Intelligent Approach for Data Collection in Wireless Sensor Networks

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Abstract: *In wireless sensor networks, one of most important issues is data collection from sensors to sink. Many researchers employ a mathematical formula to select the next forwarding node in the network-wide manner. We are motivated that surrounding environments for nodes are different in time and space. Because different situations of nodes are not considered for selecting the next forwarding node, the performance of data collection is degraded. In this paper, we present an intelligent approach for data collection in sensor networks. We model a nonlinear cost function for determining the next forwarder according to the input types whether inputs are correlated or uncorrelated for generating the output of the function. In our method, the correlated inputs are presented in a weighted sum with the dependent fashion but the uncoupled inputs with an independent fashion in the nonlinear function. The weights in the functions are determined to the direction in which the reliability of data collection maximizes. In the experimental section, we show that our method outperforms other conventional methods with respect to the efficiency in data collection from sensors to sink.*

Keywords: *Coupled input, decoupled input, wireless sensor network, intelligent data collection.*

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1. Introduction

In wireless sensor networks, one of main purposes is to deliver sensed data collected from multiple sensors to data collection device or sink. The wireless sensor network has been attracting much attention from many researchers in recent years [5]. The networks have a wide range of applications [11, 18]. Especially, they are useful in continuously acquiring information in inaccessible or perilous areas for some time duration. The issues on constructing sensor networks, such as the deployment of sensors and sinks and the data collection schemes of sinks from sensors, are well addressed in the literature of wireless sensor networks [1, 14].

In general, data delivery in a sensor network is based on the premise that data from sensor to sink are loss-tolerant due to the sheer amount of correlated data [19]. However, since a sink may take appropriate actions based on the information provided by sensors, the accuracy of the situation awareness is improved from reducing the data loss. To reduce the loss, many researchers employ a mathematical formula for data collection from sensors to sink in the network-wide manner. Conventional approaches [2, 10] usually model an optimal link cost function using more than one input metric in order to select next forwarding neighbor node. They determine the optimal coefficients in the cost function without considering the node surrounding environments such as the wireless propagation environment or the geographical environment. Some methods employ a nonlinear function for selecting the next forwarding node [21, 27]. However, they do not consider the input types whether inputs are correlated or uncorrelated for generating the output of the function even though the knowledge of input type can provide critical information. Because of this, their methods sometimes do not provide a meaningful performance. We are motivated that surrounding environments for sensor nodes are different in time and space and the characteristics of input types should be considered to improve the performance.

In our approach, the correlated inputs are presented in a weighted sum with the dependent fashion but the uncoupled inputs with an independent fashion in the nonlinear function. After modeling the nonlinear function, we determine the optimal weights to inputs from training the function to the direction that the reliability of data collection maximizes. In the experimental section, we show that our method outperforms other conventional methods with respect to the efficiency in data collection from sensors to sink.

The remainder of this paper is organized as follows. Section 2 presents the data collection problem from sensors to a sink in sensor networks and explains drawbacks of the related works. In section 3, we derive our nonlinear link cost function of selecting the next forwarding node. In addition, we present the training technique for selecting the optimal weights in the function. In section 4, the performance of our method is evaluated from the NS-2 based simulation results, and finally, we conclude in section 5.

2. Data Collection Problem

The data collection problem has been an active research area in a wireless sensor network where a path should be provided for a sink to collect sensed data from sensors. Previous researches for the data collection can be classified into mobile sink approach [3, 24] and relay node approach [7, 13]. In the first approach, a mobile sink must go back and forth between sensors to gather sensed data. It takes time for a mobile sink to travel into a transmission range of a sensor. In the meantime, the sink cannot collect the sensed data in time. Sensor nodes nearby a sink forward many data from other sensors to the sink, compared to the sensor nodes that are located far from the sink. To reduce the energy consumption of the nearby nodes, a relay node approach is derived. A Relay Node (RN) is supposed not to generate or consume data, but to just forward data from source to destination. One of the important issues in relay node approach is the optimal placement of RNs to guarantee data collection. In an environment where a sink collects data from sensors, the network topology can be changed due to the node failure or discharge of battery. In this case, it is difficult to locate optimally RNs in the environment. Typically, for applications such as a military zone, disaster area, or underwater, it is not expected to control the optimal placement of RNs. Taking these issues into consideration, we assume that an RN is deployed in a random pattern in the sensor network and we focus on the data collection from sensors to the sink in the network.

Usually, the conventional approaches for data collection model a cost function using more than one input metric to improve the performance. The Expected Transmission Count (ETX) [4], Expected Transmission Time (ETT), Weighted Cumulative ETT (WCETT) [6] metrics have employed the combined function of various inputs such as packet loss probability, bandwidth, and packet size. In many other approaches, the link cost is computed using energy-based inputs such as network lifetime and remaining energy of a node, as well as throughput and end-to-end delay [12, 17, 20, 25, 26]. However, the conventional approaches determine the unified coefficients in the cost function without considering the surrounding environments of each node. Since the surrounding environments of a node are different from each other, the performance is degraded when the unified coefficients are employed to determine the path for data collection. To solve the problem, some approaches employ for obtaining the customized coefficients for environments of each node. Self-Selective Routing (SSR) [21] attempts to find the next forwarding node with the smallest number of hops to the destination using the proposed lecture hall algorithm originated in the field of artificial intelligence. It assumes that the neighbour node with the smallest number of hops to the destination is the best candidates for forwarding data. Distributed Neural Networks Routing (DNNR) [27] employs the angle of the neighbor node to sink and remained energy of the neighbor to obtain the link cost for data delivery to the destination. It mainly focuses on reducing the energy consumption and data transmission delay. However, the reliability of data collection is affected by wireless channel condition and channel contention between nodes, as well as hops distance to the destination and data transmission delay. The approaches do not consider the input types for generating the output of the cost function. Because of this, the method is limited on performance improvement. We overcome the problem by considering the input types and the details are explained from the following section.

3. Intelligent Approach for Data Collection

In this section, we detail the proposed intelligent approach for data collection to reduce the data loss and the delay of data delivery. When a sensor intends to send its data, a path from the sensor to the sink needs to be established to deliver the data. Since the packet loss probability in a wireless multi-hop communication environment increases with the number of hops [23], we choose the hop distance from the RN serving the sensor to the sink as one of the metrics for data collection. The sink periodically floods a PROBE message over the entire network so that each RN in the network can infer the hop distance from itself to the sink through each of its neighbor RNs. The large flooding interval of a PROBE message seems adequate because the topology of the sensor network is quasi-static. It is well known that a packet loss in a wireless network can happen either due to collision or due to a weak signal [16]. Each RN periodically sends a HELLO message to its neighbor RNs as its heartbeat. Through the exchange of HELLO messages, each RN measures Received Signal Strength (RSS) and Hello message reception ratio for each of its neighbour RNs. The Hello message reception ratio reflects the impact of channel contention from neighbour RNs and represents the ratio of the number of Hello message received from a neighbour RN to the number of the Hello message sent by the RN.

Using RSSs, the reception ratios of HELLO messages, and the hop distances for neighbour RNs, a path setup process is triggered. The RNs construct the path with the following procedures.

1. *Serving RN Selection:* In this paper, the serving RN of the sensor is the RN that is the last hop of the path from a sensor to the sink. The RNs start to construct a path when they receive data from a sensor for the first time. Since wireless transmission is broadcasted in nature, more than one RN can receive the data from the sensor. Therefore, the

method to determine a serving RN is required. The serving RN of a sensor is selected in the following manner. A sensor sends a SOLICIT message to neighbouring RNs by one-hop flooding. When an RN receives the SOLICIT message, it responds with a ADVERTISE message having the maximum cost among link costs for its neighbour RNs. Then the sensor selects the RN with the largest link cost as its serving RN and it sends a CONFIRM message to the selected RN.

2. *Next-hop RN Determination:* After the serving RN for a sensor is selected, the serving RN initiates the path construction procedure by forwarding the sensed data received from the sensor to the next-hop RN. The RN receiving the data from the serving RN continues the path construction by forwarding the data to its next-hop RN. This process repeats until when the data is delivered to the sink. An RN selects the neighbour RN with the maximum link cost, as the next-hop RN for data delivery toward the sink.

Using the three metrics explained above, we show the derivation of the cost function in the following section.

3.1. Modelling a Nonlinear Cost Function for Selecting the Next Forwarding Node

In this subsection we derive the nonlinear function for selecting a serving RN and next-hop RN out of neighbor RNs by modelling a mathematical nonlinear equation. From our scientific intuition, the link cost depends on various numbers of input features. The input features are extracted from the characteristics of the wireless propagation environment and geographical environment surrounding an RN. In our paper, three inputs are extracted, i.e., RSS, denoted as x_1, the Hello message reception ratio, denoted as x_2, and hop distance, denoted as x_3. The link cost function is modeled as a nonlinear combination of the input features and their corresponding weights as seen in equation 1. In general, each weight value is determined according to the importance of its corresponding input:

$$Cost_i = f(\sum_{j=1} x_{ij} \cdot w_{ij}) \quad (1)$$

Where $Cost_i$ is the link cost of the i^{th} RN out of neighbour RNs and f is a nonlinear function. The x_{ij} is the j^{th} input and w_{ij} is its corresponding weight. Usually, the log function is commonly used as the nonlinear function because of its characteristic as follows: Many natural processes have a history dependent progression in which it begins small and accelerates to some point and then approaches to a saturation point over input features. Thus, equation 1 can be modified as follows:

$$Cost_i = \log(\sum_{j=1}^{3} x_{ij} \cdot w_{ij}) \quad (2)$$

As seen in equation 2, the function consists of the weighed sum of inputs regardless of the relationship among inputs. It is just like the black-box style connections between inputs and weights. However, we intuitively know that some inputs are highly correlated to each other like inputs x_{i1} and x_{i2}. For instance, if a neighbor node has high RSS value then it is highly possible to have high message reception ratio. To take this into the consideration, we divide the sum of weighted inputs according to whether inputs are correlated or uncorrelated. The correlated inputs are presented in a weighted sum with the dependent fashion but the uncoupled inputs with an independent fashion in the nonlinear function as seen in equation 3:

$$Cost_i = \log(\sum_{j=1}^{2} x_{ij} \cdot w_{ij}) + \log(x_{i3} \cdot w_{i3}) \quad (3)$$

From equation 3, the optimal performance of the cost function depends on the proper weight sets which can be obtained by training the function to the direction in which the reliability of data collection reaches to the maximum point. From the following subsection, we use the packet transmission success ratio as the measurement of the reliability of data collection for a convenience.

3.2. Training Weights

As mentioned, the weights in the function mean the importance of corresponding inputs for producing the link cost. So, each weight can be obtained from measuring the weight sensitivity with respect to the packet transmission success ratio. The process of training the cost function can be summarized as follows.

1. Set to 1s' to all weight weights as an initial weight set (named old weights in this paper).
2. Calculate $Cost_i$, i=1, 2, …, N, using equation 3.
3. Select the neighbour RN having max link cost and forward data packets to the selected RN.
4. Calculate the packet transmission success ratio which means the ratio of the number of packets transmitted successfully to the RN with max link cost to the total number of packets sent to the RN.
5. Vary one weight by very small amount, denoted as δ, at one time each such as equation 4. The δ is called learning ratio.

$$w_k \leftarrow w_k + \delta, k = 1,2,3. \quad (4)$$

6. Repeat the steps from 2 to 4 with the weights in 5 if there occurs any improvement on the packet transmission success ratio during the step 6, then replace the old weights to the updated weights.
7. Repeat the steps from 2 to 6 by varying the learning ratio δ such as $\delta+\Delta$ until there is no improvement on the packet transmission success ratio.

It is challenging to determine an optimal learning ratio. If we choose too large value of δ, it causes high convergence speed but it has high possibility of missing the optimal weight values. Too small value of δ is vice versa of too large value of δ where convergence speed is too small but low possibility of missing the optimal weight values. We determine the learning ratio by exhaustive empirical experiment as shown in the experimental section.

4. Performance Evaluation

We experiment our method using the NS-2 [22] simulator. We have used the log-normal model in [15] to model radio propagation environment. An RN sends a Hello message for every 100 milliseconds. IEEE 802.11 [8] is used as the MAC layer. The transmission range of a node is 250m and the total simulation time is 360sec.

4.1. Verification of the Types of the Inputs

Before we model our nonlinear cost function using three inputs as mentioned in the previous subsection, we verify the types of the inputs, i.e., whether RSS and Hello message reception ratio are correlated or not. The verification is done using the input sensitivity explained in our previous work [9]. The verification algorithm is summarized as follows.

1. Train equation 2 using the weight update algorithm in the previous subsection and then measure the link cost for each node from the trained cost function.
2. Vary one input at a time by adding small random value between 0.01 to 0.1.
3. Calculate the cost function using the input obtained in 2.
4. Obtain the input sensitivity of each input from the mean of the absolute differences of the costs.

As seen in Table 1, the input sensitivities of x_1 and x_2 together are large for either varying RSS (x_1) or Hello message reception ratio (x_2), not hop distance (x_3). Also, the input sensitivities of x_1 only are large when x_2 is varied. Thus it is verified that x_1 and x_2 are correlated each other and x_3 is uncorrelated with x_1 and x_2.

Table 1. The result of the input sensitivity.

Varied Input	Input Sensitivity of x_1	Input Sensitivity of x_2	Input Sensitivity of x_3
x_1	0.45	0.36	0.09
x_2	0.31	0.40	0.06
x_3	0.14	0.13	0.34

4.2. Validation of Our Link Cost Function

These experiments have been carried out to validate the performance of the proposed training technique in a single-hop transmission environment. We compare the performance of our method with Conventional Nonlinear method (CNL) as seen in equation 2 and the Conventional Linear method (CL) using three input features such as RSS, Hello message reception ratio, and hop distance. In CL, only one input out of the three inputs is used as the cost function at one time such as CL(x_1), CL(x_2) and CL(x_3). For the construction of the single-hop distribution network, 20 RNs are placed randomly in the 500m×500m area. To determine the optimal learning ratio δ as explained in the previous section, we train equation 2 repeatedly as varying the value of δ by 0.1 increment. Table 2 is the result of the packet transmission success ratio. From the results, we can infer that the packet transmission success ratio decreases as δ increases for our method and CNL. As seen in the Table, the value of δ is 0.3 provides the best training performance. The convergence speed is not issued in this experiment because equation 2 is trained within about 5-10 seconds. Using δ=0.3, we compare the performance of the methods by varying input values. Table 3 is the result obtained by varying the RSS for reflecting the variation of the received power in the shadowing propagation model [15] with adding log- normal random fading with zero mean and standard deviation σ_1. Typical value of shadowing deviation varies from 4.0 to 10.0 for outdoor environment. From the Table, we can see that the methods using nonlinear function are more robust despite of dynamic random fading and they improve the packet transmission success ratio by about 21% compared to CL. From the result, the performance of our method is better by about 18.2% and 29.1% respectively than that of CNL and CL because our method considers the correlation between the inputs x_1 and x_2 during training our link cost function.

To analyze the effects of collision on packet transmission success ratio, we vary the possibility of packet collision using Gaussian distribution with zero mean and standard deviation σ_2 as seen in Table 4. The method using the nonlinear function shows higher robustness and packet transmission success ratio by about 19% than CL, irrespective of the degree of packet collision. Similar to the result in Table 4, our method improves the performance by about 18.4% and 28.3% compared to that using CNL and CL. From the above results, we can conclude that our method improves the packet transmission success ratio without the burden of large overhead occurred during training.

Table 2. Packet transmission success ratio to determine the optimal learning ratio (δ).

δ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Our	0.928	0.943	0.979	0.913	0.902	0.893	0.853	0.801	0.797	0.763
CNL	0.757	0.769	0.792	0.749	0.744	0.734	0.706	0.660	0.611	0.599

Table 3. Packet transmission success ratio with varying RSS by adding log normal random fading with zero mean and standard deviation σ_1.

σ_1	Our	CNL	CL(x_1)	CL(x_2)	CL(x_3)
1.0	0.974	0.794	0.667	0.665	0.660
2.0	0.976	0.796	0.662	0.666	0.655
3.0	0.979	0.794	0.668	0.664	0.658
4.0	0.974	0.794	0.668	0.670	0.655
5.0	0.979	0.792	0.691	0.668	0.658
6.0	0.981	0.793	0.727	0.701	0.658
7.0	0.976	0.796	0.722	0.700	0.657
8.0	0.976	0.795	0.725	0.700	0.658
9.0	0.976	0.792	0.723	0.701	0.655
10.0	0.979	0.795	0.725	0.703	0.649

Table 4. Packet transmission success ratio with varying Hello message reception ratio using gaussian distribution with zero mean and standard deviation σ_2.

σ_2	Our	CNL	CL(x_1)	CL(x_2)	CL(x_3)
0.1	0.974	0.794	0.705	0.696	0.670
0.2	0.984	0.804	0.676	0.677	0.670
0.3	0.982	0.791	0.685	0.674	0.669
0.4	0.981	0.806	0.694	0.693	0.668
0.5	0.979	0.792	0.705	0.726	0.673
0.6	0.996	0.795	0.711	0.741	0.665
0.7	0.975	0.801	0.727	0.748	0.665
0.8	0.982	0.793	0.733	0.736	0.667
0.9	0.978	0.796	0.706	0.748	0.668
1.0	0.976	0.800	0.731	0.760	0.662

5. Conclusions

In this paper, we developed the nonlinear cost function for data delivery in sensor networks. The cost function was driven from the concept of the input types; correlated inputs and uncorrelated inputs. The input types can be identified using the input sensitivity as shown in the experimental section. Also, we presented the weight update algorithm for finding optimal weights in our nonlinear cost function. From the results of the performance comparison between our method and the conventional nonlinear method/the conventional linear method, we can conclude that our method outperforms with respect to the reliability of data delivery. To our best knowledge, the reason that our method can perform better than those methods is our method utilizes the relationship of input correlation. In our method, we extracted three input features to customize for sensor networks to improve the reliability of data delivery. However, we will find the way into a wide variety of applications and systems such as Intelligent Transportation System (ITS) and wireless mesh network with vastly varying requirements and characteristics. Even though these applications and systems are attracting much attention from many re-searchers, extracting input features to meet the requirements and characterizing the correlation among the inputs have not been addressed yet.

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