Geographic Routing for 3-D Wireless Sensor Networks with Stochastic Learning Automata

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Abstract

This paper introduces β-BGR, a novel geographic routing protocol for 3-D wireless sensor networks with β-type learning automata. In our protocol, the data packets are forwarded toward the destination, and nodes which hear the packet compete for becoming the next hop. A new recovery strategy with β-type learning automata is presented for the case of empty forwarding area. The β-type learning automata are performed to coordinate adaptively the forwarding area, which is oriented toward the destination location, and its dimension ensures that all nodes within it can mutually communicate with each other sensor node. Then, the efficiency of the β-BGR is shown through several simulation results under some 3-D environments.

1 Introduction

In recent years, advances in wireless technology have enabled the rapid development of wireless sensor networks. A wireless sensor network (WSN) is a kind of MANET, which means “Mobile Ad hoc Networks.” The WSNs are spatially distributed systems which consist of dozens, hundreds or even thousands of sensor nodes, interconnected through wireless connection channel. Variety of sensing capabilities result in profusion of application areas[1].

The characteristics of WSNs require more effective methods for data forwarding and processing. Most of existing routing algorithms for WSNs assume 2-dimensional topologies. However, dedicated WSN scenarios demand for algorithms that operate in 3-D environments. Geographic routing algorithm, which is termed BGR (Blind Geographic Routing), is considered as only few successful approaches for routing in 3-D WSN environments[2]. Although the performance of the BGR is much superior to the conventional geographic routing GPSR[3], the BGR has low rate in average packet delivery ratio and low properties in average hop count and average delivery time.

Therefore, we proposed β-BGR, a novel geographic routing protocol for 3-D WSNs with β-type learning automata to improve some properties, for example the average packet delivery ration, the average recovery number and so on. In the β-BGR, the data packets are forward toward the destination, and nodes which hear the packet compete for becoming the next hop. The β-type learning automata are utilized for recovery strategy for adaptive coordination of the forwarding areas.

The numerical simulation has been set up to compare the BGR and the β-BGR, then the efficiency of the β-BGR is shown through some simulation results under some 3-D environments.

2 Routing Protocols for WSNs

The WSNs are spatially distributed systems which consist of many sensor nodes, interconnected through wireless connection channel. The future of the WSNs is promising; they are being deployed in many real-world applications, in the context of Ubiquitous Computing, Ambient Intelligence, and so on.

Since the transmission range and energy resources of small sensor devices are limited, WSNs are inherently more dynamic than the wired networks as network topology can be changeable. Thus, conventional routing protocols, which are designed for wired networks such as RIP, OSPF, BGP and so on[4], generally fail to satisfy the requirements of wireless networks. These facts lead to invention of new routing protocols specifically for operation in the MANETs.

Furthermore, routing protocols on WSNs are classified into three categories: proactive, reactive and geographic routing protocols. Typically, the proactive and reactive protocols are called topology based protocols, while the geographic routing protocol is called location based protocol.
Proactive routing protocols (table-driven) need to maintain the information about the entire network topology and propagate updates when its topology is changed. On the other hand, reactive routing protocols (on-demand) need to discover the routes on demand via excessive flooding. Briefly, the topology-based protocols let the sensor devices keep information about routes. Therefore, they are not very efficient in small sensor devices for reasons as they cost the network bandwidth and intense memory storage.

In contrast to these, geographic routing can be stateless, because the next hop is chosen using the geographic information of the destination which is stored in the packet header. However, to achieve this function, sensor nodes must know their geographic information via GPS or explicitly programmed way.

3 Geographic Routing for 3-D WSNs

Greedy Perimeter Stateless Routing (GPSR) is a well-known geographic routing protocol [3]. In GPSR, each sensor node must store the neighbor information which is obtained from sending beacon messages. However, beacon messages cause an enlargement of packets, therefore BGR (Blind Geographic Routing), a novel beacon-less routing protocol, has been developed [2].

The BGR is very reliable if the sensor nodes density is sufficiently high and its algorithm is “blind” in the meaning that packets are forwarded without knowledge of the next hop node. Each node sets a timer which is depending on distance parameter to the destination, then the node whose timer is expired first will forward the packet and all the nodes other than the packet forwarding node cancel their timers.

A large number of WSNs embedded in the physical world will be 3-D, for example, the WSNs deployed on multiple floors of building, on trees of different heights, in underwater, or in space. Current studies on routing protocol for WSNs heavily focused on deployments in 2-D environment and there is a tendency to believe that results will hold even in 3-D environment. However, there are several problems in geometry that are easily solved in 2-D but are very complex in 3-D [5]. The BGR is known as one of the few successful studies of routing for 3-D WSNs.

4 BGR Algorithm

While BGR was proposed as a novel beacon-less routing protocol for 2-D WSNs, it was later extended to 3-D WSNs [2]. In the BGR, packets are forwarded via broadcast and sensor nodes which receive this broadcast determine if they are located within a special area, which is called forwarding area. The forwarding area is defined with different spatial shapes and its dimension ensures that all nodes within it can mutually communicate with each other. For example, Figure 1(a) is angle \(\theta\) sector model \((0 < \theta \leq 360)\), (b) is circle model and (c) is the Reuleaux triangle model in 2-D WSNs.

In the above BGR algorithm, the contention timer function is defined as follows:

\[
t = \text{Max}_{\text{Delay}} \cdot \left(1 - \frac{d - c}{r'}\right) \quad (1)
\]

1In this case, the forwarder node gives up delivery of the message packet

Figure 1: Forwarming Areas
Here, $0 < d - c \leq r'$ in (1) and $d$ is the distance between forwarder sensor node and destination sensor node, $c$ is the distance between candidate sensor node and destination sensor node, $r'$ is the transmission range.

Furthermore, it is not sufficient to simply add $z$ coordinates to location descriptions to apply this BGR algorithm for 3-D WSNs. The forwarding areas have to be converted into solid of revolution around the forwarder-destination axis. Hence, the 2-D angle $\theta$ sector model becomes a spherical sector (See Figure 2), the circle model becomes a sphere, and the Reuleaux triangle model becomes the solid of revolution of a Reuleaux triangle. For example, Figure 2 shows the angle $\theta$ sector model in 3-D BGR.

![Figure 2: Extended Forwarding Area (the angle $\theta$ sector model) for 3-D WSNs](image)

A problem with 3-D forwarding areas is that more sensor node density and more recovery attempts on the recovery process are required for network coverage than 2-D WSNs.

Although the performance of the 2-D BGR is much superior to the conventional geographic routing 2-D GPSR[3], the 3-D BGR has low rate in average packet delivery ratio and low performance in average hop count and average delivery time. Therefore, in this paper, we introduce the $\beta$-type learning automata[8] to the 3-D BGR (we termed it $\beta$-BGR [9]) and to improve its some routing properties. In $\beta$-BGR, the $\beta$-type learning automata are utilized for recovery strategy for adaptive coordination of the forwarding areas.

5 $\beta$-type Learning Automata

In this study, we use the learning automaton termed $\beta$-type with the reinforcement scheme which is similar to the Bayesian learning scheme. A learning automaton[7] is a feedback system connecting an automaton, which chooses an action at each time, and an environment, which produces responses to those actions (See Figure 3). We describe briefly the $\beta$-type learning automaton model as follows.

![Figure 3: Automaton-Environment Configuration](image)

(1) Environment

In general a random environment model has as its input an action $\alpha(t) \in \alpha = \{\alpha_1, \alpha_2, \cdots, \alpha_r\}$, where $\alpha$ is the action set of the learning automaton ($r$: action number), and as its response a random variable $x(t) \in X = \{x_1, x_2, \cdots, x_n\}$, where $X$ is the response set ($n$: response number). Here, we assume that $X$ is a set of distinct real numbers which indicate the degree of fault, the penalty, and $x(t)$ obeys unknown probability distribution $P_1$ on $X$ corresponding to an action $\alpha_i \in \alpha$. The random environment in which the learning automaton operates is specified by collection of $r$ unknown probability distributions $P_i = (p_{i1}, p_{i2}, \cdots, p_{in})$, which satisfy the following conditions;

$$0 \leq p_{ij} = p(t)[x(t) = x_j|\alpha(t) = \alpha_i] \leq 1,$$

$$\sum_{j=1}^{n} p_{ij} = 1, (\text{for all } i, j)$$

In the case that $2 < n < \infty$ and the probability distributions $P_i (i = 1, 2, \cdots, r)$ are stationary, the environment is called the $Q$-model stationary environment.

(2) $\beta$-type learning automaton

A $\beta$-type learning automaton consists of $r$ Bayesian estimators $BE_i$ (See Figure 4), and each $BE_i (i = 1, 2, \cdots, r)$ corresponds to an action $\alpha_i \in \alpha$. The $BE_i (i = 1, 2, \cdots, r)$ is described by a 4-tuple $<X, \Omega, \lambda_i(t), T>$, where $\Omega = \{\omega_1, \omega_2, \cdots, \omega_m\}$ is the set of its states ($m$: state number); $\lambda_i(t) =$

![Figure 4: Construction of $\beta$-Type Learning Automaton](image)
The state probability vector satisfies the following conditions:

\[ 0 \leq \lambda_{ij}(t) \leq 1, \]
\[ \sum_{j=1}^{m} \lambda_{ij}(t) = 1, \text{for all } i,j \]

For each \( BE_i \), further, we assign a real number \( \mu_k \) to each state \( \omega_j \). These real numbers \( \mu_k (k = 1, 2, \ldots, m) \) are taken to satisfy the following conditions:

\[ x < \mu_1 < \mu_2 < \ldots < \mu_m < \bar{x}, \]
\[ \bar{x} = \max(x_i), \tilde{x} = \max(x_i). \]

The interaction between a \( \beta \)-type learning automaton and a Q-model stationary environment as mentioned in (1) is stated as follows.

At the start time \( t = 0 \), every state probability vectors \( \lambda_i(0)(i = 1, 2, \ldots, r) \) is set as

\[ \lambda_{i1}(0) = \lambda_{i2}(0) = \cdots = \lambda_{im}(0) = \frac{1}{m}, \text{for all } i. \]

At time \( t \), each \( BE_i \) chooses randomly its state \( \omega_k \) according to its state probability vector \( \lambda_i(t) \), and generates the output \( \mu_i(t) = \mu_k \).

The \( \beta \)-type learning automaton chooses an action \( \alpha(t) = \alpha_i \in \alpha \) corresponding to the \( BE_i \) which generates the most lowest output and determines \( \mu(t) = \mu_i(t) \) as the output of the \( \beta \)-type learning automaton.

Thus, the \( \beta \)-type one performs action \( \alpha(t) \) to the environment and subsequently receives the reward \( x(t) \) corresponding to \( \alpha(t) \) as the environment response. Then the state probability vector \( \lambda_i(t) \) of the \( BE_i \) corresponding to the chosen action \( \alpha(t) = \alpha_i \) is updated by

\[ \lambda_i(t + 1) = T(\lambda_i(t), x(t)). \]

In above scheme, the \( \beta \)-type learning automaton changes its probabilistic structure in order to adjust itself to the environment in iterative manner.

(3) Reinforcement scheme

The reinforcement scheme \( T \) is described as follows.

\[ \lambda_{ik}(t+1) = c \lambda_{ik} x'(t) (t) \{ \mu_k(1-\mu_k) \}^{1-x'(t)} \gamma(k = 1, 2, \ldots, n) \]

where \( c \) is the normalizing constant; \( \gamma \) is the parameter which dominates the speed of convergence, \( x'(t) \) is the normalized environment response which lies in the interval \([0,1]\) and is defined by

\[ x'(t) = \frac{x(t) - x}{\bar{x} - x}. \]

Particularly when \( \gamma \) is equal to 1 the scheme is the same form as the Bayesian learning scheme.

Here, let \( c_i \) be the expected reward under an action \( \alpha_i \in \alpha \) is defined by

\[ c_i = E[x(t)|\alpha(t) = \alpha_i] = \sum_{j=1}^{n} p_{ij} x_j. \]

The value \( c_i \) is the evaluation of the action \( \alpha_i \) and it is assumed that a unique minimum of \( c_i(i = 1, 2, \ldots, r) \) exists. The ultimate goal of the learning automaton is to find the action that produces the most lowest expected penalty in iterative manner under the unknown random environment.

6 \( \beta \)-BGR Algorithm

In this paper, a novel geographic routing protocol, the \( \beta \)-BGR, for 3-D WSNs with \( \beta \)-type learning automata is proposed. First, it is assumed that we utilize the angle \( \theta \) sector model as the forwarding area.

As we mentioned in Chapter 4, the 3-D BGR has low performance about some criteria for routing due to fails which are caused by recovery attempts of the forwarding area. In 2009, we proposed a new routing protocol(We termed it "the improved BGR") with heuristic search. In the improved BGR, the initial angle parameter \( \theta \) of each sensor node’s forwarding area (the angle \( \theta \) sector model) is calculated by distance to the destination[10].

The parameter \( \theta \) of the Improved BGR is defined as follows:

\[ \theta = \frac{360}{h+1} + 180[\circ], \quad h = \left\lfloor \frac{d}{r'} \right\rfloor \]

(2)

Here, \( d \) is the distance of the forwarding sensor node and the destination sensor node, \( r' \) is radii of transmission area of the forwarding sensor node (See Figure 5).

Figure 5: Parameter \( \theta \) in the Improved BGR

Compared with the BGR, though the improved BGR has improved the rate in average packet delivery ratio, it hasn’t improved the properties in average hop count and average delivery time. The cause of these results is non-uniform sensor node density of WSNs. Therefore, we introduce the \( \beta \)-type learning automata to the BGR,
which can estimate the sensor node density around the forwarding sensor node in trial-and-error iterative manner.

\[
x(t) = \begin{cases} 
    \frac{1}{240} & \text{if recovery process is started} \\
    \frac{\theta_{60}}{240} & \text{otherwise}
\end{cases}
\]  

(3)

In general, the sensor node density is different depending on the spatial directions from the forwarder sensor node to destination sensor node. Therefore, the direction to the destination sensor node is classified into eight ranges of entire periphery of the forwarding node, then a learning automaton is associated with each range in which two or more actions are available (See Figure 6).

In the forwarding sensor node, each learning automaton coordinate adaptively the angle parameter \(\theta\) of forwarding area in the classified range. Furthermore, each learning automaton has the action set \(\alpha = \{60^\circ, 120^\circ, 180^\circ, 240^\circ\} (r = 4)\) and will choose an action \(\alpha(t) \in \alpha(t = 0, 1, 2, \cdots)\) as the angle parameter \(\theta\) of forwarding area. For example, the learning automaton determines the angle parameter \(\theta\) from among the candidates of the action set \(\alpha\) when time is \(t\).

If the recovery process is started, the learning automaton receives the environment response \(x(t) = 1\) as means of penalty, otherwise it receives \(x(t) = \frac{\theta_{60}}{240}\). The learning automaton estimates the expected sensor node density in the classified range and becomes to choose the optimal action from its action set \(\alpha\) almost surely (a.s.) when time goes infinity.

7 Experiments

7.1 Simulation Results

Simulation experiments have been conducted using the model in Chap. 6 to investigate the performance of the BGR, the improved BGR and \(\beta\)-BGR protocols under various conditions. The experiments were run with 150 sensor nodes and radii \(r\) of transmission area were set to 40[m] and the sensor nodes were randomly distributed in the Spherical space, which has radii \(R\). Here, the Spherical space radii \(R\) were varied from 40 to 200[m].

Furthermore, Max_Delay and short addition delay were set to 0.5 [s] and 0.05 [s], respectively. Then, a series of communication experiments were run between any two-sensor nodes in the WSN (there are 150 \(\times\) 149 possible pattern combinations) and each value represents the average of 10 simulation runs.

Figure 7 shows the average packet delivery ratio, which demonstrates the packet successful delivery rate from the forwarding sensor to destination sensor node. This result shows that the \(\beta\)-BGR and the improved BGR perform better than the BGR. Furthermore, X-axis means the radii \(R\) of the Spherical space, which were varied from 40 to 200[m]. Note that if the radii are high, the sensor node density in the Spherical space becomes low. On the other hand, if the radii \(R\) are low, sensor node density becomes high.

Figure 8 shows the average recovery number, which indicates the number of recovery attempts in the recovery process. This result shows that the \(\beta\)-BGR performs better than the BGR, too.

Figure 9 shows the average packet number, which demonstrates the total amount of message packets that sent by any sensor nodes. In fact, the power consumption in WSNs is considered to be determined by the total amount of message packets. This result shows that the \(\beta\)-BGR and the BGR perform better than the improved BGR and they have very close characteristics.
Strictly speaking, the characteristic of the β-BGR deteriorates only slightly when the radii are over 110[m]. However, considering that the β-BGR’s average packet delivery ratio is much superior to the BGR’s over 10[%](See Figure 7), the β-BGR’s average packet number per one successful delivery (transmission) performs better than the BGR’s. Therefore, the characteristic of the β-BGR is considered to be equal to or superior than the characteristic of the BGR.

7.2 Discussion
In both Figure 7 and Figure 8, the β-BGR improved the performance of the average packet delivery ratio and the average packet deliver time compared with the BGR.

The cause of these results is that the β-BGR improves the average recovery number(See Figure 8) by using β-type learning automata. Furthermore, in Figure 9, the average packet number indicates power consumption. Although the β-BGR’s result is bit worse than the BGR’s, they have very close characteristics. Since the results of packet number were measured only about successfully delivered packets, it can be judged that the β-BGR has better characteristics than the BGR.

In addition, even in comparison with the improved BGR, the β-BGR improved the average recovery number and the average packet number (the power consumption). Since real-time transmission requirements, energy minimization and performance optimization are very important issues in WSNs design, the β-BGR is considered to be more ideal than other protocols.

8 Conclusion
In this research, the efficiency of β-BGR was shown through some simulation results. The β-BGR employs the estimated sensor node density information by using β-type learning automata. Compared with the BGR and the improved BGR, the β-BGR achieved well balanced performance under some simulation results.

However, we don’t consider about both computational load and memory footprint of the β-BGR protocol.

Therefore, this results lead us to analyze our protocol from both points of view of practicality and theoretical explanation.

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References


