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A Novel Link Quality Prediction Algorithm for Wireless Sensor Networks

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Abstract. Ahead knowledge of link quality can reduce the energy consumption of wireless sensor networks. In this paper, we propose a cloud reasoning-based link quality prediction algorithm for wireless sensor networks. A large number of link quality samples are collected from different scenarios, and their RSSI, LQI, SNR and PRR parameters are classified by a self-adaptive Gaussian cloud transformation algorithm. Taking the limitation of nodes' resources into consideration, the Apriori algorithm is applied to determine association rules between physical layer and link layer parameters. A cloud reasoning algorithm that considers both short- and long-term time dimensions and current and historical cloud models is then proposed to predict link quality. Compared with the existing window mean exponentially weighted method, the proposed algorithm captures link changes more accurately, facilitating more stable prediction of link quality.

Keywords: wireless sensor networks, link quality prediction, Gaussian cloud transformation.

1. Introduction

Wireless sensor networks (WSNs) is multi-hop, self-organising network formed by a large number of inexpensive micro-sensor nodes which communicate with each other by radio [6]. Their purpose is to collaboratively sense, collect and process information about objects in the network coverage area and pass it on to an observer. As they are usually required to work for long periods, it is important to reduce the nodes' energy consumption. Because of the physical characteristics of the node and the volatile communication environment, the nodes are affected by multipath effects, signal attenuation and signal interference from other wireless communication protocols (Wi-Fi, GSM, Bluetooth). These uncertain spatial and temporal characteristics of data transmission present challenges for the evaluation and prediction of wireless link quality.

Link quality prediction (LQP) plays a fundamental role in WSNs routing protocols, topology control, and energy management, and so on. For instance, an effective mechanism for link quality prediction can help routing protocols choose better link for data transmission, reduce data retransmission requirements and the number of routings, and improve network throughput and the reliability of data transmission. The topology control mechanism in WSNs relies on link quality to eliminate unnecessary links and improve the stability of the network, which is beneficial for prolonging the lifetime of the whole network. In WSNs energy management applications, LQP can predict changes of the current link, reduce node energy consumption, and improve the efficiency of network communication by selecting the appropriate transmission power.

This paper proposes a cloud reasoning-based link quality prediction algorithm based on multiple parameters, which classifies link quality parameters according to the cloud model. This algorithm overcomes the subjectivity of link quality classification, as different link quality parameters can represent different aspects of link quality. The algorithm, named Apriori, mines association rules between physical parameters and link layer parameter. In order to validate the algorithm, it is compared with the smoothed packet received ratio (SPRR) prediction method using a testbed platform. The results show that the proposed algorithm provides more stable prediction of link quality changes.

This paper makes two main contributions: 1) it uses a cloud model to eliminate subjective factors in the classification of link quality; 2) it proposes a cloud reasoning-based link quality prediction algorithm for wireless sensor networks. In This paper, we select PRR as an indicator of link quality and use cloud model to eliminate subjective factors in the classification of link quality. Based on cloud reasoning process, a novel link quality prediction algorithm is proposed for WSNs. Section 2 analyses the related researches of link quality prediction. Section 3 proposes the key algorithms in predicting the link quality at the next moment. Section 4 describes the experimental scenarios and experimental results to verify the effectiveness of the algorithm. Section 5 makes conclusions.

2. Related Work

Methods of WSNs link quality prediction fall into three categories-based on communication link characteristics, probability estimation and intelligent learning. The physical layer parameters involved in prediction include the received signal strength indication (RSSI), link quality indicator (LQI) and signal-to-noise ratio (SNR). Link layer parameters involved in the prediction include the packet reception ratio (PRR). The prediction methods based on probability estimation predict successful reception probability of the future packets. The prediction methods based on intelligent learning are related to pattern recognition, Bayesian networks, support vector machines (SVM) and so on.

Paper [6] proved the occurrence of SNR patterns resulted by the joint effect of human motion and radio propagation, then it used the cross-correlation to predict (XCoPred) algorithm to predict link quality variation. Paper [18] proposed a link quality prediction model based on supervised learning. It used machine learning to automatically discover correlations between readily-available features and the quality of interest. Paper [12] presented a machine learning based algorithm to link availability prediction in low power WSNs routing. The results of experiments showed that the algorithm has accurate predicting availability of intermediate quality links. Paper [8] proposed 4C based on machine learning, taking the physical parameters and link layer parameters as the input set. It took advantage of a Bayesian classifier, logistic regression and artificial neural network (ANN) to predict link quality, then predicted successful reception probability of the next packet. It had higher precision but lower sensitivity. Paper [9] proposed the temporal adaptive link estimator with no off-line training (TALENT) to predict short-term fluctuation in transition area links. Without prior knowledge and intervention, the algorithm can achieve rapid adaptation to network conditions.

Due to the resource consumption problem caused by asymmetric links, paper [13] applied dual-tree topology to record the receiving and the transmitting link quality parameters of the two nodes. The experiment showed that this algorithm can effectively reduce the hop from the source node to destination node. Paper [11] proposed a built-in learning-based WSNs link quality estimation algorithm that input link quality parameters (RSSI, SINR and PRR), node energy information, the expected number of transmissions (ETX), the expected energy consumption (EEC) and the expected number of retransmissions (ENR) to predict link quality. This method can improve the transmission rate but has poor real-time performance. Paper [3] proposed a link quality prediction algorithm based on fuzzy comprehensive theory and the Bayesian network. While it solved the marginalization problem of link quality, the algorithm required parameters that are independent of each other, and lacked assessment of link quality variability. Paper [10] proposed a generic link quality evaluation framework based on machine learning and was verified by LQI. The experimental results showed that the method is accurate for evaluating stable links, but not fluctuating ones.

Paper [20] applied a neighbourhood-based non-negative matrix factorization algorithm to predict link quality in WSNs. It learned latent features of the nodes from the information of past data transmissions combing with local neighborhood structures. Paper [2] fully considered the reliability, volatility and asymmetry of link and channel quality to construct corresponding link indicators. It applied the theory of fuzzy to obtain a fuzzy link quality estimator (F-LQE). Paper [15] compared reliability, stability and agility performance of ETX, 4-Bit and F-LQE. It noted that F-LQE is more reliable and stable, but has less agility for smart grid environment monitoring. Paper [16] combined a fuzzy theory and SVM to put forward a link quality prediction model that can reduce the effects of noise and outliers. It used a chaotic particle swarm optimisation algorithm to optimise the parameters of the SVM model. The model had better prediction performance than a backward propagation (BP) neural network. Paper [5] applied a Markov chain model to describe packet loss in wireless links, pointing out that link package rates tended to be the same over very short periods of time. Paper [19] proposed a window mean exponentially weighted moving average (WMEWMA) link quality evaluation algorithm based on exponentially weighted moving average (EWMA) filter. This algorithm can predict the next-moment PRR through a historical set of PRRs, but the lack of physical parameters can lead to lower accuracy.

Cloud models are widely applied for evaluation, prediction and algorithm improvement [14] because of their advantages of fuzzy and stochastic processing. Considering the randomness of links and the fuzziness of link quality in WSNs, this paper proposes a novel link quality prediction algorithm. The self-adaption Gaussian transformation algorithm is used to classify link quality parameters. Association rules between physical layer parameters and link layer parameters are mined by the Apriori algorithm [1]. A novel cloud reasoning-based link quality prediction algorithm is proposed by combining historical cloud and current cloud information.

3. Cloud Reasoning-based Link Quality Prediction Algorithm

The cloud reasoning-based link quality prediction algorithm can be divided into three parts: division of link quality parameters, determination of association rules and establishment of a prediction model. The self-adaptive Gaussian transformation (S_GCT) algorithm is used to classify link quality parameters. The Apriori algorithm is applied to find out rules between the physical-layer parameters (RSSI, SNR, LQI) and the link-layer parameter PRR. A cloud reasoning-based algorithm is proposed to predict link quality. Fig. 1 illustrates a flowchart of the prediction model.

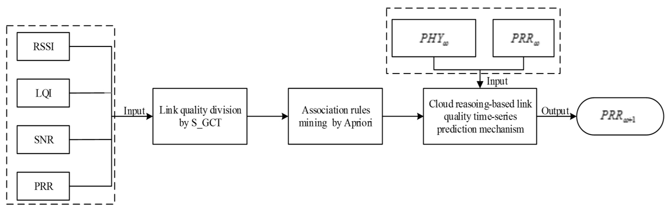


Fig. 1. Cloud reasoning-based link quality prediction algorithm

3.1. Division of Link Quality Parameters

The S_GCT algorithm automatically forms multiple concepts consistent with human cognition, and appropriate granularity based on the statistical distribution of the actual data. This process can reflect the process of human cognition from low to high levels. The self-adaptive Gaussian transformation is iteratively convergent by calling the heuristic Gauss cloud transformation algorithm (H_GCT), and the Gauss cloud transformation strategy is formulated according to the confusion degree (CD). The confusion degree can be used to characterise the degree of dispersion of the Gauss cloud distribution. Larger CDs usually involve greater overlap of adjacent Gauss clouds, hence, concepts are poorly defined. Conversely, smaller CDs involve less overlap, so that concepts easily reach consensus. The threshold of the general CD is 0.5. The CD can be calculated according to Equation (1).

$$CD = \frac{3He}{En} \tag{1}$$

Where *He* represents the hyper-entropy of the cloud model, and *En* represents the entropy of the cloud model.

The S_GCT algorithm specifies the Gauss cloud transformation strategy according to the CD, and the basic area between adjacent concepts will not overlap (CD $\leq$ 0.5) through iteration. The self-adaptive Gaussian transformation algorithm is set out as Algorithm 1.

The data sets of the different parameters can be processed by S_GCT, and the different link quality parameter can be divided into different levels. In this paper, parameters SNR LQI, RSSI and PRR are divided into various levels, such as (SNR1, SNR2, SNR3, SNR4, SNR5), (LQI1, LQI2, LQI3, LQI4, LQI5, LQI6, LQI7), (RSSI1, RSSI2, RSSI3, RSSI4) and (PRR1, PRR2, PRR3, PRR4, PRR5, PRR6, PRR7, PRR8, PRR9, PRR10).

Algorithm 1 S_GCT(p_Eve,β)

Input: p_Eve: sample set for every parameter, β: confusion degree
Output: p_Clu: list of M cloud model parameters

initial M, $M>0$
repeat
  compute Gauss cloud digital features $H\_GCT(p\_Eve, M)$
  add Gauss cloud digital features to the list $p\_Clu.Add(Ex, En, He, CD)$
until p_Eve is empty
repeat
  clear list $p\_Clu.Clear()$
  the Gauss component is reduced by 1 $M = M - 1$
  repeat
    compute Gauss cloud digital features $H\_GCT(p\_Eve, M)$
    add Gauss cloud digital features to the list $p\_Clu.Add(Ex, En, He, CD)$
  until p_Eve is empty
  if $M == 1$ **then** close
  end if
until $CD_k<\beta$

3.2. Association Rules Mining

The link quality prediction algorithm based on cloud reasoning is essentially a kind of regression reasoning prediction. In this paper, the Apriori algorithm is applied to mine the association rules between the physical parameters and link layer parameter.

Firstly, we save the divided data in the database D. Secondly, we find out rules with the Apriori algorithm, like {RSSI1, LQI2, SNR1, PRR1}. The rule is defined as “If RSSI low and LQI low and SNR low then PRR low”. More rules will be shown in Table 1.

Table 1. Partial association rules

Rule antecedent			**Rule consequent**
RSSI1	SNR2	LQI1	PRR1
RSSI1	SNR2	LQI2	PRR1
⋮	⋮	⋮	⋮
RSSI2	SNR4	LQI5	PRR10
RSSI3	SNR5	LQI7	PRR10
RSSI4	SNR6	LQI7	PRR10
RSSI6	SNR7	LQI7	PRR10

3.3. Link Quality Prediction with Time Series

In this paper, a cloud reasoning-based link quality prediction algorithm is used to predict link quality by considering short and long term dimensions. The short term dimension generates the current cloud through the current physical parameters, while the long term dimension generates the historical cloud through the link layer parameter. The current cloud and the historical cloud are integrated into an integrated cloud model which is used to predict link quality [4].

For the current physical layer parameters, we determine the maximum membership degree of association rules by the three condition single-rule cloud generator algorithm (3CSR_CG). Corresponding to the link layer parameters in the maximum membership degree rule, the cloud model is selected as the current cloud. The 3CSR_CG algorithm is shown as Algorithm 2.

Algorithm 2 3CSR_CG(X_1,X_2,X_3,Y,x)

Input: X_1: the first front cloud model parameters, X_2: the second front cloud model parameters, X_3: the third front cloud model parameters, Y: the back cloud model parameters, x: the specific vector
Output: u: membership degree, b: the drop
1: computer the first random variable $Esx_1 = NORM(Enx_1, pow(Hex_1, 2))$
2: computer the second random variable $Esx_2 = NORM(Enx_2, pow(Hex_2, 2))$
3: computer the third random variable $Esx_3 = NORM(Enx_3, pow(Hex_3, 2))$
4: computer the membership of x $u = membership(x, Esx_1, Esx_2, Esx_3)$
5: computer the back cloud random variable $Esy = NORM(Eny, pow(Hey, 2))$
6: **if** up **then**
7: $b = Ey - deviate(u, Esy)$
8: close
9: **end if**
10: $b = Ey + deviate(u, Esy)$

We select *N* latest PRR values as drops, and the cloud model is identified as a historical cloud by using the no-degree backward Gaussian cloud algorithm (NB_GCT), shown as Algorithm 3.

Algorithm 3 NB_GCT(p_Eve)

Input: p_Eve: sample set
Output: p_Clu: cloud model parameters
1: computer sample set mean $Ex = MEAN(p\_Eve)$
2: computer first order absolute central moment $C = FirstMoment(p\_Eve)$
3: computer second order absolute central moment $S = SecondMoment(p\_Eve)$
4: computer entropy of sample set $En = sqrt(pi/2) \times C$
5: computer hyper entropy of sample set $He = sqrt(S - pow(En, 2))$
6: compose Gauss cloud digital features $p\_Clu = (Ex, En, He)$

A integrated cloud can be obtained by combining current cloud with historical cloud. Then a set of PRR value can be obtained by using the forward Gaussian cloud algorithm (F_GCT) shown as Algorithm 4.

Algorithm 4 F_GCT(p_Clu,N)

Input: p_Clu: cloud model parameters, N: the number of drop
Output: V: list of drop and membership degree

1: initial n, $n = 0$
2: **repeat**
3: computer the random variable of expected value $Es = NORM(En, He)$
4: computer the random variable of drop $s = NORM(Ex, Es)$
5: computer membership of drop $y = membership(s, p\_Clu)$
6: add drop and membership to list $p\_Clu.add(s, y)$
7: n increased by 1 $n = n + 1$
8: **until** $n \geq N$

The cloud reasoning-based link quality prediction algorithm sets Input$_N$ as the input vector: Input$_N$=[PRR$_N$,PHY$_N$], where PRR$_N$ is the historical PRR value of the latest N moments before the prediction point. Other than PRR$_N$, which is historical, PHY$_N$ consists of values of RSSI, LQI and SNR at the present time. Input$_N$ is inputed into the prediction algorithm and the drops can be output from Algorithm 2 and Algorithm 4.

4. Experiments and Analysis

The testbed consists of a single-hop network with four TelosB TX (transmitter) nodes and one TelosB RX (receiver) node positioned in outdoor and indoor environments, respectively. These nodes are equipped with a CC2420 wireless transceiver chip designed according to IEEE802.15.4. The RX node is connected to a computer via a USB port. We developed link quality test platform to monitor and analyse the experimental results (Fig. 2). The software tools we used include MATLAB and SPSS. Experimental parameters are shown in Table 2.

4.1. Design of Experimental Scenes and Data Collection

In WSNs, sensing data is easily affected by environmental noise, channel interference and multipath propagation in the process of transmission. In order to guarantee the diversity of the data samples and consider the influence of various interference sources, the experiments are conducted in three scenarios, such as a corridor in a building, a forest on the university campus and a road (Fig. 3). In each scenario, a miniature star WSNs network is deployed to test the link quality.

The corridor scene is used mainly to simulate indoor smart home situation of WSNs. Paper [17] showed that if a Wi-Fi signal is in a WSN area, the WSNs signal will be greatly affected. So indoor scenes are important in assessing WSNs link quality. The campus forest scene is used to simulate applications in field environments where signals are mostly

Table 2. Testbed parameter settings

Parameter	Value
Transmit	0 dBm
Channel	26
Modulation mode	DSSS-O-QPS
Transmission speed	250kbits/s
Number of packets	30
Packet sending interval	0.2 Second
Test cycle	10 Senconds
Number of nodes	4
Location	East,West,South,North

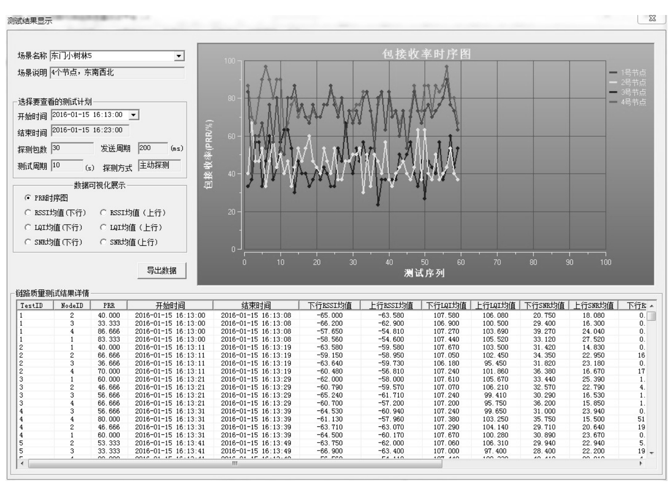
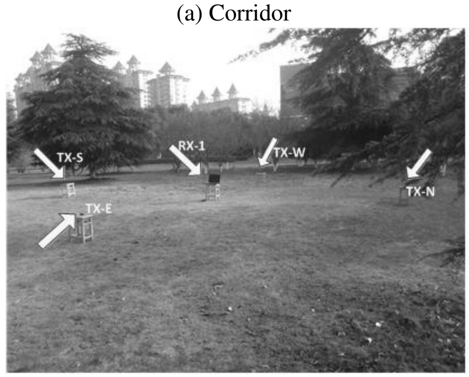
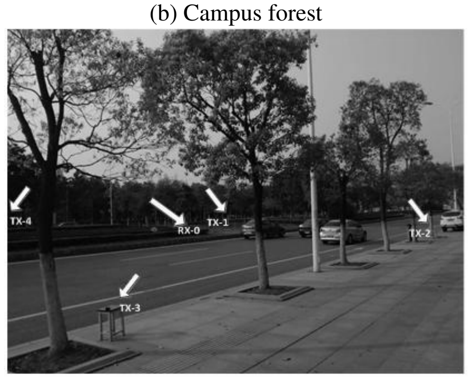


Fig. 2. Link quality testbed platform

(a) Corridor



(b) Campus forest

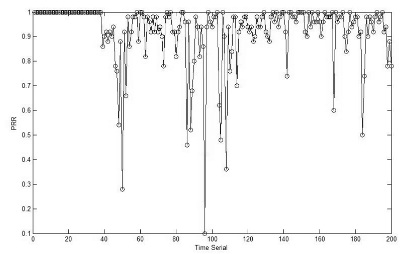


(c) Road

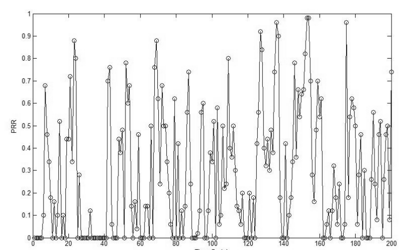
Fig. 3. Experimental scenes

affected by multipath propagation caused by obstacles. The road scene simulates intelligent transportation applications. Here, interference mainly comes from environmental noise, which subjects radio link signals to reflection, refraction and diffraction, etc..

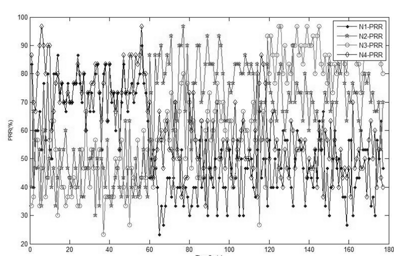
Experimental data are collected from all scenes, and PRR timing diagrams are drawn using MATLAB to facilitate analysis of the WSNs link characteristics (Fig. 4).



(a) Corridor



(b) Road



(c) Campus forest

Fig. 4. The PRR in different scenes

In Fig. 4(a), the time period from samples 30 to 200 is the students' lunchtime. Here, the link quality is largely impacted by mobile phones, other wireless devices and random walking. Fig. 4(b) shows the link PRR to fluctuate violently. The link communication state is very unstable with large burst. Random changes in the number of vehicles on the road, interference and wireless equipment inside vehicles [7], etc., have a direct impact on changes of PRR. The results show that the road scene has relatively large burst, instability and volatility of link quality. In Fig. 4(c), N1-PRR, N2-PRR, N3-PRR, N4-PRR are the four of the PRR timing diagram. Compared with the road scene, the interference in the campus forest is static, and the sources are mainly multipath propagation caused by trees, stones and other obstacles. Therefore, the volatility of the link quality is relatively large, but the communication link is relatively stable with relatively small burst.

4.2. Experimental Results of Link Quality Parameters Classification

The S_GCT algorithm is used to classify link quality parameters on the basis of different link quality parameter data sets. The corresponding Gauss curves and digital features are shown in Fig. 5 and Table 3 to Table 6. As we can see, different link quality parameter data sets result in different levels.

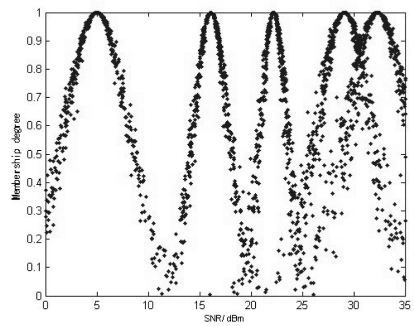
Table 3. Digital features of the cloud classification of SNR

Concept	Expectation	Entropy	Hyper-entropy	CD
Lower	5.0	3.10	0.30	0.29
Low	16.1	1.70	0.20	0.35
Medium	22.2	1.30	0.20	0.46
High	29.1	2.70	0.40	0.44
Higher	32.3	3.0	0.50	0.50

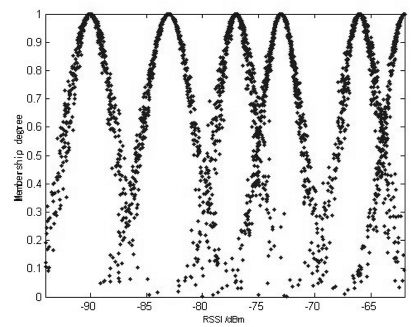
As shown in Table 3, SNR finally generates 5 concepts. The distribution of the first four concepts' expectation is relatively dispersed with less confusion degree. The fifth concept has highest confusion degree and its expectation is close to that of the fourth concept. Meanwhile, it can be inferred that SNR is not particularly good at distinguishing very good links from very good links.

Table 4. Digital features of the cloud classification of RSSI

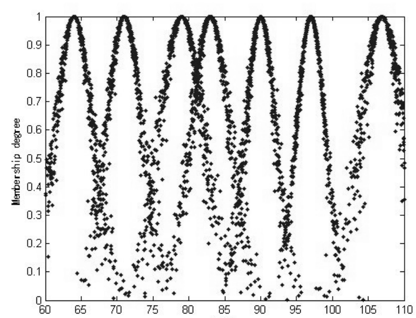
Concept	Expectation	Entropy	Hyper-entropy	CD
Lower	-90	2.10	0.30	0.43
Low	-83	2.30	0.20	0.26
General	-77	1.80	0.30	0.50
Medium	-73	1.80	0.20	0.33
High	-66	1.80	0.30	0.50
Higher	-62	1.80	0.18	0.30



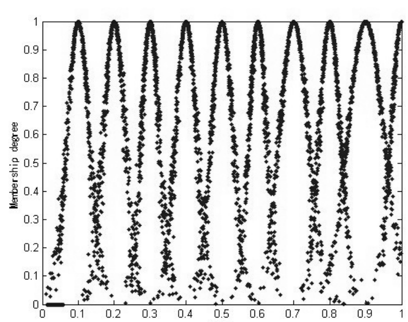
(a) SNR Gauss curve



(b) RSSI Gauss curve



(c) LQI Gauss curve



(d) PRR Gauss curve

Fig. 5. Gauss curves

As shown in Table 4, RSSI finally generates 6 concepts. The distribution of the all concepts' expectation is relatively uniform. When RSSI is low, its confusion degree is relatively small, which shows that RSSI has better ability to distinguish the lower links from the low links. Compared with SNR and LQI, the entropy and hyper-entropy of RSSI is small, which shows that RSSI has better ability to distinguish link quality than SNR and LQI.

Table 5. Digital features of the cloud classification of LQI

Concept	Expectation	Entropy	Hyper-entropy	CD
Very low	64	2.6	0.30	0.35
Lower	71	2.5	0.30	0.36
Low	79	3.0	0.40	0.40
General	83	2.7	0.35	0.39
High	90	2.1	0.25	0.36
Higher	97	2.0	0.15	0.23
Very high	106.9	3.0	0.50	0.50

As shown in Table 5, LQI finally generates 7 concepts. The confusion degree of the all concepts expectation is relatively high. While LQI has a smaller granularity, the expectation of low concept and general concept are close, and LQI is hard to distinguish the lower links from general links.

Table 6. Digital features of cloud classification of PRR

Concept	Expectation	Entropy	Hyper-entropy	CD
Extremely low	0.1	0.030	0.003	0.29
Very low	0.2	0.030	0.040	0.42
Lower	0.3	0.025	0.035	0.42
Low	0.4	0.030	0.003	0.30
General	0.5	0.030	0.003	0.30
Medium	0.6	0.025	0.003	0.36
High	0.7	0.040	0.003	0.26
Higher	0.8	0.030	0.003	0.30
Very high	0.9	0.050	0.003	0.18
Extremely high	1.0	0.030	0.003	0.30

As shown in Table 6, PRR finally generates 10 concepts. The distribution of the all concepts' expectation is uniform very well. The entropy of all concepts is almost same, and the CDs of all concepts are lower, which indicate PRR has good ability to distinguish the link quality.

Compared with SNR, RSSI and LQI, the entropy and the hyper-entropy of PRR are the lowest, which means link layer parameters of WSNs are the best indicator of link quality.

4.3. The Experimental Result

According to the current trend of the link, the cloud reasoning-based link quality prediction algorithm we proposed is practical and effective. In order to verify the effectiveness of the prediction algorithm, we select two 50 groups PRR prediction obtained by SPRR and the proposed prediction algorithm respectively. The SPRR is based on the principle of WMEWMA. Int this experiment, the window size to 5, the factor is set to 0.5, the value of the previous historical time is set to 5. The experimental results are shown in Fig. 6.

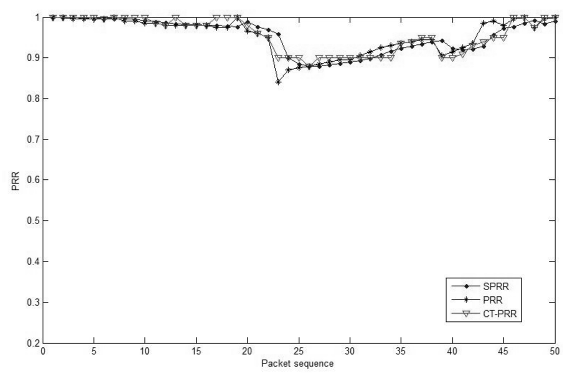


Fig. 6. Comparison of SPRR, PRR and CT-PRR

In Fig. 6, M-PRR represents the experimental measurement values of PRR, and SPRR represents the PRR prediction values based on the SPRR prediction algorithm. CT-PRR represents the PRR prediction values based on cloud reasoning-based link quality prediction algorithm. The experimental results show that the two prediction algorithm have little difference in stability. For the prediction of sensitivity, the CT-PRR values are relatively good, such as predicted values in sample interval 22 to 24 and sample interval 35 to 40. Because the cloud model of the time series takes into account both short- and long-term time dimensions, CT-PRR relative to SPRR can predict the dynamic link more effectively.

5. Conclusions

This paper proposes a method based on intelligent learning for the link quality prediction of WSNs. It introduces link quality parameters classification and prediction methods using a Gaussian cloud transform algorithm. By establishing association rules between physical layer parameters (RSSI, LQI, SNR) and the link layer parameter PRR, we can use LQI, SNR and RSSI information to predict the future PRR values. Compared with the existing method based on WMEWMA, the experimental results demonstrate that the proposed algorithm more accurately captures link changes, leading to more stable predictions of link quality.

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