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Topological Information Based Reliable Routing Scheme for Ad Hoc Networks

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Abstract: Generally in ad hoc it is necessary for one mobile host to enlist the aid of others in forwarding a packet to its destination. In a fast changing ad hoc network, the routing tables will be out of data on a regular basis. Current routing algorithms are not adequate to tackle this problem. This study focuses on the use of topological information for routing in ad hoc network. The approach is to use topological information to train the Artificial Neural Network (ANN) for identifying the various subnets. Once the subnets are identified another ANN is used to elect the backbone node. This collection of backbone nodes forms the backbone network. A combination of AODV and DSDV protocols were used on the backbone network and on the local subnet for performance analysis. The AODV-DSDV protocols achieved a better delivery fraction and end-to-end delay than by using AODV alone. Implementation was carried out by using NS2.

Key words: Ad hoc networks, network topology, ad-hoc routing protocols, artificial neural network

INTRODUCTION

There has been a growing general interest in infrastructure-less or ad-hoc wireless networks recently as evidenced by the introduction of Mobile Ad-hoc Network (MANET). A working group has been established within the Internet Engineering Task Force (IETF), whose charter is to address IP routing in ad-hoc networks (Hayes, 1999).

MANET is an autonomous system of mobile hosts connected by wireless links, the union of which can be compared to an arbitrary graph. The routers are allowed to move randomly and can organize themselves arbitrarily; hence the network's wireless topology may change rapidly and unpredictably. Such a network may operate in a standalone fashion, or may be connected to the larger fixed network, viz., internet (manet-charter, www.ietf.org).

Ad-hoc networks are suited for use in situations where infrastructure is either not available, not trusted or should not be relied on in times of emergency. A few examples include: military soldiers in the field; sensors scattered throughout a city for biological detection; an infrastructure-less network of notebook computers in a conference or campus setting; the forestry or lumber industry; rare animal tracking; space exploration; undersea operations and temporary offices such as campaign headquarters (Ramanathan *et al*., 2002).

The field of ad-hoc network is growing and challenging and there are still many challenges that are required to be met. One of the biggest challenge is routing-how to relay data packets from one node to other and how to do it in efficient and robust way. A number of ad-hoc network routing protocols (Reactive, Proactive) (Hass and Tabrizi, 1998) with various design choices have been proposed like Temporally-Ordered Routing Algorithm (TORA) (Park and Corson, 1997), Destination-Sequence Distance Vector (DSDV) (Perkins and Watson, 1994), Ad-hoc On-Demand Distance vector (AODV) (Das *et al*., 2002), Wireless Routing Protocol (WRP) (Murthy *et al*., 1995) and Dynamic Source Routing (DSR) (Johnson *et al*., 2002) etc. Current Routing Algorithms are not adequate to tackle the increasing complexity of such networks and it is not clear that any particular algorithm or class of algorithm is the best for all scenarios. Each protocol has definite advantages and disadvantages and is well suited for certain situations (Royer *et al*., 1999).

In fast changing networks where it is not possible to collect routing data from whole network because new nodes and links can appear or disappear at different time scales, the routing tables can be out of date regularly. This could mean traffic loss. It is possible to deliver data even without the knowledge of the routing table, for example by flooding (Park and Corson, 1998). Usually this technique uses a disproportional amount of network resources just to keep the network traffic flowing.

Recent research by Adamic *et al.* (2001) showed that data traffic can be delivered efficiently to destinations even if routing tables are not available just by exploiting some local topological knowledge of the network (in this case the probability distribution of the links).

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Another recent research by Ali *et al.* (2003) deals with a neural network based approach that different network topological patterns can be differentiated by using their eigen values and adjacency matrix. Research by Mujica *et al.* (2005) evaluates a self-organizing routing protocol for ad hoc network, called NEUron Routing Algorithm (NEURAL). NEURAL uses a 2-hop acknowledgment mechanism to monitor the local information in order to be used for route selection method, classification procedures and learning algorithms.

In this study, we approach the problem of routing by looking into the topological properties of the nodes in the network. An ANN model has been used to identify the subnets using the topological information and another ANN model is used to elect the backbone nodes in the local subnets that form the backbone network. Routing protocols are used in the local subnets and in the backbone network for communication. This approach can be used to improve the performance of an ad-hoc network when the routing information is lost or obsolete and instead of propagating the information update of whole routing table, which is time consuming use the local topological information for routing.

WHAT IS ARTIFICIAL NEURAL NETWORK?

Artificial Neural Networks are a computational metaphor inspired by studies of the brain and nervous system in biological organisms. They are highly idealized mathematical models of how we understand the essence of these nervous systems. The basic characteristics of a neural network are

- It consists of many simple processing units, called neurons that perform a local computation on their input to produce an output.
- Many weighted neuron interconnections encode the knowledge of the network.
- The network has a learning algorithm that lets it automatically develop internal representations.

One of the most important properties of ANN is its ability to generalize which means that ANN can generate a satisfactory set of outputs from inputs that are not used during its training process (Rumelhart *et al.*, 1986).

GENERAL ARCHITECTURE FOR OUR ROUTING MODEL

Routing is critical to effectively and efficiently operate an ad hoc network. This study presents a new routing scheme for an ad hoc network using neural network. Here mobile nodes are grouped into subnets, backbone nodes are elected in the subnets to form backbone network and two independent routing protocols are applied, one in the backbone network and the other one in the local subnets. This scheme is quite similar Xu and Gerla (2002), but the difference is the use of ANN for grouping mobile nodes into different subnets and backbone node election. In order to dynamically identify and maintain the local subnets because of node mobility, the use of neural network for subnet identification is the natural choice. After identification of the subnets we do the election process for backbone node. This election process is done with the help of neural network. The architecture for our routing scheme is shown in Fig. 1.

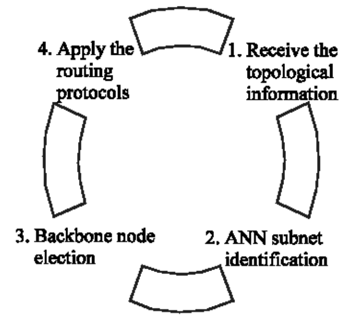

Fig. 1: Architecture of the new routing scheme

Whenever the nodes want to communicate, the source node attaches the backbone node address of its subnet to the data packet. If the destination node is in the local subnet it will be routed by using the routing protocol used in the local subnet and if the destination is in some other subnet, then the local backbone node will route the data packet to the destination subnet with the help of the routing protocol used in the backbone network. Generally, even same or different routing protocols can be used in the local subnets and in the backbone network.

COLLECTING THE TOPOLOGICAL INFORMATION

The Global Positioning System (GPS) is a satellite-based navigation system made up of a network of 24 satellites placed into orbit by the US Department of Defense. GPS was originally intended for military applications, but in the 1980s, the government made the system available for civilian use. GPS works in any weather conditions, anywhere in the world, 24 h a day. There are no subscription fees or setup charges to use GPS.

GPS satellites circle the earth twice a day in a very precise orbit and transmit signal information to earth. GPS receivers take this information and use triangulation to calculate the user's exact location. A GPS receiver must be locked on to the signal of at least three satellites to

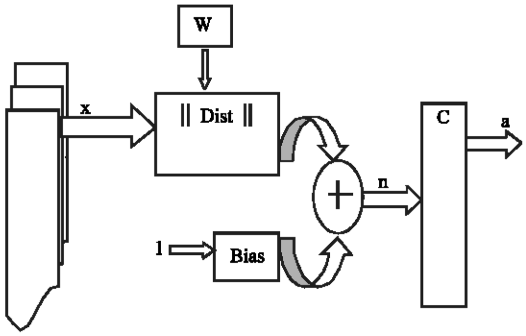

Fig. 2: ANN for identifying the various subnets

calculate a 2D position (latitude and longitude) and track movement. With four or more satellites in view, the receiver can determine the user's 3D position (latitude, longitude and altitude). Once the user's position has been determined the information's are transferred to the ANN for further processing.

THE ANN MODEL FOR SUBNET IDENTIFICATION

Neural Networks have been applied for solving the wide variety of problems such as storing and recalling data or patterns, classifying patterns, performing general mappings from input patterns to output patterns, grouping similar patterns, or finding solutions to constrained optimization problems etc (Fausett, 1994).

The ANN model for classifying the different subnets is shown in the Fig. 2.

This neural network learns to classify input vector $x = (x_1, x_2, \ldots\ldots\ldots, x_m)^T$ according to how they are grouped in the input space as $y_i = \sum_{j=1}^{M} w_{ij}x_j$, where w_{ij} is the (i, j)th element of the weight matrix W, connecting j input to the ith unit.

Let i = k be the unit in the feedback layer such that $y_k = \max_i (y_i)$ then $W_k^T x \geq W_i^T x$ for all i. A straight forward implementation of the weight adjustment is to make $\Delta w_{kj} = \eta (x_j - w_{kj})$

So that

$$\begin{aligned} w_k (m+1) &= w_k (m) + \Delta w_k (m) \\ &= w_k(m) + \eta(x - w_k(m)) \end{aligned}$$

ELECTION OF BACKBONE NODES

In the earlier methods such as the one in (Xu and Gerla, 2002), the backbone nodes are pre-assigned and then scattered around the terrain. But, here in our method after identification of the different subnets an election process with the help of an ANN will start. The winners in the individual subnets will be called as backbone nodes and the network among them will be called as backbone network.

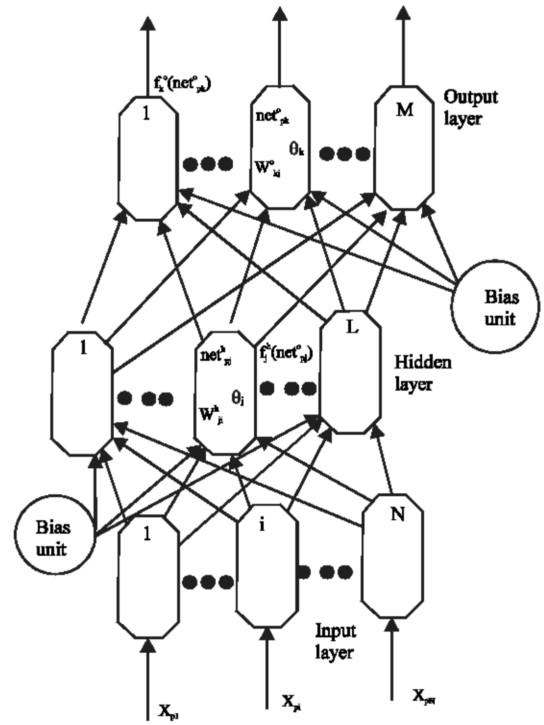

Fig. 3: ANN for backbone network

The node with highest reliability will be selected as backbone node. The ANN will be provided with reliability of the nodes as input. The reliability of the nodes are calculated as follows:

$$R_N = r_{c_1} * r_{c_2}$$

where, c_1 is the nodes hardware and c_2 is the battery of the node. The values of r_{c_1} and r_{c_2} depends upon various constraints and also $0 \leq r_{c_1}, r_{c_2} < 1$.

The ANN model for the election process is shown in the Fig. 3.

An input vector, $X_p = (x_{p1}, x_{p2}, \ldots\ldots, x_{pN})^T$, is applied to the input layer of the network. The input units distribute the values to the hidden-layer units. The net input to the jth hidden unit is

$$net_{pj}^h = \sum_{i=1}^{N} w_{ji}^h x_{pi} + \theta_j^h$$

where, w^h_{ji} is the weight on the connection from the ith input unit, θ^h_j is the bias term. The "h" superscript refers

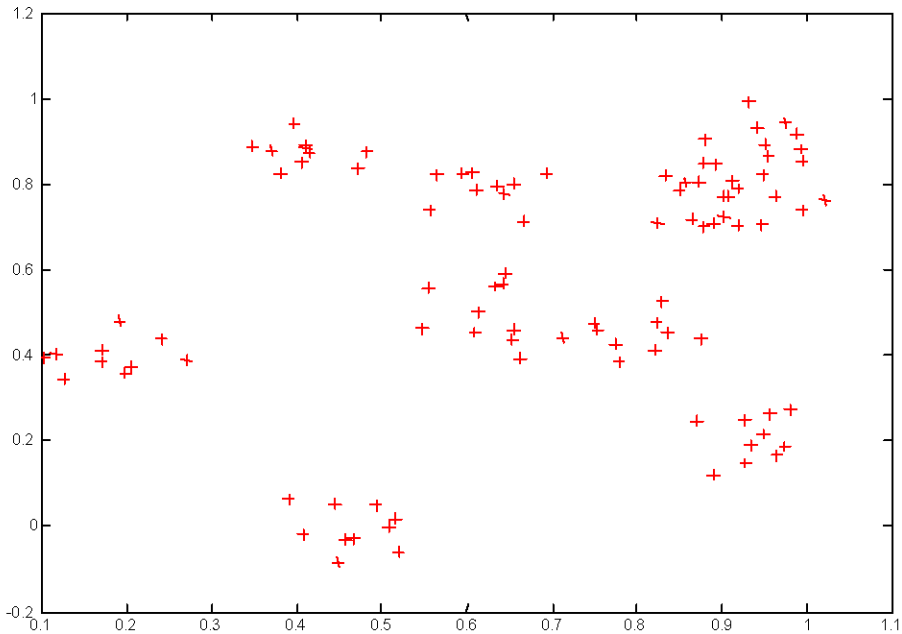

Fig. 4: Location of the nodes

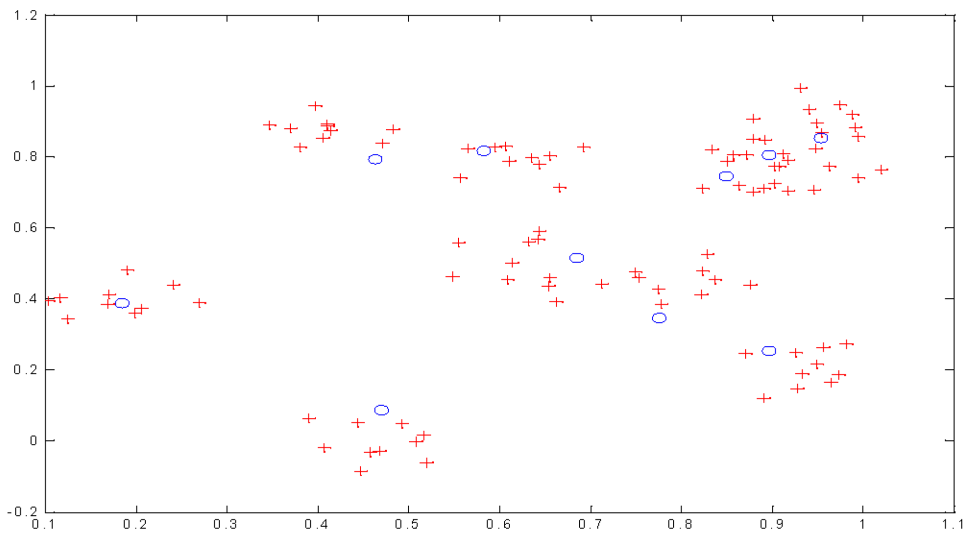

Fig. 5: Classification of different substances

to quantities on the hidden layer. Assume that the activation of this node is equal to the net input, then the output of this node is

$$i_{pj} = f_j^h(net_{pj}^h)$$

The equations for the output node are

$$net_{pk}^o = \sum_{j=1}^{L} w_{kj}^o i_{pj} + \theta_k^o$$

$$o_{pk} = f_k^o(net_{pk}^o)$$

where, the "o" superscript refers to quantities on the output layer.

APPLYING ROUTING PROTOCOLS

With the help of this routing scheme, the small size subnets available in the large scale network is identified using the ANN model and then another ANN is used to elect the backbone nodes in each subnet to form the backbone network. The ANN's are discussed in the previous two sections. Separate routing protocols are used within the subnets and across the subnets. All nodes in the same local subnet including the backbone node run the same routing protocol limited within the subnet. Backbone node, in addition, run another routing protocol in the backbone network and are in charge of routing data packets to destinations outside the local subnets.

In this study the use of DSDV protocol in the local subnet and the use of AODV protocol in the backbone network are preferred over the use of AODV protocol in both the local subnets and the backbone network.

IMPLEMENTATION

Three phases are used to implement the new routing scheme. The first phase is used to know how artificial another artificial neural network is used to identify the different subnets, the second phase uses neural network to elect the backbone node and the final phase applies the routing protocols in the local subnets and the backbone network.

Phase1: Subnet identification: In order to implement this phase, the Artificial Neural Network model given in Fig. 2 is used. For the location of mobile node random sets of clustered data points were generated. These data points are plotted in Fig. 4.

After the location of nodes is known, the ANN model should be able to identify the subnets. The ANN model classified these points into natural classes. After training the network for about seven epochs the neural network identified the subnets as shown in Fig. 5.

Phase 2: Backbone node election: After the identification of the different subnets the ANN model given in Fig. 3 is used to elect the backbone nodes in the different identified subnets. The following graph shows the accuracy of the ANN model. Fig. 6 shows the total squared error for the election process using the input as reliability of the nodes.

From Fig. 6, it can be seen that the sum of squared error suddenly drops down after first epoch and then after third epoch of training. It means that the ANN elects the backbone nodes very quickly.

Phase 3: Applying routing protocols: In this section NS2, a network simulator is used to apply the routing protocols and compare the results. A large scale network of

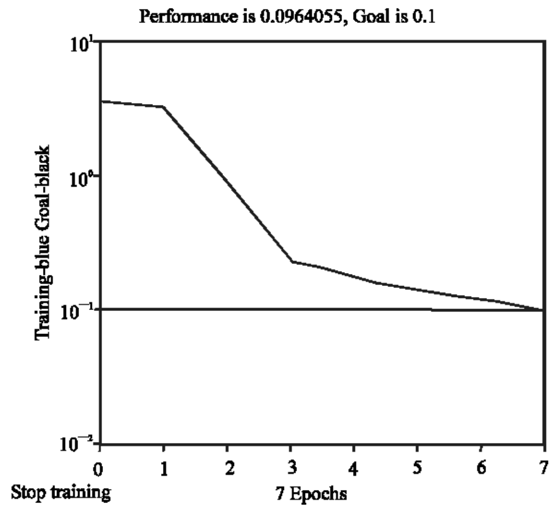

Fig. 6: Squared error

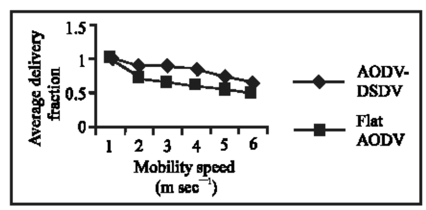

Fig. 7: Average delivery fraction

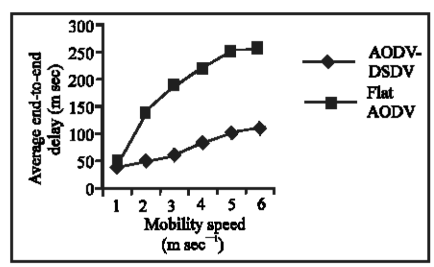

Fig. 8: End-to-End delay

1000 mobile nodes is deployed. The terrain size is as large as 3200×3200 m. Each mobile node has an IEEE 802.11 wireless radio with transmission range as 200 m. The DCF mode of IEEE 802.11 is used and channel bandwidth is set to 2M, following the standard. Node mobility model is random waypoint mobility Rumelhart *et al.* (1998). Traffic sources are 30 CBR (Constant Bit Rate). About 100 subnets are identified and 100 backbone nodes are elected during the simulation. Source-Destination pairs are randomly selected throughout the network. Data packet size is fixed as 512 bytes. Packet sending rate is 2 packets/sec. The pause time is kept as 30 sec and the mobility speed is varied to compare the performance.

From Fig. 7 and 8, it can be seen that the AODV-DSDV protocols achieve a better delivery fraction and end-to-end delay than Flat AODV. The Long end-to-end delay of Flat AODV is due to the nature that AODV has to delay data packets while finding the available route.

CONCLUSIONS

This study approaches the problem of routing in ad hoc network from a new angle by looking into the topological information of a network. The results show that ANN was able to identify the various subnets properly and also it shows that how quickly the ANN elects the backbone network. Analysis results shows that the AODV-DSDV protocols achieved a better delivery fraction and end-to-end delay than by using AODV alone. Thus this new routing scheme will be the next step towards the use of topological information for reliable routing in ad-hoc network.

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