LETTER

A Localization Method Based on Partial Correlation Analysis for Dynamic Wireless Network

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SUMMARY Recent localization methods for wireless networks cannot be applied to dynamic networks with unknown topology. To solve this problem, we propose a localization method based on partial correlation analysis in this paper. We evaluate our proposed localization method in terms of accuracy, which shows that our proposed method can achieve high accuracy localization for dynamic networks with unknown topology.

key words: *wireless communication, localization, partial correlation analysis*

1. Introduction

In wireless networks, the location information of a node is very important in terms of search and rescue, target tracking, and data collection. A method called range-free localization or range-based localization has been proposed as a localization method for wireless networks [1], [2]. However, these methods require knowing which node is within the communication radius of which node (i.e., “who is within the communication range of whom” [3]), and can only be applied to networks with known topology. In addition, even if the topology is known, it cannot be applied to dynamic networks because the topology will not be known when it changes. In order to solve the problem mentioned above, we propose a correlation analysis based localization method that can be applied to dynamic networks with unknown topology. In our proposed method, the location is calculated based on the network topology that is derived using correlation analysis.

2. Proposed Method

In this paper, we focus on a network with N_s sensor nodes and N_a anchor nodes. Each sensor node i sends data packets by flooding to all other nodes. Each anchor node k knows its own location coordinates $(x_a^k,\ y_a^k)$ and the coordinates of the other anchor nodes, records packet time series $s(t_i^p)$ (length of packet p received from sensor node i at time t), and estimates network topology and location coordinates $(x_s^i,\ y_s^i)$ of each sensor node i. The flow of our proposed localization method is shown in Fig. 1. At the initial sate, the anchor nodes do not know the location and the coordinates of sensor nodes. Three steps are periodically executed based on correlation analysis in order to estimate the location of sensor nodes. Since the discrete packet time series $s(t_i^p)$ cannot be used for correlation analysis, the anchor node transforms $s(t_i^p)$ into a continuous time series $f_i(t)$ using kernel density estimation in the first step, which can be obtained by the following equation [4].

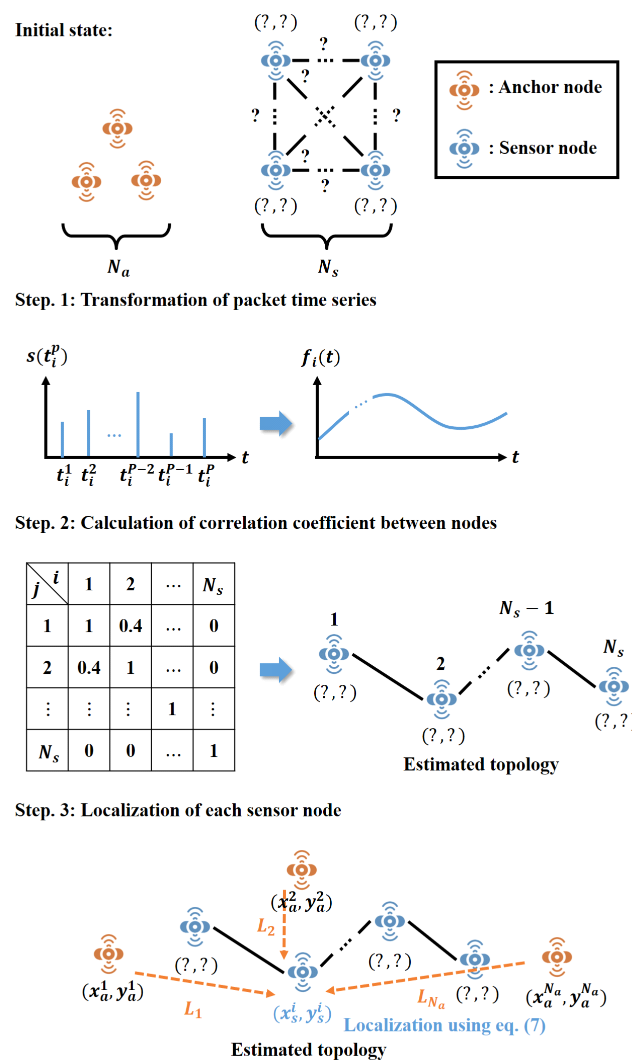

Fig. 1 Flow of the proposed localization method.

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$$f_i(t) = \frac{1}{P}\sum_{p=1}^{P} K(t - t_i^p)s(t_i^p), \quad (1)$$

$$K(t - t_i^p) = \frac{1}{2}\left(1 + \cos\frac{2\pi(t - t_i^p)}{T}\right), \quad (2)$$

where $-\frac{T}{2} \leq t - t_i^p \leq \frac{T}{2}$, P is the number of packets received from sensor node i, T is the bandwidth, and $K(t)$ is the hanning window function.

In the second step, the anchor node estimates network topology using correlation analysis. Cross correlation analysis [5] and partial correlation analysis [6] are used as correlation analysis approaches. For cross correlation analysis approach, the cross correlation coefficient ρ_{ij} between sensor nodes i and j can be derived based on continuous time series $f_i(t)$ and $f_j(t)$ as follows,

$$\rho_{ij} = \frac{\langle f_i(t) - \langle f_i(t)\rangle\rangle\langle f_j(t) - \langle f_j(t)\rangle\rangle}{\sigma_i\sigma_j}, \quad (3)$$

where $\langle * \rangle$ denotes the mean and σ denotes the standard deviation. The partial correlation coefficient γ_{ij} between sensor nodes i and j is defined as follows,

$$\gamma_{ij} = \frac{\langle e_i(t) - \langle e_i(t)\rangle\rangle\langle e_j(t) - \langle e_j(t)\rangle\rangle}{\sigma_i\sigma_j}, \quad (4)$$

where $e_i(t)$ and $e_j(t)$ are the residuals between sensor nodes, respectively, which can be derived based on the continuous time series $f_i(t)$ and $f_j(t)$ as follows,

$$f_i(t) = a_0 + \sum_{s \neq i,j}^{N_s} a_s f_s(t) + e_i(t), \quad (5)$$

$$f_j(t) = b_0 + \sum_{s \neq i,j}^{N_s} b_s f_s(t) + e_j(t), \quad (6)$$

where a_s and b_s are regression constants of sensor node s.

Based on the correlation coefficient ρ_{ij} or γ_{ij} derived by Eq. (3) or Eq. (4), the anchor node determines if sensor nodes i and j are connected. If the correlation coefficient exceeds a predefined threshold value, it is determined as "connected"; otherwise, it is determined as "not connected" [7]. This determination is executed for all combinations of sensor nodes.

In the final step, the anchor node estimates the location of all sensor nodes. In this step, the distance between anchor node k and sensor node i, i.e., L_{ki}, is firstly calculated according to the number of hops between the anchor node k and the sensor node i by using DV-hop algorithm [8]. The number of hops can be calculated from the network topology estimated in the second step. Then, the location coordinates of sensor nodes i, i.e., $(x_s^i,\ y_s^i)$ can be derived based on L_{ki} and the location coordinates of anchor nodes $(x_a^k,\ y_a^k)$ as follows,

$$\begin{cases} L_{1i} = \sqrt{(x_a^1 - x_s^i)^2 + (y_a^1 - y_s^i)^2}, \\ L_{2i} = \sqrt{(x_a^2 - x_s^i)^2 + (y_a^2 - y_s^i)^2}, \\ L_{ki} = \sqrt{(x_a^k - x_s^i)^2 + (y_a^k - y_s^i)^2}. \end{cases} \quad (7)$$

3. Performance Evaluation

3.1 Simulation Setting

Our simulation model consists of a 60 (m) × 60 (m) area with 3 anchor nodes and 9 sensor nodes. 3 anchor nodes are statically placed in a density of 1 node per 400 m^2 [9]. Any two nodes are connected through a direct (single-hop) path if they are placed in each other's communication range; otherwise, they are connected through an indirect (multi-hop) path. The network connectivity changes when nodes newly enter or completely leave the communication range of other nodes. Each sensor node communicates with other nodes by using simple flooding as a routing protocol. In this paper, we focus on the performance of one-time localization by our proposed method. The localization is performed once after data transmission of all sensor nodes completes in order to estimate final locations of sensor nodes. We use accuracy of topology estimation (%) and location error (m) as evaluation metrics, which can be derived as follows,

$$\text{Accuracy of topology estimation} = \frac{\text{Number of combinations of sensor nodes are correctly estimated}}{\text{Number of combinations of all sensor nodes}} \times 100, \quad (8)$$

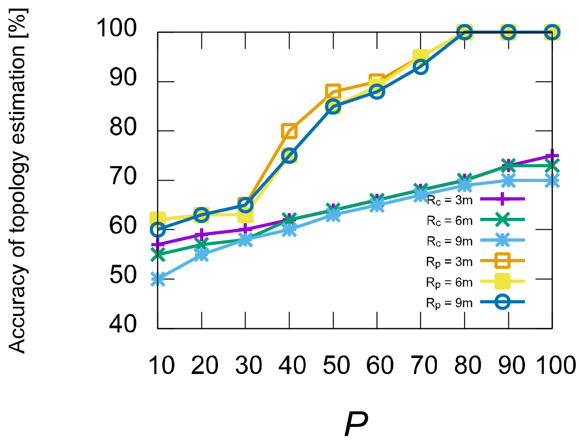
$$\text{Location error} = \frac{1}{N_s}\sum_{i=1}^{N_s}\sqrt{(X_i - x_s^i)^2 + (Y_i - y_s^i)^2}, \quad (9)$$

where $(X_i,\ Y_i)$ is the actual location coordinates of sensor node i. Note that the numerator in Eq. (8) includes not only the number of combinations of directly connected sensor nodes, but also the number of combinations of directly unconnected ones in order to evaluate the number of estimation errors due to the effect of spurious correlation or other factors. The simulation results are evaluated by100 trials.

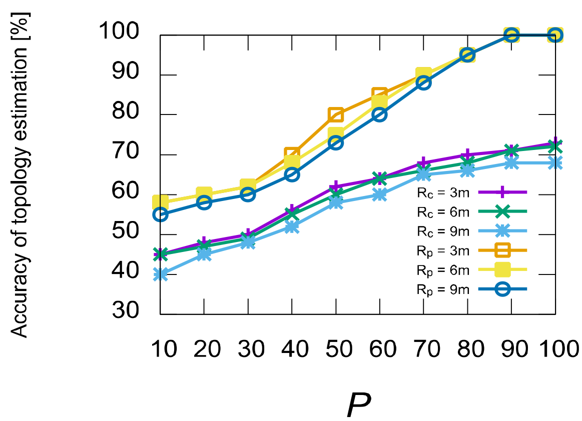
3.2 Simulation Results

Figure 2 shows the accuracy of topology estimation by cross and partial correlation analyses when P varies from 10 to 100 with $N_s = 10$ and $N_s = 20$, respectively. In the simulation, 9 sensor nodes are placed randomly. The movement ranges of each sensor node for cross correlation analysis and partial correlation analysis are denoted as R_c and R_p, respectively. All sensor nodes move randomly within R_c (m) and R_p (m) around its initial location. From Fig. 2, we can see that the partial/cross correlation analyses achieve higher estimation accuracy as P (i.e., the length of time series) increases. This result indicates that our proposed method can provide an accurate topology estimation by an appropriate setting for the length of time series. We can also see that the accuracy of topology estimation analyzed by the partial correlation is higher than that analyzed by cross correlation. The reason is that the partial correlation analysis can eliminate the effect of spurious correlation between two nodes that are not connected actually [10].

Figure 3 shows the location error of the proposed

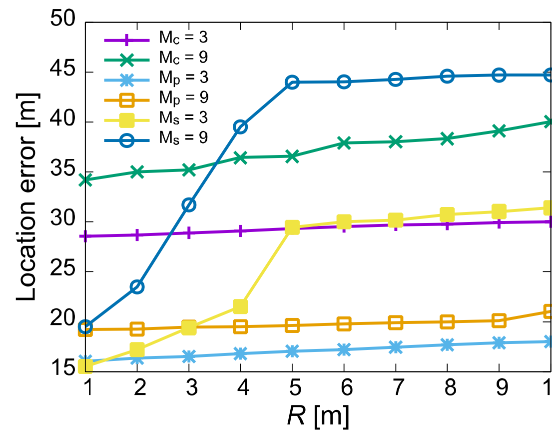


(a) N_s = 10.

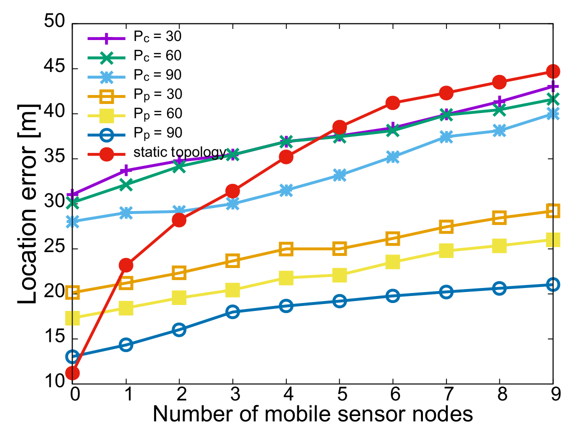


(b) N_s = 20.

Fig. 2 Comparisons of topology estimation accuracy of cross correlation and partial correlation analyses.



(a) P = 100.



(b) R = 10 (m).

Fig. 3 Location errors estimated by the conventional method, the proposed method with cross-correlation and partial correlation analyses.

method with the variational numbers of received packets and mobile sensor nodes. In the simulation, N_s is fixed at 9 while the number of mobile nodes among all sensor nodes varies. For example, when the number of mobile sensor nodes is zero, there are 9 sensor nodes and they do not move from their initial locations during the simulation period. M_c and M_p are defined as the numbers of mobile sensor nodes for cross correlation analysis and partial correlation analysis, respectively. Meanwhile, P_c and P_p are defined as the numbers of the received packets for cross correlation analysis and partial correlation analysis, respectively. To evaluate the effectiveness of our proposed method for dynamic wireless network, we also compare our proposed method to static topology method where the localization is based on static topology information which is defined as initial network connectivity among sensor nodes. M_s is the number of mobile sensor nodes for the static topology method. The mobile sensor nodes move randomly within R (m) around its initial location. From Fig. 3, we can see that our proposed method can achieve lower location error than the static topology in all cases. The reason is that localization by our proposed method is based on the topology information after the network changes, which can infer the correct location of the sensor nodes more accurately in real time.

4. Conclusion

In this paper, we proposed a localization method based on correlation analysis for dynamic networks with unknown topology. Simulation results shown the effectiveness of our proposed method in localization for dynamic networks with unknown topology. Moreover, simulation results also shown that the accuracy of topology estimation analyzed by the partial correlation is higher than that analyzed by cross correlation. We used simple flooding as a routing protocol in our experiments because of its simplicity of implementation. However, an excessive flooding of data packets may cause collision and congestion, which may induce lower accuracy of topology estimation and localization. In future work, we will apply more efficient routing protocols such as [11], [12] and evaluate the influence of them on estimation accuracy.

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