Poster: Channel Prediction Based on BP Neural Network for Backscatter Communication Networks

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Abstract

Due to the large amount of sensor data in the backscatter network, parallel transmission and rate adaptation are constrained by channel quality. In this paper, we propose a channel prediction scheme for backscatter networks. The scheme consists of two parts: a monitoring module and a prediction module. The monitoring module, which uses the data of the acceleration sensor to monitor the movement of the node itself, and uses the link burstiness metric to monitor the burstiness caused by the environmental change, thereby determining that new data of channel quality is needed, and the prediction module predicts the channel quality of the next stage by using the BP neural network algorithm. The experimental results show that the channel prediction accuracy is high and the relatively stable read rate can be maintained.

1 Introduction

Some of the existing methods in backscatter communication networks do not fully consider spatial diversity and frequency diversity. The precondition for Blink [1] is to assume that all nodes experience the same channel quality, using specific calculations to monitor mobility and rate selection. CARA [2] observed an opportunity to increase throughput through channel-aware rate selection. It proposes a channel-aware rate adaptation method that takes into account spatial diversity and frequency diversity, but requires a small interval of time to probe channel quality and increases the overhead of channel probing. Because the downlink rate can also greatly affect the overall throughput, RAB [3] focuses more than on the choice of uplink rate selection, which is for overall throughput. In order to avoid collision, it also proposes filter-based probing to effectively estimate the channel.

We consider channel diversity and want to reduce the probe overhead. Because the channels are correlated, violent mutations rarely occur, so we use predictive methods to reduce the number of probes. Therefore, this paper mainly proposes a framework of channel prediction based on BP neural network. We set up the monitoring module, and set the acceleration threshold and link burst threshold respectively to monitor whether the channel quality at the current time needs to be re-acquired, and continuous probing is avoided.

2 Channel Selection

We propose a framework for channel selection in a backscatter communication system, which has two parts: a monitoring module and a prediction module. Since CRFID is often embedded in an object or attached to an object, the two states will affect the quality of the channel, the movement of the object itself, and interference from surrounding objects or other wireless networks. Therefore, we use the acceleration sensor to monitor the movement of the object itself, use the link burstiness metric to determine changes in the surrounding environment. We can judge whether the channel quality has changed by two monitoring indicators. If the channel quality has changed, it is necessary to re-probe the channel quality for learning. Figure 1 plots the framework.

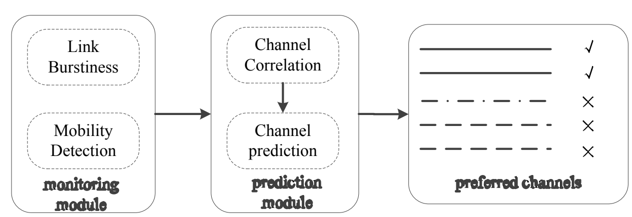

Figure 1: Framework overview

2.1 Monitoring Module

Conditional packet delivery functions (CPDFs) improves the success and failure of packet length vector transmission to briefly represent burstiness. The Kantorovich-Wasserstein (KW) distance [4] and the conditional packet transfer function are combined to express the burstiness as a single scalar. Therefore, this method is used to measure the proximity of CPDF to an ideal burst link. In other words, the KW distance between two vectors is the average of the absolute differences of the corresponding elements of the two vectors. The burstiness metric β is defined as follows:

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$$\beta=\frac{KW(I)-KW(E)}{KW(I)} \tag{1}$$

Where E is the CPDF of the empirical link in question, and I is the CPDF of the independent link with the same packet reception ratio.

Figure 2 plots the link burstiness of the channels we observe at different locations, and the loss rate of these channels is neither 100% nor 0%. We can observe that these channels exhibit high burstiness when $\beta > 0.75$. Therefore, we set up a threshold for the link burst metric as 0.75. When $\beta > 0.75$, it indicates that the link is bursty and the surrounding environment changes.

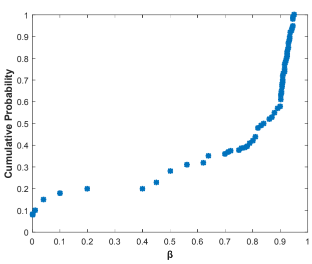


Figure 2: The burstiness metric value for the links

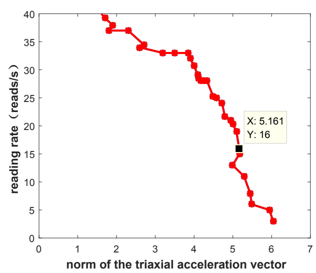


Figure 3: The relationship between norm of the acceleration vector and reading rate

When the sensor moves, the value of the triaxial accelerometer will definitely change, so we can judge whether it is static or mobile as follows:

$$B_t = |Accel_x + Accel_y + Accel_z| \tag{2}$$

Where $Accel_{x,y,z}$ are the value of triaxial accelerometer, B_t is the modulus of the vector formed by the triaxial accelerations.

Figure 3 plots the relationship between acceleration data and channel read rate. We found that when the modulus of the triaxial accelerations is bigger than 5.1, the channel quality is bad for read data, so we set up a threshold for B_t as 5.1. When B_t >5.1, it means the sensor node moves.

2.2 Prediction Module

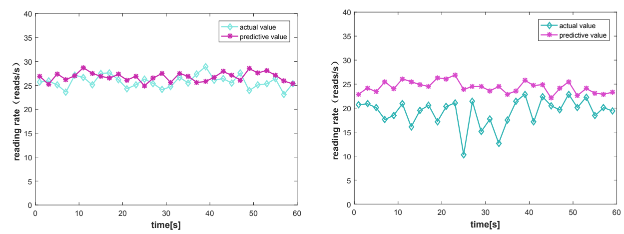
We use the prediction algorithm based on BP neural network to predict the next stage channel quality. For the first input of the input layer we construct a m × n matrix C, m and n are the available channels and the number of nodes, respectively. In C, C_{ij} represents the reading rate of the node j at channel i; the second input is the m × 1 matrix A, indicating the RSSI of each channel; the third input is the m × 1 matrix B, indicating packet loss rate per channel. The output data is a predicted matrix containing the read rate, RSSI, packet loss rate, and a list of preferred channels. The predicted data read rate, RSSI, and packet loss rate are replenished as training data.

3 Evaluation

In this section, we evaluated our framework through experimentation and simulation. In the experiment we used Impinj Speedway reader and passive CRFID as nodes. We evaluated the effects of our prediction algorithm, using simulation experiments and five randomly arranged tags.

We compared our prediction algorithm with the channel quality under real conditions. The real value is selected by random hopping, that is, the channel is randomly selected every 2s. Therefore, in order to reduce the overhead of frequent detection of acceleration, we set a probe every 2s, which is consistent with the frequency hopping time and reduces the detection overhead.

We compared them in a stable environment and an unstable environment. The comparison results are shown in Figure 4. As shown in Figure.4(a), our algorithm is similar to the actual effect. Because the channel quality is stable in stable conditions, the prediction algorithm does not show superiority. However, as shown in Figure.4(b), the effect of the prediction algorithm is significantly higher than that of random hopping.



(a) Stable environment (b) Unstable environment

Figure 4: Comparison the reading rate between the prediction algorithm and the actual conditions

4 Conclusions

This paper proposes a framework about channel prediction that considers both spatial diversity and frequency diversity. The threshold of the data of the acceleration sensor and the link burst metric are set, thereby obtaining the retraining moment. Through a certain amount of experiments, we find that the channel prediction accuracy is high and the relatively stable read rate can be maintained.

ACKNOWLEDGEMENT

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5 References

[1] Pengyu Zhang, Jeremy Gummeson, and Deepak Ganesan. Blink:a high throughput link layer for backscatter communication. pages 99–112, 2012.

[2] Wei Gong, Haoxiang Liu, Kebin Liu, Qiang Ma, and Yunhao Liu. Exploiting channel diversity for rate adaptation in backscatter communication networks. In *INFOCOM 2016 - the IEEE International Conference on Computer Communications, IEEE*, pages 1–9, 2016.

[3] Wei Gong, Si Chen, and Jiangchuan Liu. Towards higher throughput rate adaptation for backscatter networks. In *IEEE International Conference on Network Protocols*, pages 1–10, 2017.

[4] Yossi Rubner, Carlo Tomasi, and Leonidas J. Guibas. A metric for distributions with applications to image databases. In *International Conference on Computer Vision*, page 59, 1998.