2008 International Symposium on Nonlinear Theory and its Applications
NOLTA'08, Budapest, Hungary, September 7-10, 2008

Grouping of Mobile Nodes in MANET Using an ART Network

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Abstract—A mobile ad-hoc network (MANET) is a technology to form a network autonomously with no infrastructure. This technology enables the establishment of impromptu networks for communication between mobile nodes with communication devices in disaster zones, and other various circumstances. MANET has great potential as a means of realizing a new communication environment not available through conventional networks. In the MANET, each mobile node not only operates as a communication node but also as a relay node to maintain the communication environment under a network topology that changes dynamically. In this paper, we propose a grouping scheme of mobile nodes in MANET using an adaptive resonance theory network. Through numerical simulations, we show effectiveness of our method and discuss its development potential.

1. Introduction

Various communication services, such as inter-vehicle communications, which are communication services in intelligent transport systems, natural environmental monitoring using sensor networks, and emergent communications between mobile nodes in such the case of emergency as disaster have been provided. Recently, as a means of realizing communication services stated above, a mobile ad-hoc network (MANET) has been intensively researched with great interests [1]-[4]. MANET, which is a network formed autonomously with no infrastructure, has great potential as a new communication form not available through conventional networks. If direct communication is not possible between communication nodes far away from each other, MANET realizes information exchange by multi-hop communication using intermediate nodes. Each mobile node not only operates as a communication node but also as a relay node to maintain the information communication environment. This technology enables the establishment of impromptu communication networks for between mobile nodes with communication devices in disaster zones and other various circumstances with no infrastructure. However, it is not easy to maintain the information communication environment under a network topology that changes dynamically.

In this paper, we propose a grouping scheme of mobile nodes in MANET using an adaptive resonance theory network [5]-[8]. By using the proposed scheme, the distribution status (and its change) of nodes in MANET can be easily grasped in a base station. The grouping information obtained by the proposed scheme can be effectively used for maintaining the MANET communication environment. The rest of the paper is organized as follows. Section 2 describes the proposed grouping scheme. Section 3 presents the results of simulation experiments verifying the effectiveness of the proposed scheme. Finally, Section 4 concludes this study with a summary and plans for future work.

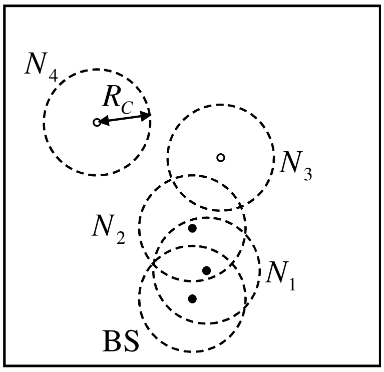


Figure 1: A communication model of mobile nodes and a base station (BS) in MANET.

2. A Grouping Scheme of Mobile Nodes in MANET

In this section, we explain the proposed grouping scheme of mobile nodes in MANET using a radial basis adaptive resonance theory (RBART) networks[5]. Fig. 1 shows the communication model of mobile nodes and a base station (BS) in MANET. Each mobile node which forms MANET exists in an area on a two dimensional plane. The BS is allocated at a point in the area, and observes the positional information of mobile nodes which can communicate to the BS. The BS can identify each mobile node. Each mobile node has communication range R_C, and can communicate to the other mobile nodes and BS if they exist in the communication range. Each mobile node not only operates as a communication node but also as a relay node to maintain the information communication environment. If a mobile node N_i has a communication route to the BS, the positional information of N_i can be observed by the BS. Otherwise, the positional information of

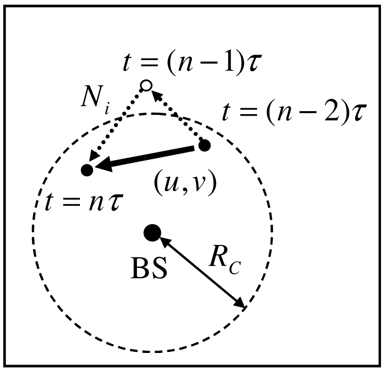


Figure 2: Calculation of the mobility information. In this example, the mobility information of N_i, $(u_i(n\tau), v_i(n\tau))$, is calculated by the positional information at $t = n\tau$ and $t = (n-2)\tau$.

N_i can not be observed by the BS. In the figure, the BS can observe the positional information of N_1 and N_2, but can not observe the positional information of N_3 and N_4.

The BS calculates the mobility information of the observed mobile nodes using their positional information as shown in Fig. 2. Let $(x_i(n\tau), y_i(n\tau))$ be the position of N_i at the time $t = n\tau$, where n is a nonnegative integer and τ is a constant time interval. And let $(x_i((n-m)\tau), y_i((n-m)\tau))$ be the the position of N_i at the time $t = (n-m)\tau$, where m is a positive integer and $(n-m)\tau$ is the most recently observed time. In the figure, N_i is observed at $t = (n-2)\tau$, but is not observed at $t = (n-1)\tau$. In this case, $(n-2)\tau$ is the most recently observed time for N_i at $t = n\tau$. Then, the following mobility information of N_i is calculated.

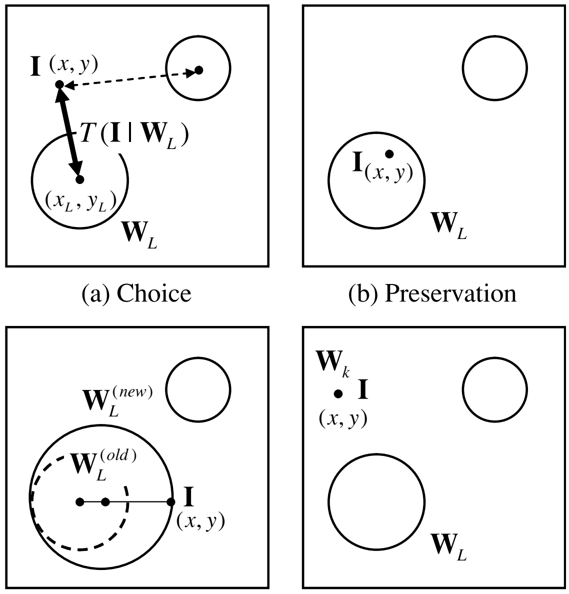
$$\begin{aligned} u_i(n\tau) &= \frac{x_i(n\tau) - x_i((n-m)\tau)}{m\tau} \\ v_i(n\tau) &= \frac{y_i(n\tau) - y_i((n-m)\tau)}{m\tau} \end{aligned} \tag{1}$$

In the proposed scheme, the positional information $(x_i(n\tau), y_i(n\tau))$ and mobility information $(u_i(n\tau), v_i(n\tau))$ are input to the RBART networks. Hence, the input to the RBART networks is four dimensional input vectors $(x_i(n\tau), y_i(n\tau), u_i(n\tau), v_i(n\tau))$. The RBART network has k categories, and the l-th category $\mathbf{W}_l$ has the following vector.

$$\mathbf{W}_l = (x_l, y_l, u_l, v_l, r_l, n_l), \quad l \in \{1, 2, \cdots, k\} \tag{2}$$

where (x_l, y_l) denotes the center of the category, and (u_l, v_l) denotes the mobility of the category. r_l denotes the radius of the category, and n_l denotes the number of input vectors included in the category. As a four dimensional input vector $\mathbf{I} = (x, y, u, v)$ is applied, choice functions $T(\mathbf{I}\,|\mathbf{W}_l)$ are calculated for each category. $T(\mathbf{I}\,|\mathbf{W}_l)$ is given by the following Euclidian distance between the category $\mathbf{W}_l$ and the input $\mathbf{I}$.

$$T(\mathbf{I}\,|\mathbf{W}_l) = \sqrt{(x_l - x)^2 + (y_l - y)^2} \tag{3}$$



(a) Choice (b) Preservation

(c) Learning (d) Creation

Figure 3: Basic algorithm of the radial basis adaptive resonance theory (RBART) networks.

Next, a category $\mathbf{W}_L$ having a minimum positional choice function is chose (see Fig. 3(a)).

$$T(\mathbf{I}\,|\mathbf{W}_L) = \min_l T(\mathbf{I}\,|\mathbf{W}_l). \tag{4}$$

Next, the following mobility choice function $S(\mathbf{I}\,|\mathbf{W}_L)$ is calculated.

$$S(\mathbf{I}\,|\mathbf{W}_L) = \sqrt{(u_L - u)^2 + (v_L - v)^2} \tag{5}$$

Let ρ be a positional vigilance parameter, and let φ be a mobility vigilance parameter. If the category $\mathbf{W}_L$ includes the input $\mathbf{I}$ and $S(\mathbf{I}\,|\mathbf{W}_L) \le \varphi$ is satisfied, the category $\mathbf{W}_L$ is preserved (see Fig. 3(b)). Otherwise, the category $\mathbf{W}_L$ is learned or a new category is created. If $T(\mathbf{I}\,|\mathbf{W}_L) \le \rho$ and $S(\mathbf{I}\,|\mathbf{W}_L) \le \varphi$ are satisfied, the category $\mathbf{W}_L = (x_L, y_L, u_L, v_L, r_L, n_L)$ is learned. Then, the current category $\mathbf{W}_L^{(old)}$ is updated to the following category $\mathbf{W}_L^{(new)}$ (see Fig. 3(c)).

$$\begin{aligned} x_L^{(new)} &= \frac{1}{2}\left(r_L^{(old)}\left(\frac{x_L^{(old)} - x}{T(\mathbf{I}\,|\mathbf{W}_L)}\right) + x_L^{(old)} + x\right) \\ y_L^{(new)} &= \frac{1}{2}\left(r_L^{(old)}\left(\frac{y_L^{(old)} - y}{T(\mathbf{I}\,|\mathbf{W}_L)}\right) + y_L^{(old)} + y\right) \\ r_L^{(new)} &= \sqrt{(x_L^{(new)} - x)^2 + (y_L^{(new)} - y)^2} \\ u_L^{(new)} &= \frac{n_L^{(old)} \cdot u_L^{(old)} + u}{n_L^{(old)} + 1} \\ v_L^{(new)} &= \frac{n_L^{(old)} \cdot v_L^{(old)} + v}{n_L^{(old)} + 1} \\ n_L^{(new)} &= n_L^{(old)} + 1 \end{aligned} \tag{6}$$

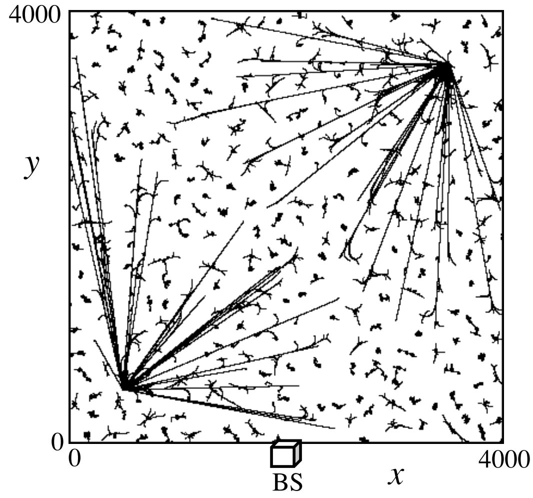


Figure 4: A model of mobile nodes.

Note that (u_L, v_L) corresponds to the averaged mobility of mobile nodes included in the category $\boldsymbol{W}_L$. If the input $\mathbf{I}$ does not satisfy both the above preservation and learning conditions, let $k = k + 1$ and a new category is created (see Fig. 3(d)).

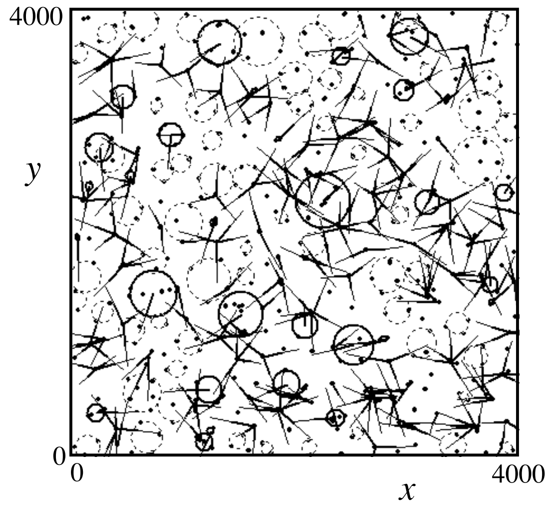
$$\mathbf{W}_k = (x, y, u, v, 0, 1). \tag{7}$$

For all the input vectors at $t = n\tau$, the above procedure is applied. As the first input is applied, no category exist. Then, the new category must be created.

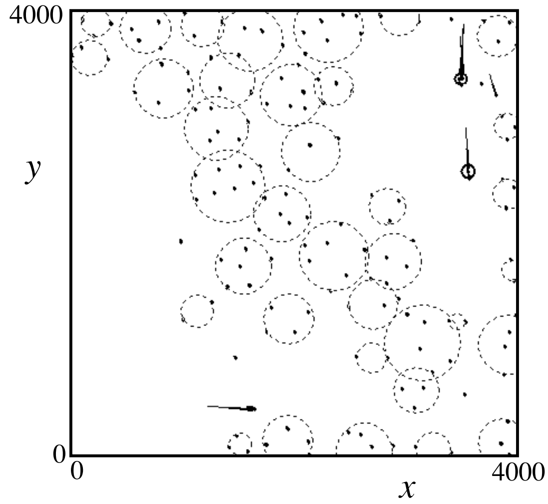
In this paper, grouping of mobile nodes is carried out based on the positional information and mobility information using the RBART networks. Using such a grouping in every constant time interval τ, the distribution status (and its change) of nodes in MANET can be easily grasped in the BS.

3. Numerical Simulations

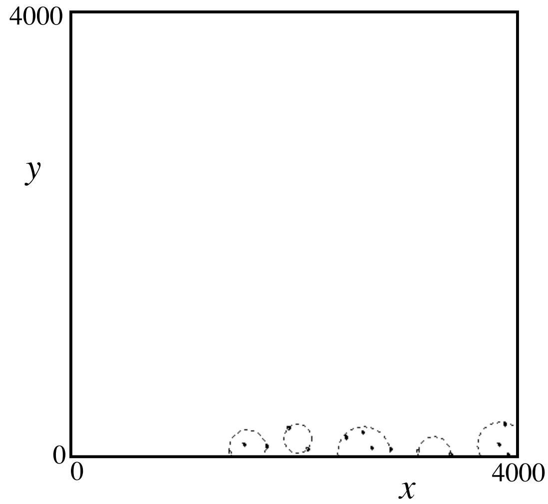
We perform numerical simulations for a model of mobile nodes as shown in Fig. 4. 1000 mobile nodes are allocated as random initial positions in the area (x, y) where $0 \leq x \leq 4000$ and $0 \leq y \leq 4000$. In the mobile nodes, 50 (5%) mobile nodes are *Lead* nodes and 950 (95%) mobile nodes are *Follow* mobile nodes. Two target points $(500, 500)$, $(3500, 3500)$ exist in the area. *Lead* mobile nodes choose the nearest target point from each position, and move to the target point directly. *Follow* mobile nodes has a visual range whose radius is $R_V = 100$. If *Lead* mobile nodes exist in the visual range, the *Follow* mobile node move to the centrobaric direction of the found *Lead* mobile nodes. If no *Lead* mobile node exist and the other *Follow* mobile nodes exist in the visual range, the *Follow* mobile node move to the centrobaric direction of the found *Follow* mobile nodes. If any other mobile nodes does not exist in the visual range, the *Follow* mobile node move to the random direction. The mobility of each mobile node



(a) $t = 100$ ($k = 596$)



(b) $t = 2100$ ($k = 50$)



(c) $t = 3400$ ($k = 5$)

Figure 5: The results of grouping using radial basis ART networks ($\rho = 400$, $\varphi = 0.5$). k denotes a number of created categories.

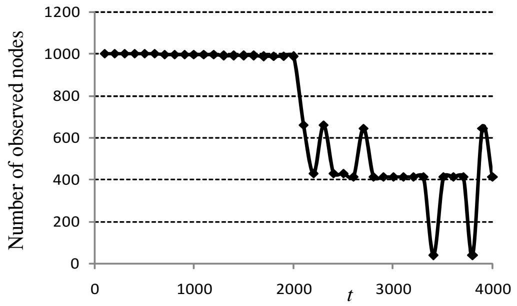


Figure 6: A transition of observable mobile nodes.

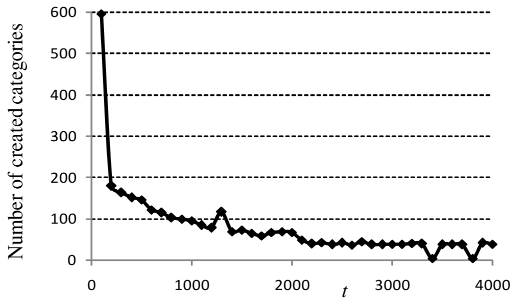


Figure 7: A transition of created categories.

is 1 per unit time. Fig. 4 shows trajectories of each mobile node from $t = 0$ to $t = 4000$. The BS is allocated at $(2000, 0)$, and observes the positional information of each mobile node by a constant time interval $\tau = 100$. The communication range of each mobile node and BS is set to $R_C = 400$. The positional vigilance parameter is set to $\rho = 400$, and the mobility vigilance parameter is set to $\varphi = 0.5$.

Fig. 5 shows results for grouping of observable mobile nodes using the RBART network. Let *Rest* category be the category where $V_l \leq \varphi$ is satisfied, and let *Move* category be the category where $V_l > \varphi$ is satisfied, where

$$V_l = \sqrt{u_l^2 + v_l^2}.$$

In the figure, the solid circles and solid lines denote *Move* categories and their moving directions, respectively. The dashed lines denote *Rest* categories. Using the proposed scheme, we can visually grasp node distribution, its status such as *Move* or *Rest*, and their transition.

Fig. 6 shows a transition of observable mobile nodes. For $t \leq 2000$, almost mobile nodes can be observed by the BS. For $t > 2000$, the number of the observable mobile nodes decreases. Fig. 7 shows a transition of created categories. At $t = 100$, many categories are created (see Fig. 5(a)). Because, *Follow* mobile nodes move to various directions in the initial state. Therefore, they are classified into the different categories due to the mobility vigilance parameter. There exist the mobile nodes which relay the positional information from many other mobile nodes. If their mobile nodes can not relay the positional information due to their movements, many mobile nodes can not be observed in the BS. From such a reason, at $t = 3400$ and $t = 3800$, the number of observable mobile nodes decrease significantly and the number of the created categories also decreases significantly (see Fig. 5(c)). Using the proposed scheme, these unstable relaying mobile nodes can be easily grasped.

4. Conclusions

This paper has proposed a grouping scheme of mobile nodes in MANET using an adaptive resonance theory network. Through simulation experiment, it has been confirmed that the distribution status (and its change) of nodes in MANET can be easily grasped by gathering location information (and mobility information) of each node in a base station periodically. For future study, we have the following two studies in mind.
1) Evaluation by more detailed simulation experiments in various situations. 2) Proposal on practical use of grouping information obtained by the proposed scheme to maintain the MANET communication environment.

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