Chapter 16
Eigenvector Centrality-Based Mobile Target Tracking in Wireless Sensor Networks

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ABSTRACT

We propose an eigenvector centrality-based tracking algorithm to trace the trajectory of a mobile Radioactive Dispersal Device (RDD) in a wireless sensor network. The sink constructs an adjacency matrix in which the entry for edge (i, j) is the sum of the signal strengths reported by sensor nodes i and j in their respective neighborhoods over a sampling time period. The sink uses this adjacency matrix as the basis to determine the Eigenvector Centralities (EVC) of the vertices with respect to the radioactive signals sensed in the neighborhood. We hypothesize that sensor nodes that have a high EVC (suspect nodes) for the sampling time period are within the vicinity of the RDD within that period. We propose that the arithmetic mean (calculated by the sink) of the X and Y coordinates of the suspect sensor nodes be considered as the predicted location of the RDD at a time instant corresponding to the middle of the sampling time period. We evaluate the difference between the predicted and exact locations of the RDD trajectory over time as a function of different operating parameters.

INTRODUCTION

Wireless sensor networks (WSNs) are well-known for use in environment monitoring applications, including applications wherein a mobile target is tracked based on some characteristic signals (quantified in the form of data) emanating from the target and sensed by the sensor nodes in the vicinity. The sensor nodes forward the sensed/processed data (the level of processing depends on the application and the nature of the sensor nodes deployed) to a control center (called the sink). The sink aggregates the received data and further processes it to evolve a trajectory for the mobile target. To minimize information redundancy and conserve energy, sensor nodes form a data gathering tree (rooted at a leader node) among themselves and forward their individual data as part of an aggregated data packet along this tree. Several energy-efficient data gathering algorithms (Meghanathan, 2012) have been proposed in the literature.

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In this chapter, we envision an application of WSNs wherein a mobile radioactive dispersal device (RDD) arbitrarily moves around in the network emanating low-level radiations. Each sensor node operates within a transmission range and sensing range (sensing range is half the transmission range) and is static. As it would be hard and even erroneous to distinguish low-level radiations emanating from different sources, each sensor node is assumed to be able to obtain a cumulative strength of all the radioactive signals (including the strength of the signals emanating from the RDD, if any is moving within the sensing range of the node) sensed within its sensing range. Each sensor node is assumed to maintain a sum of the cumulative strengths of the signals detected in its sensing range over a sampling time period at the end of which the sensor nodes report their individual value for the sum of the signal strengths to the sink. The sink is assumed to know the entire topology of the WSN and could hence construct an adjacency matrix at the end of each sampling time period based on the signal strength data received from the individual sensor nodes. An entry for edge \((i, j)\) in the adjacency matrix indicates the sum of the signal strength data received from nodes \(i\) and \(j\). If the RDD is within the vicinity of a sensor node \(s\) and the majority of its neighbors during a sampling time period, then node \(s\) is a good candidate for being considered as part of the calculations for predicting the location of the RDD during this period. We use this idea as the basis for our research and propose to compute the principal eigenvector (Newman, 2010) of the adjacency matrix of signal strengths, as defined above. The entries in the principal eigenvector correspond to the eigenvector centralities (EVC) of the vertices (one EVC value per node) with respect to the strength of the signals sensed in the neighborhood for the sampling time period. Sensor nodes that were within the vicinity of the RDD are more likely to have higher EVC values compared to nodes in whose neighborhood the RDD was not present during the sampling time period. We propose that we choose the top \(x\) number of sensor nodes that have the highest EVC values (call these as suspect sensor nodes, in this chapter \(x = 5\)) and consider the arithmetic mean of the X and Y coordinates of these suspect sensor nodes as the predicted location of the RDD at a time instant corresponding to the middle of the sampling time period. We evaluate the effectiveness of the proposed scheme by calculating the distance between the predicted and exact locations of the RDD (referred to as the distance error) at time instants corresponding to the middle of the sampling time periods for the duration of the entire simulation (energy-unconstrained scenarios) or until the network gets disconnected due to the failure of one or more sensor nodes (energy-constrained scenarios). The median of these distance errors is the performance metric used to evaluate the effectiveness of the proposed tracking algorithm. We hypothesize the median distance error to be dependent on the RDD velocity, the transmission range (and in turn the sensing range) of the sensor nodes and the sampling time period. For a fixed value of these operating parameters, as the network gets depleted of the sensor nodes due to energy exhaustion, the median distance error is expected to increase. We conduct extensive simulations evaluating the median distance error as a function of the above operating parameters.

In addition to being useful for tracking a mobile radioactive device, the proposed EVC-based mobile target tracking algorithm has several other potential applications in both scientific and commercial domains. These include: the tracking of diffusion of a gas in a field (based on the concentration of the gas in the different neighborhood); tracking the spreading of a disease in a particular area over a period of time (based on the information about the number of cases reported in the neighborhood of each node); tracking the path taken by fire in a forest and deploying the fire fighters in appropriate location, based on the heat intensity reported by the fire-resistant sensor nodes (Vijayalakshmi & Muruganand, 2015).