechanism is the best way to implement it [1]. If task and the node are regarded intelligently as two independent bodies in the market, it is helpful to solve the problem of self-organizing resource and task management for wireless sensor networks through constructing microeconomic model and relying on market regulation.

For the self-organizing resource and task management for wireless sensor networks, this paper discusses the optimization problems of resources and tasks by mobile agents. It designed a self-organizing microeconomics system by using market mechanism principles in microeconomics and mobile agents. Further, it proposes the market-based resource allocation policy named MRA and scheduling policy named MTS, which satisfied the optimal division of network resources with effective scheduled tasks. Last, this paper applies MRA and MTS strategy to target tracking scenario as simulation experiments.

2. Wireless Sensor

A wireless sensor network is a kind of fully distributed system without center node. By means of randomly delivery, many sensor nodes are densely deployed in monitoring area. The integration of these sensor nodes includes sensor unit, data processing

unit and communication module. They are connected by wireless channel, self- forming the network system [2].

The architecture of wireless sensor network is shown in Fig. 1, including sensor node, sink and manager node.

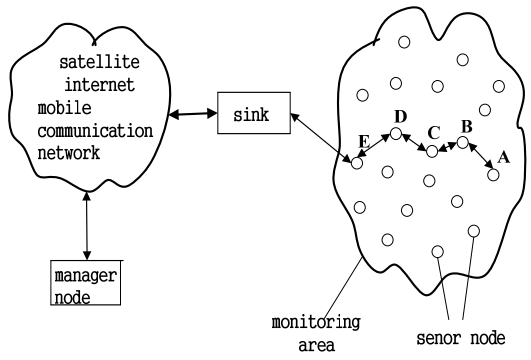

Fig. 1. The architecture of wireless sensor network.

Wireless sensor network has the distinguishing features of large scale, high density, distributed, limited node ability, multi-hop routing, self-organizing, data-centered and application related.

3. Mobile Agent Model

3.1. The Structure of the Mobile Agent

The structure of the mobile agent which is suitable for wireless sensor networks is put forward in this paper, as shown in Fig. 2, mainly including agent identity, data space, routing table and processing code.

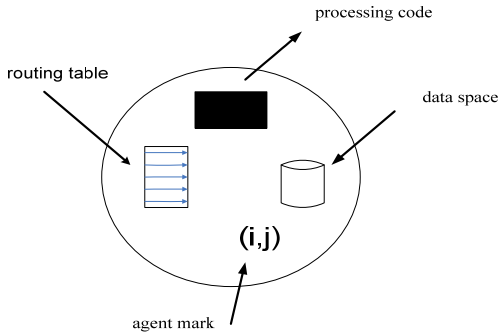

Fig. 2. The structure of the mobile.

3.2. Software Architecture of Wireless Sensor Networks Based on Mobile Agent

Software architecture of wireless sensor networks based on mobile agent is shown as Fig. 3. The part in middle box is middle ware in mobile agent, which abstracts communication protocol and memory management involved in task processing, shields the complexity of the underlying network environment and provides a user oriented application management platform for the upper application through the coordination of interaction between mobile agents and nodes [3]. Logically, middle ware of mobile agent, which is in software level between operation system and upper application, is on network layer, but it is in nodes physically.

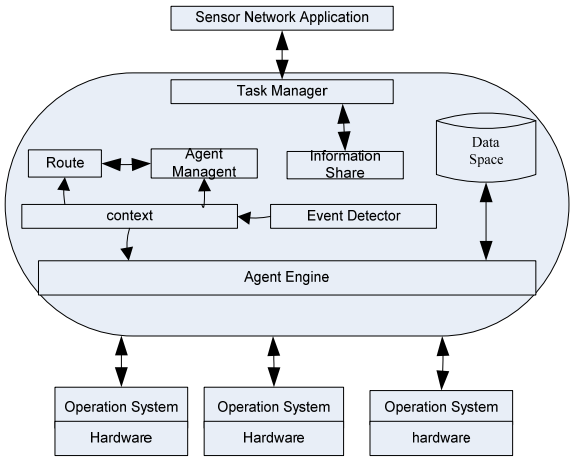

Fig. 3. Software architecture of wireless sensor networks based on mobile agent.

Context refers to the network information, mainly describing the state of the network environment and mobile agent migration. Event Detector monitors the events in network, including network status change and migration request of mobile agent. Route is routing mechanism of mobile agent, which can adjust routing strategy according to the variation of Context. Agent Manager manages the life cycle of mobile agent, including creation, initialization and destruction of mobile agent, acquisition routing information from Route, increase and reduction of the number of mobile agent according to Context. Data Space is the data buffer that preserves part of the fusion result carried by mobile agent. Information Share is the mechanism of information sharing between mobile agents, which blend data information of each Data Space. Mobile agents access to global information network through collaboration in order to better support application tasks. Task Manager decomposes all the required tasks and distributes to mobile agent to deal with based on specific application scenario. Agent Engine hands out or receives mobile agent, assisting mobile agent to complete migration with Data Space.

3.3. Application Framework of Middle Ware in Mobile Agent

In this paper, the application framework of middle ware in mobile agent is prepared to support

the self-organizing management for wireless sensor network, as shown in Fig. 4.

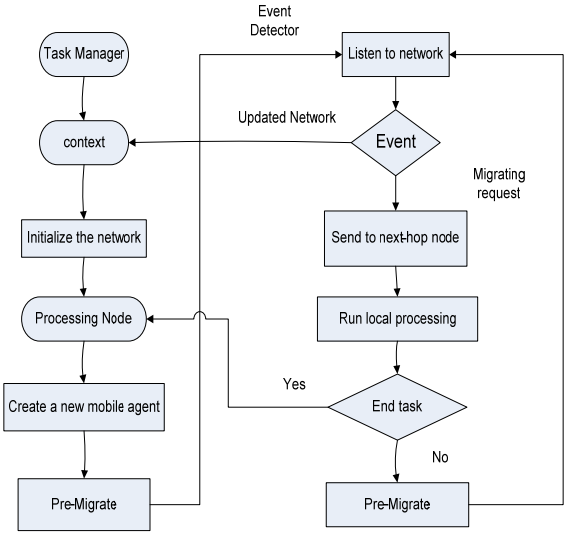

Fig. 4. Application framework of middle ware in mobile agent.

3.4. Calculation

Mobile agent carries processing code and data space. The length of data size is M bite and D bite respectively [4]. If use wireless channel with BWbps bandwidth to transmit these data, then the time that node transmits mobile agent is

$$t_{tran} = \frac{W + D}{B W}, \quad (1)$$

Signal attenuation caused by path loss can be measured by the following relative amount (use dB as unit):

$$PL(d_{i,j}) = 10\log(p_{i,t} / p_{j,r}), \quad (2)$$

Therefore, path loss (PL) along route R can be calculated as follows:

$$PL(R) = \sum_{k=0}^{H-1} 10\log(p_{k+1,t} / p_{k,r}), \quad (3)$$

Time delay (DT) along the whole route can be calculated like this:

$$TD(R) = t_{0,setup} + \sum_{k=0}^{H-1} \{t_{k,acp} + t_{k,proc} + t_{tran}\}, \quad (4)$$

Signal accumulated (SA) by mobile agent along the whole route R is shown as

$$SA(R) = \sum_{k=1}^{H-1} S_k \quad (5)$$

4. Model of Self-Organizing Management for Wireless Sensor Networks Based on Self-Organizing Microeconomics

If task and the node are regarded intelligently as two independent bodies in the market, it is helpful to solve the problem of self-organizing resource and task management for wireless sensor networks through constructing microeconomic model and relying on market regulation.

4.1. The Framework of Self-Organizing Microeconomics Model

The premise of the market mechanism requires supply and demand in the market. In wireless sensor networks, the two sides of supply and demand respectively refer to sensor nodes with certain resources and tasks to be performed. Therefore, it is necessary to intelligently regard task and the node as two independent bodies in the market [6]. After that, the paper designs such a self-organizing microeconomics scenario: the application is decomposed into several task sequences oriented to sub application; the system creates several mobile agents; each mobile agent with one task sequence and a budget fund to find the most appropriate nodes for these tasks and then complete the present task by using resources on nodes; nodes provide resources to agents according to the requirement of current task, and based on its energy consumption conditions adjust the prices of the resources; later agent continues to migration till all the tasks in a sequence are completed. The above scenario can be shown in flow chart 5.

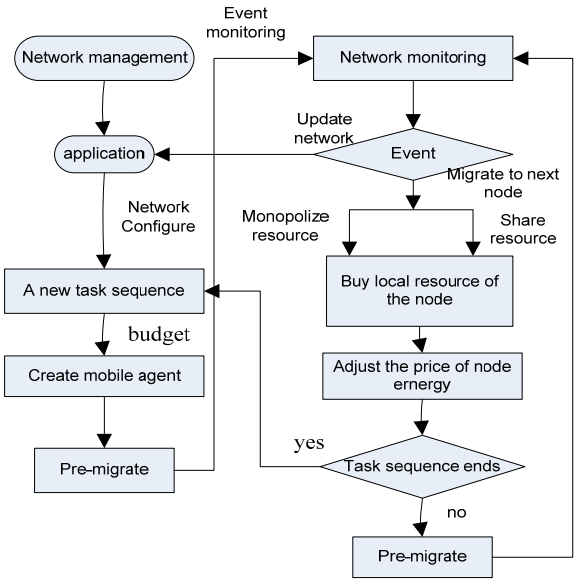

Fig. 5. The flow chart of self-organizing microeconomics scenario.

This scenario adopts an event-driven mechanism, distributes the new task sequence by timely capturing the changes of network conditions (such as topological changes and target mobile), schedules the task to the appropriate nodes through assisting migration of mobile agent and explores the status of other agents on the node so as to decide the ways to buy resource on the node (single node monopolizes the resources on the node or multiple agents sharing the resources on the node by means of bidding). In this way, this scenario can be adaptive to dynamically changing network environment flexibly.

4.2. Price Adjustment Mechanism in Self-organizing Microeconomics

With the enlightenment of realization of market independent adjustment through price adjustment mechanism in self-organizing microeconomics, it designs a adjust mechanism for energy price in order to provide the use of resources for tasks as well as to timely adjust the prices of node energy, which achieves the goal of mutual optimization of task and resource.

In self-organizing microeconomics scenario, mobile agent use the resource on the node fro the current task by paying certain money. Due to the corresponding consumption caused by resource use, so nodes need to adjust the price according to energy consumption condition after completing the task, so as to avoid excessive energy consumption. Therefore, this paper establishes the following price adjustment mechanism to decide energy sales price of node.

$$\eta_m^j = \frac{\alpha}{(1 - e^{-E_m^j / B})}$$

where α is the proportionality coefficient; β is the sensitivity, reflecting the sensitivity degree of price on energy consumption; E_m^j is the left energy of node j before price adjustment. For the node j, whose primary energy is E_0^j, the left energy E_m^j after completing the mth task is shown as follows: $E_m^j = E_m^j - \sum_{n=1}^{m} \sigma_n^j$ σ_n^j is the size of task load which node j deals with the nth task.

4.3. Market-based Resource Allocation

In self-organizing microeconomics scenario, node should provide its resources for the task that carried by the agent when mobile agent is buying resource on node. The key that influences the efficiency of task execution is to reasonably and optimally distribute resources for the node. Because there are many agents and they submit the tasks and buy the resources simultaneously, so we can divide the transaction mode between agents and nodes into two types; one is single agent monopolizing node resource and the other is multiple agents sharing node resource. Here, market-based resource allocation (MRA) is designed in this paper.

4.4. Market-based Task Scheduling

In self-organizing microeconomics scenario，the process that mobile agent carries task to migrate is also the process that schedules the task to appropriate node. The key to task scheduling is to seek the appropriate scheduling node with considering the limitation of node energy consumption. Here, marker-based task scheduling (MTS) is designed in this paper.

4.5. Example Analysis

Using the target tracking as an application scenario, this paper assesses the market-based resource allocation and marker-based task scheduling.

4.5.1. Performance Evaluation of MAR

This paper applies MAR to compute resource allocation in target tracking scenario. So it blends the estimated target motion direction data with application organization, forming 10 subtasks with different priority. There are 20 computing task in each sequence. 10 mobile agents are distributed in the network, with each mobile agent carrying one task sequence, which seeks the appropriate node for each calculation. It mainly evaluates the efficiency, distribution and balance performance in simulation.

This paper uses the ratio between the time needed in completing task sequence under an ideal non congestion case and the actual case to measure the agent's execution efficiency. If the ration is greater, then it shows the execution efficiency is higher.

In order to test whether the agent's execution efficiency can reflect its priority, this paper tests each agent execution efficiency with the change of its priority under different network congestion environment, as shown in Fig. 6.

From Fig. 6, we can see that execution efficiency increases with the increase of agent priority, which shows MAR can calculate the difference of task priority through agent's execution efficiency. The higher priority of task sequence, the quicker the task is completed.

This paper equally shares MAR and traditional resource allocation and also compares with first-come-first- served. It analyzes the allocation performance of these three strategies through testing their difference in execution efficiency. Changing conditions of execution efficiency with priority under these three strategies is shown in Fig. 7.

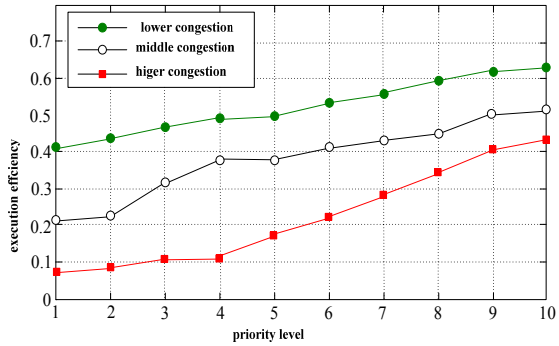

Fig. 6. Changing conditions of execution efficiency with priority under different network congestion environment.

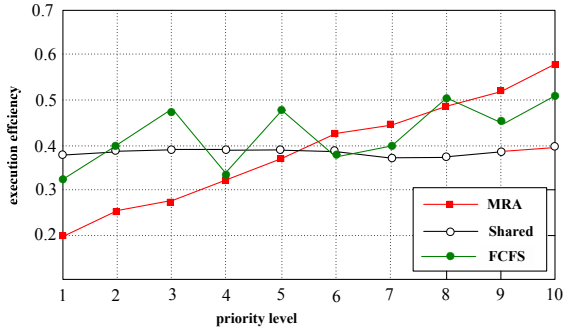

Fig. 7. Changing conditions of execution efficiency with priority under these three strategies.

From Fig. 7, we can see that execution efficiency of MRA is increased steadily and rapidly with the increase of task priority. This is because agent with bigger priority level wins more computing rate in the bidding game so they can rapidly complete the tasks in sequence with high execution efficiency.

This paper defines a standard deviation to measure the degree of energy distribution difference between N nodes.

$$\delta = \sqrt{\frac{\sum_{j=1}^{N} (E^{j} - E^{mean})^2}{N}}, \tag{6}$$

where E^{j} is the energy on jth node; E^{mean} is the arithmetic mean value of each node energy. The bigger the standard deviation δ, the smaller the energy difference between nodes. The changing condition of standard deviation with task execution time under three allocation strategies is shown in Fig. 8.

4.5.2. Performance Evaluation of MTS

In simulation, Starting from listening to the target near the network, we calculate node behaviors every 20 seconds until 1000 seconds. The distribution of node behaviors after calculation is shown in Fig. 9.

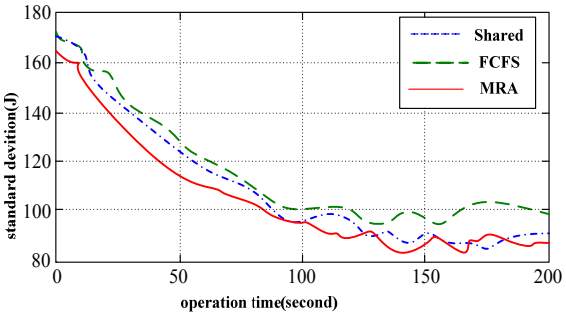

Fig. 8. A balanced comparison of three allocation strategies.

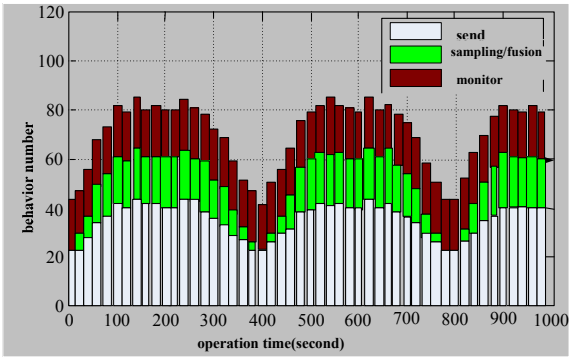

Fig. 9. The distribution changes of behaviors on time series.

From Fig. 9, we can see that from monitoring to target closing to the network, data collection behavior and data forwarding behavior within network gradually increase, which shows more and more nodes are involved in target tracking.

In this paper, we calculate the error value(tracking error) of two scheduling strategies to target motion under different energy budget. The changing condition of average tracking error with node mean energy budget is shown in Fig. 10.

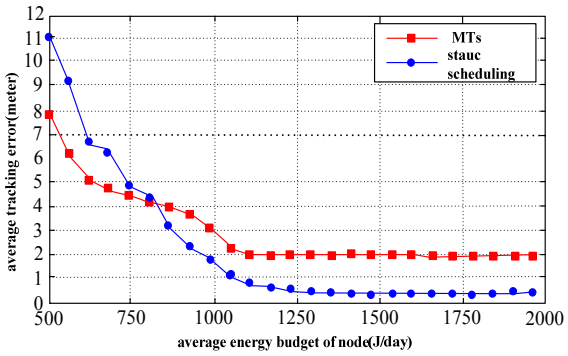

Fig. 10. Tracking error comparison between MTS and static scheduling.

From Fig. 10, the tracking error of two strategies gradually decreases with the increase of energy budget until stable. This is because increasing node mean energy budget can effectively enhance estimated accuracy of single node to target azimuth so as to decrease tracking error of multi-node data.

In order to extent network longevity, task scheduling should make the energy distribution of nodes become equilibrium after effective scheduling. By means of standard deviation, this paper calculates the changing condition of standard deviation in time series of these two strategies, as shown in Fig. 11.

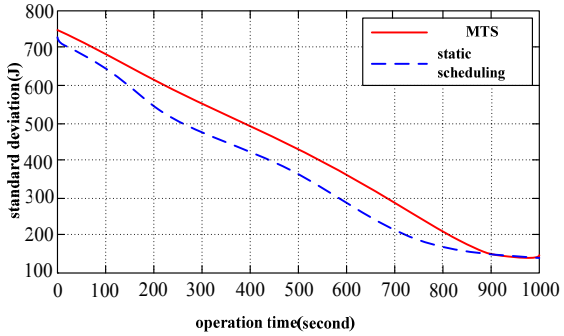

Fig. 11. Energy balance performance comparison between MTS and static scheduling.

From Fig. 11, we can see that standard deviation of energy eventually converges to a steady value under two strategies, which is because two strategies do a lot of task scheduling with the operation of network so as to limit the energy difference of each node to extremity and achieve the same energy equilibrium effect finally.

The simulation experiment shows that MRA can effectively distribute computing resources in the network and its distribution and balance performance are better than the traditional allocation strategy. In addition, MTS can effectively schedule task within network and its energy has a greater improvement than static scheduling.

5. Conclusion

This paper designs a self-organizing microeconomics system in which the application tasks were scheduled onto nodes by mobile agents while distribute their resource consumption across network. Further, it proposes the market-based resource allocation policy named MRA which satisfied the optimal division of the single capacity for multiple tasks. For harmonizing the resource allocation and task scheduling, it also proposes a market-based task scheduling policy named MTS which scheduled tasks to the set of optimal nodes. Last, this paper applies MRA and MTS strategy to target tracking scenario as simulation experiments. The simulation experiment shows that MRA can effectively distribute computing resources in the network and its distribution and balance performance are better than the traditional allocation strategy. In addition, MTS can effectively schedule task within network and its energy has a greater improvement than static scheduling. MTS can adaptive to the dynamic changes of network and the distribution of energy equalization network. Compared with traditional scheduling strategy, MTS can greatly increase the utilization of network energy without losing fewer tracing accuracy. Meanwhile, it also can achieve the same energy equilibrium effect as static scheduling.

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