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Lightweight, Fluctuation Insensitive Multi-Parameter Fusion Link Quality Estimation for Wireless Sensor Networks

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ABSTRACT Accurate and agile link quality estimation is essential for wireless sensor networks. Using the mapping models between physical layer parameters and packet reception ratio, link quality can be estimated with advantages of high agility and low overhead. However, existing estimators based on physical layer parameters fail to utilize link quality information carried by different physical layer parameters efficiently and effectively and fail to effectively solve the problem that physical layer parameters fluctuate greatly, which makes them difficult to describe link conditions really. In this study, a lightweight, fluctuation insensitive multi-parameter fusion link quality estimator is proposed. Two physical layer parameters, Signal-to-Noise Ratio and Link Quality Indicator are preprocessed by exponential weighted Kalman filtering to get more stable estimation values. Then, these two parameters are fused using lightweight weighted Euclidean distance to fully utilize link quality information carried by them. On this basis, link quality is estimated quantitatively with the mapping model of the fused parameter and packet reception ratio, which is constructed by logistic regression. Experimental results show that the proposed estimator could reflect link quality more realistically. Compared with similar estimators, estimate error of the proposed one is reduced by 18.32% to 60.11% under moderate and bad links with large fluctuations, by 1.42% to 83.43% under sudden changed links, and by 16.64% to 65.61% under a long-time link. More importantly, computation overhead of the proposed estimator is equivalent to that of single-parameter estimators, but much less than other multi-parameter fusion estimators. Compared with the later, computation overhead is reduced by 72.36% to 95.61%.

INDEX TERMS Link quality estimation, wireless sensor network, lightweight, multi-parameter fusion, fluctuation insensitive, exponential weighted Kalman filtering, weighted Euclidean distance, logistic regression, signal-to-noise ratio, link quality indicator.

I. INTRODUCTION

In recent years, wireless sensor networks (WSNs) have been increasingly deployed in many fields including military investigation, environmental monitoring, industrial control, home automation, and so on [1]. Hundreds and thousands of sensor nodes can self-organize to form multi-hop networks autonomously. WSNs typically use low power radio transceivers, which make the wireless links less stable and fluctuate greatly [2]. In order to improve network transmission efficiency and minimize packet retransmission overheads caused by low quality links, accurate and agile link quality estimation is necessary for finding the best end-to-end routes. Therefore, performance of link quality estimation is critical for the design of WSNs. In order to reduce energy wastes caused by frequent link switches, a good link quality estimator should not only be insensitive to instantaneous link fluctuations, but also respond quickly when sudden changes arise.

Using the mapping models between physical layer parameters and packet reception ratio (PRR), link quality can be estimated conveniently. Although it has advantages of high

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agility and low overhead, these physical layer parameters are always very unstable [2]. Therefore, existing estimators usually use window averaging or Kalman filtering to preprocess these parameters to reduce fluctuations. However, the processing effect is not satisfactory. Moreover, existing estimators either take only one physical layer parameter into consideration, which makes them difficult to describe link conditions accurately, or employ too complicated multi-parameter fusion methods, which could not offer a good balance among accuracy, agility and low overhead. In this study, a Lightweight, Fluctuation Insensitive multi-parameter fusion Link Quality Estimator (LFI-LQE) is proposed. Two physical layer parameters, Signal-to-Noise Ratio (SNR) and Link Quality Indicator (LQI), are preprocessed by exponential weighted Kalman filtering to get more stable estimation values. Then, these two parameters are fused using lightweight weighted Euclidean distance to fully utilize link quality information carried by them. On this basis, link quality is estimated quantitatively with the mapping model of the fused parameter and PRR, which is constructed by logistic regression.

The contributions of this study are as follows: 1) Correlations between different physical layer parameters and PRR are compared, and SNR and LQI which are more correlated to PRR are chosen as target parameters. 2) An exponential weighted Kalman filtering based preprocessing method is proposed, which could obtain more stable estimations. 3) A lightweight multi-parameter fusion method based on weighted Euclidean distance is proposed, which combines advantages of SNR and LQI under different link quality efficiently and effectively and achieves a fused parameter WED (weighted Euclidean distance) which is more correlated to PRR. 4) A mapping model between WED and PRR is constructed by logistic regression. 5) On this basis, a link quality estimator that could offer a good balance among accuracy, agility and low overhead is proposed.

The rest of this paper is organized as follows. In Section II, related works are given. This is followed by the acquisition method of experimental data in Section III. Design motivation and algorithm description of the proposed estimator are described in Section IV. Performance comparisons with similar estimators are discussed in Section V. Finally, conclusions are presented and suggestions are made for future works.

II. RELATED WORKS

PRR is the most direct metric for link quality estimation. However, as it always takes long time to get accurate PRR, the agility of using PRR directly is very poor [3]. This problem could be solved by using physical layer parameters. Physical layer parameters used for link quality estimation include Received Signal Strength Indicator (RSSI), LQI, and SNR. SNR can be calculated by subtracting background noise from RSSI. When there are no co-channel interferences, the noise floor usually remains stable for a few seconds or even minutes. As a result, changes of SNR with time are mainly caused by changes of RSSI [2]. Compared with LQI, RSSI has smaller variance, which makes it more stable when performing fast link quality estimation [4]. Nevertheless, compared with RSSI, correlation between LQI and PRR is higher [2], [5], [6].

In fact, which physical layer parameter is better for link quality estimation is an unanswered question at present [3]. Baccour *et al.* [3] pointed out that average LQI is better than average RSSI for link quality estimation. However, it is difficult to estimate link quality of moderate links only using LQI. Meanwhile, the background noise will change when environment or node changes, which would affect the correlation between RSSI and PRR. Srinivasan and Levis [4] found that RSSI has better symmetry and therefore believed that it has more potential. By analyzing correlations between RSSI, LQI and PRR, Bildea *et al.* [7] pointed out that RSSI could not be used to identify good links, while LQI could effectively distinguish good, moderate and bad links. Gomes *et al.* [8] pointed out that only using LQI may overestimate the link quality under bad links. For this reason, link quality estimators based on all these parameters had drawn much attention in recent years.

Mean value or variance of physical layer parameters could be used to analyze link quality qualitatively. The results in [2] showed that LQI has low variance under good links and very high variance under moderate and bad links. So, it could be used as an indicator to quickly identify good links. Srinivasan and Levis [4] found that when average RSSI is larger than -86dBm, PRR is always higher than 0.9. As a result, it could be used to quickly identify good links. Average RSSI is used in EasiLQE to select the size of next window adaptively [9]. Four-Bit uses LQI to quickly identify whether a link has high quality or not, and then estimates link quality through calculating uplink and downlink's expected transmission counts [10]. Boano *et al.* [11] calculated variances of LQI with different number of samples and pointed out that variance of LQI could be used to identify good links, and the number of samples required was one order of magnitude lower than using average LQI.

By constructing mapping models between physical layer parameters and PRR, link quality could be analyzed quantitatively. As these physical layer parameters are usually very unstable, they must be preprocessed by window averaging or Kalman filtering. Gomes *et al.* [8] established a polynomial mapping model between mean value of normalized RSSI and PRR for link quality estimation in industrial environment. Gomes *et al.* [12] proposed LETX, which estimates link quality by constructing a piecewise linear model between average LQI and PRR. Luo *et al.* [13] used Cubic model to fit the relation between average LQI and PRR. Shu *et al.* [14] proposed K-CCI, in which Kalman filtering is used to preprocess LQI and link quality is estimated by constructing a mapping model between smoothed LQI and PRR. Senel *et al.* [15] proposed KLE, in which Kalman filtering is used to preprocess RSSI. Then, SNR is computed by subtracting background noise from the smoothed RSSI and link quality is estimated by constructing a mapping model between SNR and PRR.

The schemes above only use one physical layer parameter for link quality estimation, which fail to fully utilize link quality information carried by different physical layer parameters. Therefore, it is difficult to describe real link quality accurately. In recent years, several schemes have been proposed to fuse multiple physical layer parameters for link quality estimation. Boano *et al*. [16] designed a new metric Triangle by calculating Euclidean distance between mean values of SNR and LQI, which is used for fast classification of link quality. Zhao *et al*. [17] proposed a new metric S_m by combining two physical layer parameters, RSSI and LQI, which is also used for classification of link quality. Although these two fusion methods are simple, they could not be used to estimate link quality quantitatively. Baccour *et al*. [18] proposed FLQE (Fuzzy Link Quality Estimator), which uses fuzzy logic to fuse four link parameters, namely smoothed PRR (SPRR), link stability factor (SF), link asymmetry level (ASL) and average SNR (ASNR). Since FLQE is too stable, Rekik *et al*. [19] and Jayasri and Hemalatha [5] adjusted the link parameters involved in fuzzy logic respectively to achieve more agile and accurate estimations. Opt-FLQE replaces the SF in FLQE with the smoothed required number of packet retransmissions (SRNP) of the sender [19]. ELQET (Enhanced Link Quality Estimation Technique) uses four link parameters, namely PRR obtained by LQI mapping, SNR obtained by Kalman filtering, coefficient of variation of PRR and average LQI, to characterize link quality [5]. Experimental results showed that ELQET is more accurate. However, agility of fuzzy logic based estimators is always poor. At the same time, using fuzzy logic to fuse multiple link parameters will introduce much more computation overhead.

Recently, some studies employed machine learning algorithms to process or fuse physical layer parameters, in order to improve accuracy of link quality estimation. Fu *et al*. [20] proposed RADIUS, a thresholding method based on Bayes theory, which uses mean value and variance of RSSI to identify the degradation of links, namely, from good links to bad links. Marinca and Minet [21] took LQI as input and utilized prediction game to construct an expert system model for link quality estimation. Liu and Cerpa [22] proposed 4C, which is a machine learning based link quality prediction scheme that uses naive Bayes classifier, neural networks and logistic regression to train historical data of RSSI, SNR, LQI and PRR offline and predicts PRR effectively. Liu and Cerpa [23] proposed TALENT, which is a real-time link quality prediction model that uses stochastic gradient descent online learning algorithm for training logistic regression classifier using PRR and LQI values. Shu *et al*. [24] proposed a link quality classification model, which fuses two physical layer parameters LQI and RSSI and trains mean values of them by support vector machine. WNN-LQE employs wavelet neural network to predict SNR and its variance of the next time, and then estimates link quality quantitatively using the mapping model between SNR and PRR constructed by Gaussian probability density function [25]. Although such machine learning based methods did improve accuracy, it has great disadvantages of high computation overhead and poor efficiency. Therefore, it is hard to be employed by sensor nodes which have limited computing power.

In summary, there are mainly two problems for existing link quality estimators based on physical layer parameters. Firstly, effect of preprocessing physical layer parameters using window averaging or Kalman filtering is unsatisfactory. These methods work well when the link is stable. However, when the link fluctuates greatly, there still are large fluctuations for the estimated values after preprocessing. Secondly, existing estimators either take only one physical layer parameter into consideration, which makes them difficult to describe link conditions accurately, or employ too complicated multi-parameter fusion methods, which could not offer a good balance among accuracy, agility and low overhead. In order to achieve more accurate link quality estimation, it is necessary to preprocess physical layer parameters effectively. Meanwhile, a lightweight multi-parameter fusion algorithm should be designed to realize efficient fusion and best use of multiple physical layer parameters without increasing too much computation overhead.


(a) (b) (c)

FIGURE 1. Experimental fields: (a) Playground, (b) Corridor, and (c) Rooftop.

III. EXPERIMENTAL DATA ACQUISITION

In order to obtain link quality data with different characteristics, several experimental fields were chosen, as shown in Fig. 1. Among which, there were not only typical outdoor environment which has simple propagation channel and low external interferences but also semi-enclosed environment which has complex propagation channel and high external interferences. Experiments were conducted with two TelosB nodes, one as transmitter and the other as receiver. TinyOS 2.1 operating system was used, which uses NesC language for programming [26].

Modeling data were collected from all experimental fields mentioned above. In these experiments, transmit power and distance between two TelosB nodes were changed to produce different link quality. At each distance, 500 packets were sent and PRR was calculated using the number of successfully received packets. At the same time, mean values of SNR and LQI of successfully received packets were calculated. To obtain data for performance comparisons, long time experiments were conducted in the semi-enclosed environment, in which external interferences such as walking people and WiFi signals were present. In all experiments, channel 26 was used. At each distance, three transmit powers, 0dBm, −15dBm, and −25 dBm, were used.

IV. LIGHTWEIGHT, FLUCTUATION INSENSITIVE MULTI-PARAMETER FUSION LINK QUALITY ESTIMATOR

A. DESIGN MOTIVATION

According to the analysis in Section II, there is still room for improvement in the preprocessing and fusion methods of physical layer parameters. When physical layer parameters fluctuate greatly, the effects of window averaging and Kalman filtering are unsatisfactory. In order to make link quality estimators offer a good balance among accuracy, stability and agility, requirements for physical layer parameter preprocessing are as follows: on one hand, estimators should be insensitive to instantaneous link fluctuations to avoid frequent link switches, which would waste energy and increase delay; on the other hand, estimators also should respond quickly when sudden changes arise. In order to fulfil these requirements, by analyzing amounts of experimental data, this study proposed to preprocess physical layer parameters using exponential weighted Kalman filtering. Its performance is better than window averaging and Kalman filtering. Considering the order of writing, detailed algorithm description and performance comparison results will be presented in Section IV-C and Section V-B respectively.

In order to fully utilize link quality information carried by different physical layer parameters without increasing too much computation overhead, lightweight multi-parameter fusion algorithms should be designed. Boano *et al.* [16] and Zhao *et al.* [17] had proposed two simple fusion methods, which integrate multiple physical layer parameters by calculating Euclidean distance between the origin and the point composed of mean values of physical layer parameters.

Boano *et al.* [16] combined two physical layer parameters to generate a new metric Triangle. This metric calculates Euclidean distance between the origin and the point composed of mean values of SNR and LQI, as shown in (1).

$$Triangle = \sqrt{SNR^2 + LQI^2} \tag{1}$$

Zhao *et al.* [17] proposed a new metric S_m by fusing two physical layer parameters, RSSI and LQI, as shown in (2). Link quality is classified according to values of S_m. Compared with RSSI and LQI, S_m is more correlated with PRR and its variance is smaller.

$$S_m = \sqrt{(RSSI + 100)^2 + LQI^2} \tag{2}$$

Although these two methods provide a feasible way for lightweight fusion of physical layer parameters, there are some drawbacks in practice: Firstly, they were designed for link quality classification, but not for estimating link quality quantitatively. Secondly, both methods ignore the impact of different ranges of physical layer parameters on the fused metrics. Thirdly, S_m does not consider the impact of noise floor changes on link quality estimation [17].

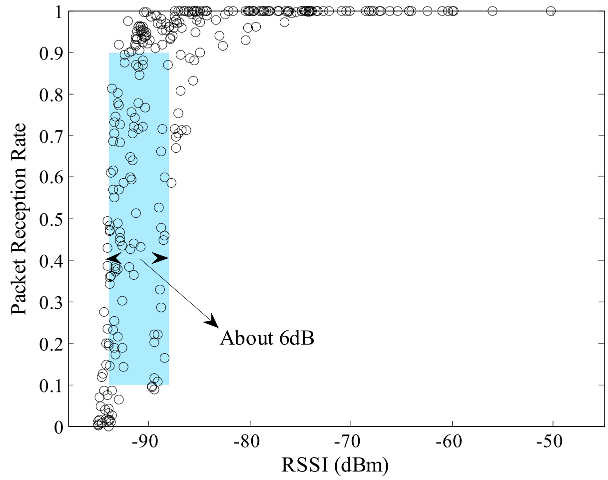

FIGURE 2. RSSI and PRR in all experimental fields.

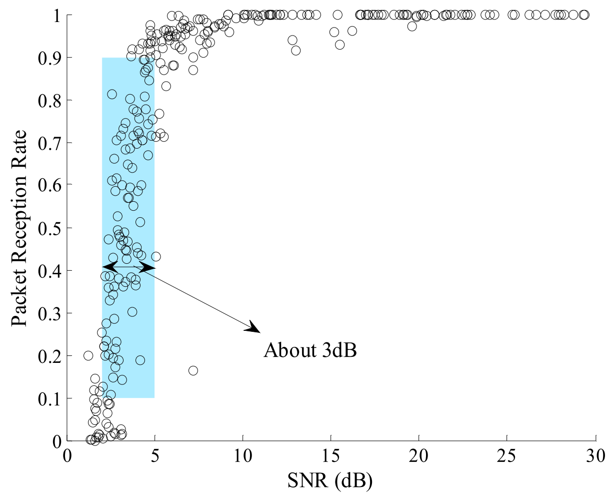

FIGURE 3. SNR and PRR in all experimental fields.

Fig. 2 to 4 show the relationships of RSSI, SNR, LQI and PRR respectively. It can be seen from Fig. 2 that there are obvious translations for the relationships between RSSI and PRR in different environments, because the noise floor would change when environment or node changes. As a result, RSSI could not be used for link quality estimation directly. It can be further confirmed by Fig. 3, in which the SNR calculated by RSSI and noise floor is more correlated with PRR. Fig. 4 shows that LQI and PRR are also highly correlated. In order to analyze correlations between RSSI, SNR, LQI and PRR quantitatively, their Spearman and Kendall correlation coefficients were calculated, as shown in Table 1. It is obvious that correlations between SNR, LQI and PRR are much higher than the correlation between RSSI and PRR.

Furthermore, by examining Fig. 2 to 4 carefully, we can find that the ranges of RSSI and SNR are −95dBm to −85dBm and 2dB to 10dB respectively when PRR changes from 0 to 1. However, the corresponding range of LQI is 60 to 105. It means that the impact of LQI on S_m and Triangle is

TABLE 1. Correlation coefficients of RSSI, SNR, LQI and PRR.

Parameter	Spearman correlation coefficient	Kendall correlation coefficient
RSSI	0.8633	0.6862
SNR	0.9374	0.7886
LQI	0.9356	0.7822

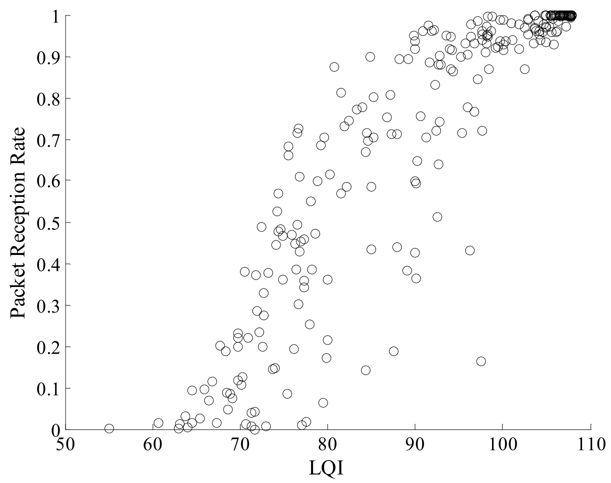

FIGURE 4. LQI and PRR in all experimental fields.

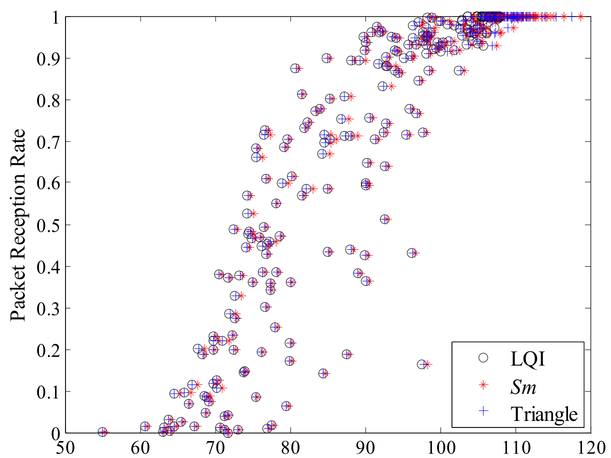

FIGURE 5. Relationships of LQI, S_m, Triangle and PRR in all experimental fields.

much higher than that of RSSI and SNR. Fig. 5 shows the relationships of LQI, S_m, Triangle and PRR. It is obvious that the relationships between S_m, Triangle and PRR are not so dissimilar from that between LQI and PRR. It means that the effects of RSSI and SNR are almost completely covered by LQI. The weight of RSSI or SNR in the new metrics should be increased to realize more effective fusion of these parameters. According to the above analysis, a multi-parameter fusion method based on weighted Euclidean distance was proposed to fuse SNR and LQI, which are more correlated with PRR. Considering the order of writing, detailed algorithm description will be presented in Section IV-D.

B. OVERALL STRUCTURE OF LFI-LQE

For ease of description, overall structure of LFI-LQE proposed in this study is firstly given, as shown in Fig. 6. Two physical layer parameters, SNR and LQI, are preprocessed by exponential weighted Kalman filtering to get more stable estimation values. Then, these two parameters are fused using lightweight weighted Euclidean distance to fully utilize link quality information carried by them, which would not increase too much computation overhead. On this basis, link quality is estimated quantitatively with the mapping model of WED and PRR, which is constructed by logistic regression.

C. EXPONENTIAL WEIGHTED KALMAN FILTERING OF PHYSICAL LAYER PARAMETERS

In order to make link quality estimators to offer a good balance among accuracy, stability and agility, this study proposed to preprocess physical layer parameters using exponential weighted Kalman filtering to obtain more stable and accurate estimation values. The time update equations of Kalman filter are as follows:

$$x_k^- = x_{k-1} \tag{3}$$
$$P_k^- = P_{k-1} + Q \tag{4}$$

The filter measurement equations are:

$$K_k = P_k^- \left(P_k^- + R\right)^{-1} \tag{5}$$
$$x_k = x_k^- + K_k(z_k - x_k^-) \tag{6}$$
$$P_k = (1 - K_k)P_k^- \tag{7}$$

where z_k is the measured value of SNR or LQI at the k-th window. x_k^- and x_k are the *priori* and *posteriori* estimates of SNR or LQI respectively. P_k^- and P_k are the variances of *priori* and *posteriori* estimation error, and K_k is the optimal Kalman gain.

Q and R are the process noise variance and measurement noise variance, respectively. Generally, the process noise and measurement noise are assumed to be Gaussian noise [15], [16]. Q can be computed at the initialization process by computing the variance of $x_k - x_{k-1}$ over a set of inputs. Since it is possible for Q to change slowly over time, it is reasonable to estimate Q periodically. An error in the exact value of Q only effects the convergence of the estimate and not its accuracy [15]. For SNR, the value of R can be calculated as the variance of noise floor [15]. For LQI, the value of R can be calculated as the variance of LQI [16].

Normal operation of the Kalman filter also requires the following two parameters: x_k's initial value x_0 and P_k's initial value P_0. x_0 can be calculated as the mean value of SNR or LQI in the first time window. For the Kalman filter to be optimal, P_k^- or P_k needs to be calculated, which implicitly includes the initial condition P_0. However, due to the fact that this initial value is not known, no Kalman filter is optimal in practice. Fortunately, it can be asymptotically optimal under certain conditions, no matter what the initial guess on P_0 is [15]. A common practice is to use Q as the initial guess of P_0.

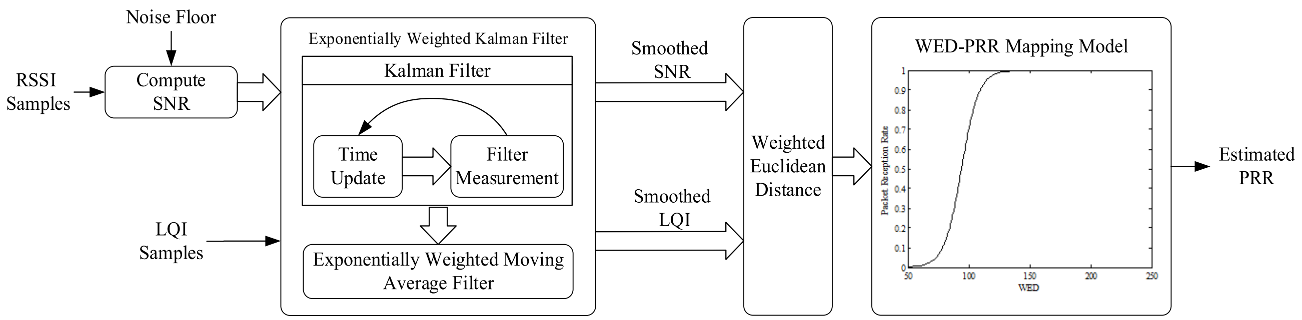

FIGURE 6. Block diagram of LFI-LQE.

To further reduce fluctuations of physical layer parameters, exponential weighted average filtering was adopted to process the SNR or LQI estimates produced by Kalman filtering. Its calculation formula is as follows:

$$X_k = \lambda \times X_{k-1} + (1-\lambda) \times x_k \tag{8}$$

where λ is the smoothing factor which belongs to (0, 1), x_k is the estimate produced by Kalman filtering. Furthermore, (8) could be written as:

$$X_k = \sum_{i=1}^{k} \lambda^{k-i}(1-\lambda)^i x_i + \lambda^k X_0 \tag{9}$$

where x_0 is generally used as X_0 in practice. Therefore, we have:

$$X_k = \sum_{i=0}^{k} \lambda^{k-i}(1-\lambda)^i x_i \tag{10}$$

As x_k is asymptotically optimal, the exponential weighted Kalman filter expressed in (8) will also be asymptotically optimal. On the other hand, according to the stability of Kalman filter, the stability of the exponential weighted Kalman filter is only affected by smoothing factor λ. The larger the λ, the more stable the estimation. λ could be adjusted according to actual demands. In this study, the value of λ is set to 0.4.

D. LIGHTWEIGHT MULTI-PARAMETER FUSION BASED ON WEIGHTED EUCLIDEAN DISTANCE

Based on the analysis in Section IV-A, a lightweight multi-parameter fusion method based on weighted Euclidean distance was proposed, as shown in (11). The impact of SNR on the fused metric WED is increased by adjusting its weight.

$$WED = \sqrt{(SNR \times \beta)^2 + LQI^2} \tag{11}$$

where β is the weight factor of SNR. In this study, the value of β is 10 according to the ranges of SNR and LQI.

Fig. 7 shows the relationships of LQI, S_m, Triangle, WED and PRR in all experimental fields. It is obvious that the range of WED is 65 to 140 when PRR changes from 0 to 1, which is larger than the ranges of LQI, S_m and Triangle. That is to say, WED could be used to describe PRR more accurately than LQI, S_m and Triangle. Table 2 shows the Spearman and Kendall correlation coefficients of S_m, Triangle, WED and PRR. It is obvious that the correlation between WED and PRR is the highest. As can be seen from Table 1, compared with the correlation between LQI and PRR, the correlations between S_m, Triangle and PRR show little improvement, because they ignore the impacts of different ranges of physical layer parameters on the fused metrics.

TABLE 2. Correlation coefficients of S_m, triangle, WED and PRR.

Parameter	Spearman correlation coefficient	Kendall correlation coefficient
S_m	0.9380	0.7879
Triangle	0.9375	0.7862
WED	***0.9428***	***0.8010***

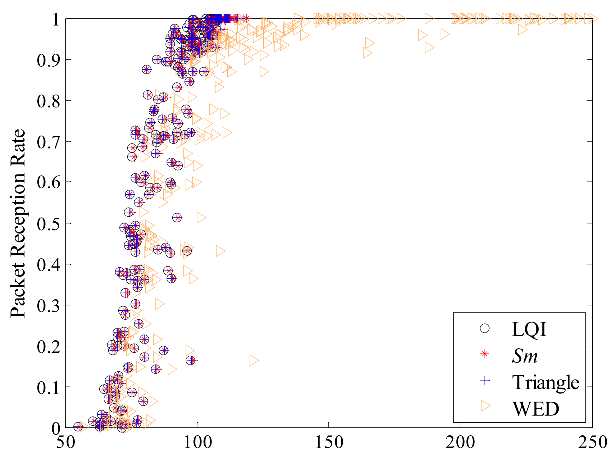

FIGURE 7. Relationships of LQI, S_m, Triangle, WED and PRR in all experimental fields.

E. MAPPING MODEL BASED ON LOGISTIC REGRESSION

In order to estimate link quality quantitatively, it is necessary to construct a mapping model between WED and PRR. Logistic regression is often used to fit the S-shaped relationship of measured data as shown in Fig. 7 [23], [27]. Therefore, it was chosen to establish the mapping model between WED and PRR. The expression of the logistic regression model is shown in (12).

$$g(z) = \frac{1}{1+e^{-z}} \tag{12}$$

where z is a linear function. Let $z = at + b$. For convenience of expression, set the parameter matrix (a,b) as θ, then z can be expressed as:

$$z = \theta t \tag{13}$$

As a result, general form of the logistic regression model is:

$$h_\theta(t) = \frac{1}{1+e^{-\theta t}} \tag{14}$$

where t is the input sample and $h_\theta(t)$ is the probability that the input sample is classified into a certain class. $h_\theta(t)$ is classified using a two-class method, and the model output has corresponding relationship with the binary sample output $y(y \in \{0, 1\})$. The threshold of $h_\theta(t)$ is set to 0.5: when $h_\theta(t)$ is greater than or equal to 0.5, y is 1; when $h_\theta(t)$ is less than 0.5, y is 0. According to above descriptions:

$$P(y|t;\theta) = h_\theta(t)^y(1-h_\theta(t))^{1-y} \tag{15}$$

where $P(\cdot)$ is the probability of a sample. Likelihood function can be used to solve the model's coefficient θ, which expression is:

$$L(\theta) = \prod_{i=1}^{m} (h_\theta(t^{(i)}))^{y^{(i)}}(1-h_\theta(t^{(i)}))^{1-y^{(i)}} \tag{16}$$

where m is the number of input samples. Loss function of the model could be obtained by taking logarithm of (16):

$$\begin{aligned} J(\theta) &= -\log L(\theta) \\ &= -\sum_{i=1}^{m} (y^{(i)} \log(h_\theta(t^{(i)})) \\ &\quad +(1-y^{(i)})\log(1-h_\theta(t^{(i)}))) \end{aligned} \tag{17}$$

When $J(\theta)$ takes the minimum value, θ is optimal, which could be obtained using gradient descent method. Update process of θ in the gradient descent method is as follows:

$$\theta_j := \theta_j - \alpha \frac{\delta}{\delta_{\theta_j}} J(\theta) \tag{18}$$

where α is the step size of the gradient descent method. Derivative of $J(\theta)$ could be obtained using (17), as shown in (19).

$$\begin{aligned} \frac{\delta}{\delta_{\theta_j}} J(\theta) &= -\frac{1}{m}\sum_{i=1}^{m}\Bigg(y^{(i)}\frac{1}{h_\theta(t^{(i)})}\frac{\delta}{\delta_{\theta_j}}h_\theta(t^{(i)}) \\ &\quad -(1-y^{(i)})\frac{1}{1-h_\theta(t^{(i)})}\frac{\delta}{\delta_{\theta_j}}h_\theta(t^{(i)})\Bigg) \\ &= -\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}\frac{1}{g_\theta(\theta t^{(i)})}-(1-y^{(i)})\frac{1}{1-g_\theta(\theta t^{(i)})}\right) \\ &\quad \times \frac{\delta}{\delta_{\theta_j}} g_\theta(\theta t^{(i)}) \\ &= -\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}\frac{1}{g_\theta(\theta t^{(i)})}-(1-y^{(i)})\frac{1}{1-g_\theta(\theta t^{(i)})}\right) \\ &\quad \times g_\theta(\theta t^{(i)})(1-g_\theta(\theta t^{(i)}))\frac{\delta}{\delta_{\theta_j}}\theta t^{(i)} \\ &= -\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}(1-g_\theta(\theta t^{(i)}))-(1-y^{(i)})g_\theta(\theta t^{(i)})\right)t_j^{(i)} \\ &= -\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)}-g_\theta(\theta t^{(i)})\right)t_j^{(i)} \\ &= \frac{1}{m}\sum_{i=1}^{m}\left(h_\theta(t^{(i)})-y^{(i)}\right)t_j^{(i)} \end{aligned} \tag{19}$$

Therefore, the update process of θ could be written as:

$$\theta_j := \theta_j - \alpha\frac{1}{m}\sum_{i=1}^{m}\left(h_\theta(t^{(i)})-y^{(i)}\right)\cdot t_j^{(i)} \tag{20}$$

Using the WED and PRR data shown in Fig. 7 as input, the optimal mapping model between WED and PRR could be obtained as follows:

$$PRR = \frac{1}{1+e^{-0.1416\times WED+13.3085}} \tag{21}$$

V. PERFORMANCE COMPARISONS AND ANALYSIS

A. EVALUATION PARAMETERS

Coefficient of variation (CV) is generally used to assess stability and agility of the estimated values quantitatively [3]. CV is defined as the ratio of the standard deviation to the average of estimated values, as shown in (22).

$$CV = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(E(i)-\frac{1}{n}\sum_{i=1}^{n}E(i)\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}E(i)} \tag{22}$$

where $E(i)$ denotes the estimated value of the i-th window and n is the number of estimated values. Smaller CV means more stable SNR or LQI estimations. In addition, Root Mean Squared Error (RMSE) was chosen as the evaluation parameter for estimation accuracy, as shown in (23).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(E(i)-R(i))^2}{n}} \tag{23}$$

where n is the number of estimated values, $E(i)$ and $R(i)$ are the estimated value and practical value of the i-th window, respectively. The smaller RMSE is, the closer estimated values and practical values are.

B. EFFECTS OF EXPONENTIAL WEIGHTED KALMAN FILTERING

Wireless links are typically classified into three categories according to their PRR values, which are good links, moderate links and bad links [2]. Three links all with length

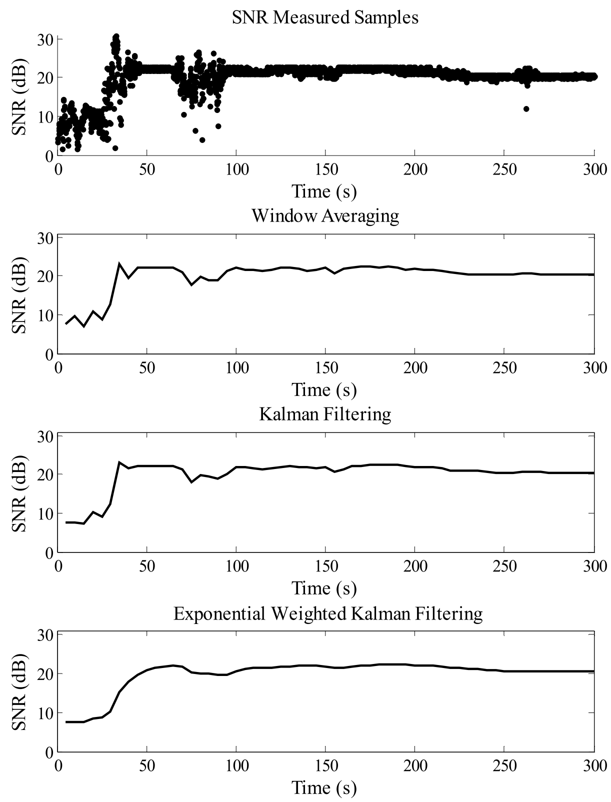

FIGURE 8. **Processing effects of SNR under the good link.**

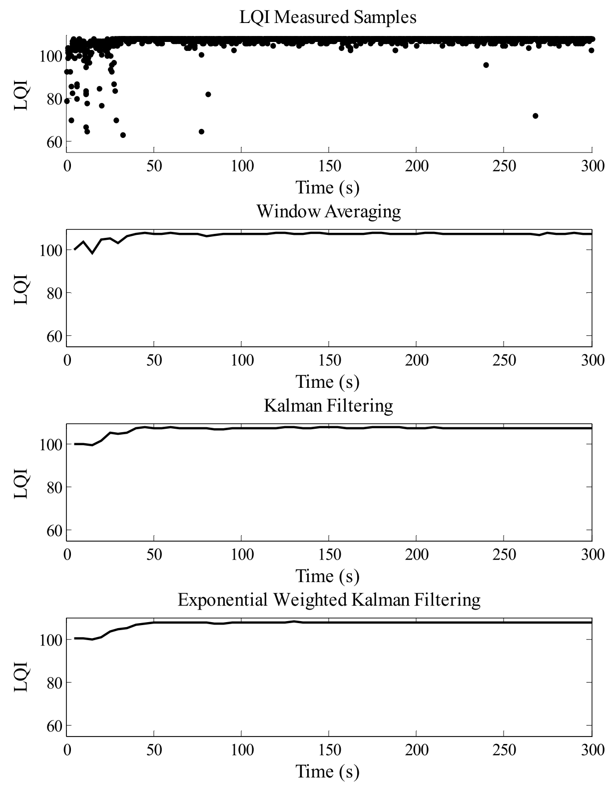

FIGURE 9. **Processing effects of LQI under the good link.**

of 300s were chosen from the long-time experiments, and processed by window averaging, Kalman filtering and exponential weighted Kalman filtering respectively. Time windows of these filters are all set to 5s. These links include a good link with PRR greater than 95%, a moderate link, and a bad link with a few received packets.

Fig. 8 and Fig. 9 show the processing effects of SNR and LQI under the good link. It can be seen that these three methods all get good results under the good link due to the large number of packets received. Fluctuation of the estimated values obtained by exponential weighted Kalman filtering is smaller than window averaging and Kalman filtering.

Fig. 10 to 13 show the processing effects of SNR and LQI under the moderate link and the bad link respectively. Under the moderate link that fluctuates greatly and the bad link with a few received packets, fluctuation of the estimated values obtained by exponential weighted Kalman filtering is obviously smaller than window averaging and Kalman filtering. Although Kalman filtering reduces the fluctuation to some extent compared with window averaging, its processing effect is not satisfactory due to the large fluctuations of moderate link and bad link themselves. These unexpected fluctuations could be further suppressed by exponential weighting average filtering the outputs of Kalman filtering, which is also the reason why the effect of exponential weighting Kalman filtering is better than other preprocessing methods.

Table 3 shows the CVs of SNR and LQI estimations obtained by different preprocessing methods under the moderate and bad link. Since different preprocessing methods all get good results under the good link, their effects under the good link were not compared and analyzed quantitatively. It can be seen that CVs of the estimations obtained by exponential weighted Kalman filtering proposed in this study are the smallest, which means that its estimations are the stablest.

TABLE 3. **CVs of SNR and LQI estimations under the moderate and bad link.**

Link Type	Parameter	Window averaging	Kalman filtering	**Exponential weighted Kalman filtering**
Moderate link	SNR	0.2226	0.2060	***0.1399***
	LQI	0.0896	0.0753	***0.0666***
Bad link	SNR	0.2320	0.1693	***0.1264***
	LQI	0.0836	0.0585	***0.0505***

C. LINK QUALITY ESTIMATORS FOR COMPARISON

KLE, K-CCI, LETX, 4C, FLQE, and ELQET were chosen to compare with the proposed estimator. Among them, KLE, K-CCI, LETX, and 4C all take only one physical layer parameter into consideration. However, the parameter types, preprocessing methods and mapping models they employ are different. Since the test environments are different, parameters of the mapping models given in original papers are not directly applicable to this study. Therefore, if not clearly stated, parameters of the mapping models given below are all fitted using the test data in this study.

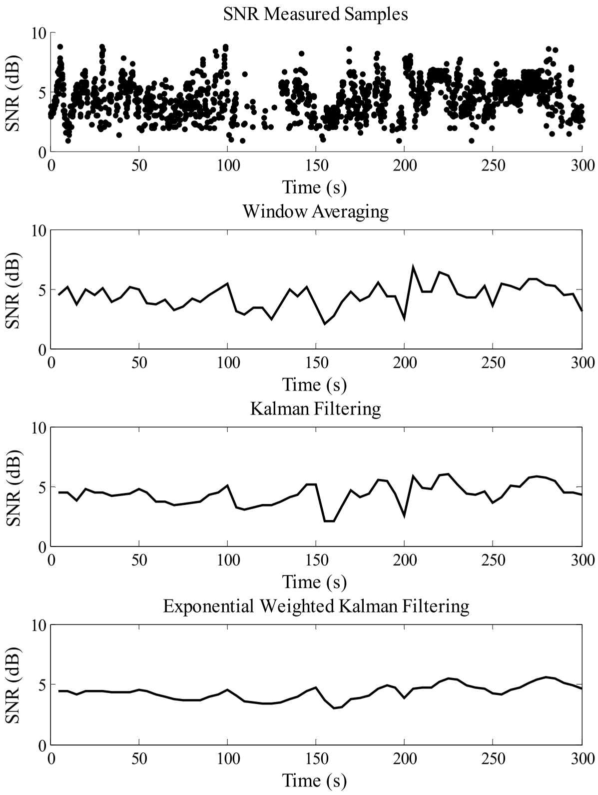

FIGURE 10. Processing effects of SNR under the moderate link.

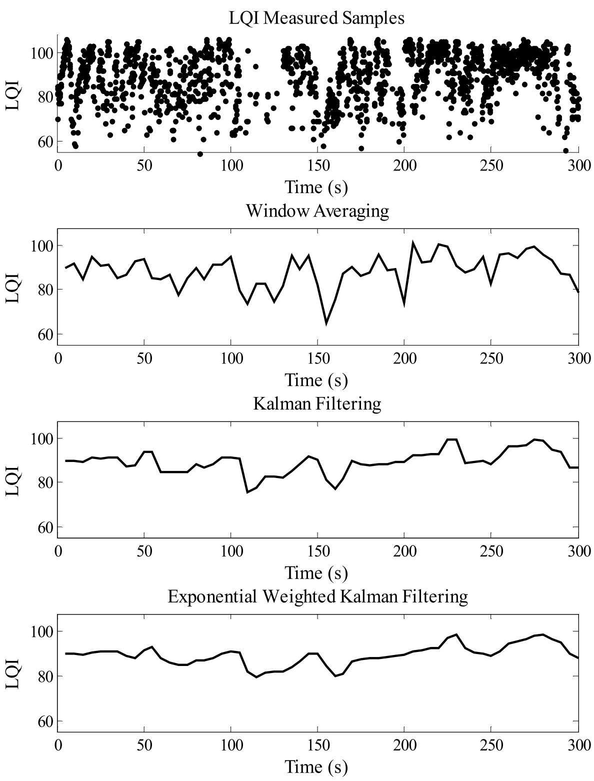

FIGURE 11. Processing effects of LQI under the moderate link.

KLE uses Kalman filtering to preprocess RSSI and calculates SNR by subtracting background noise from smoothed RSSI values. Then, a mapping model between SNR and PRR

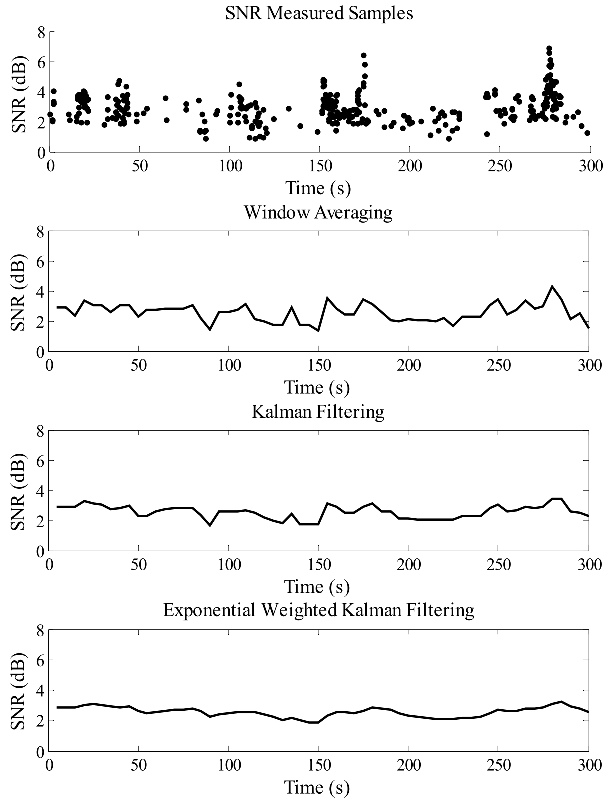

FIGURE 12. Processing effects of SNR under the bad link.

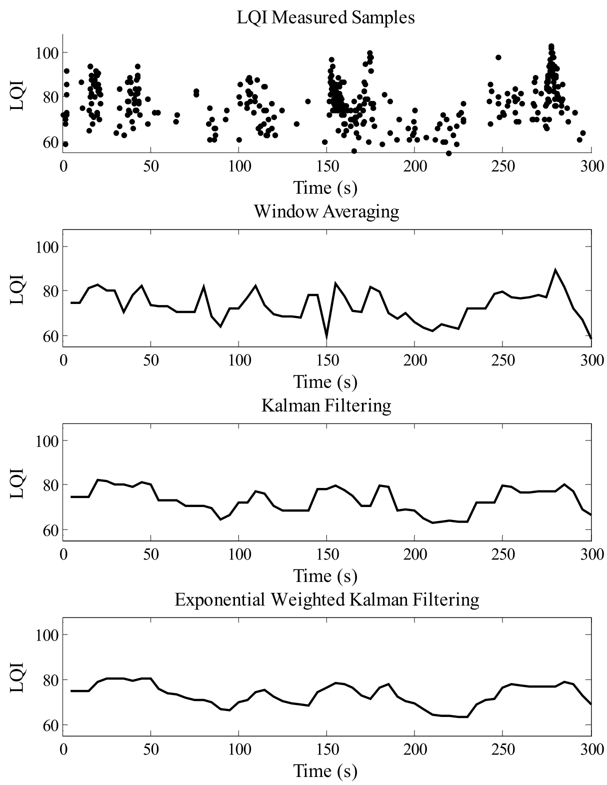

FIGURE 13. Processing effects of LQI under the bad link.

are employed to estimate link quality quantitatively [15]. Estimated PRR of the i-th window is:

$$PRR_{KLE}(i) = f(SNR(i)) \tag{24}$$

where $f(\cdot)$ represents the mapping model between SNR and PRR, which can be implemented in the form of lookup table.

K-CCI uses Kalman filtering to preprocess LQI and then estimates link quality quantitatively using a mapping model between LQI and PRR, which is constructed using Cubic model [14]. The estimated PRR of i-th window is:

$$PRR_{K-CCI} = \begin{cases} 1, & LQI > 104 \\ 0.000006331 \times LQI^3 - 0.001996 \times LQI^2 & \\ + 0.2257 \times LQI - 8.013, & 66 < LQI \leq 104 \\ 0, & LQI \leq 66 \end{cases} \quad (25)$$

Both LETX and 4C use window averaging to preprocess LQI and then estimate link quality quantitatively by establishing mapping models between LQI and PRR [11], [22]. LETX uses a piecewise linear model, as shown in (26), while 4C uses logistic regression to construct the mapping model between LQI and PRR, as shown in (27).

$$PRR_{LETX} = \begin{cases} 1, & LQI > 102 \\ 0.02041 \times LQI - 1.0825, & 78 < LQI \leq 102 \\ 0.05 \times LQI - 3.39, & 68 < LQI \leq 78 \\ 0.0005556 \times LQI - 0.02778, & 50 \leq LQI \leq 78 \end{cases} \quad (26)$$

$$PRR_{4C} = \frac{1}{1 + e^{22.5247 - 0.269 \times LQI}} \quad (27)$$

Both FLQE and ELQET use fuzzy logic to fuse multiple parameters, but different types of parameters are used [5], [18]. FLQE uses four link parameters, namely smoothed PRR (SPRR), link stability factor (SF), link asymmetry level (ASL) and average SNR (ASNR). As other candidate estimators only consider one-way transmission, the ASL parameter was removed for fairness when implementing FLQE. The estimated PRR of i-th window is:

$$FLQE = \alpha_1 \times FLQE_{i-1} + 100 \times (1 - \alpha_1) \times \mu_1(i) \quad (28)$$

where the smoothing factor α_1 is 0.9, and $\mu_1(i)$ is as follows:

$$\mu_1(i) = \beta_1 min(\mu_{SPRR}(i), \mu_{SF}(i), \mu_{ASNR}(i)) + (1 - \beta_1) mean(\mu_{SPRR}(i), \mu_{SF}(i), \mu_{ASNR}(i)) \quad (29)$$

where the smoothing factor β_1 is 0.6.

ELQET also uses four link parameters, namely PRR obtained by LQI mapping, SNR obtained by Kalman filtering, coefficient of variation of PRR and average LQI. The estimated PRR of i-th window is:

$$ELQET(i) = \alpha_2 \times ELQET(i-1) + (1 - \alpha_2) \times \mu_2(i) \quad (30)$$

where the smoothing factor α_2 is 0.8, and $\mu_2(i)$ is as follows:

$$\mu_2(i) = \beta_2 \min(\mu_{PRR}(i), \mu_{SA}(i), \mu_{ASNR}(i), \mu_{ALQI}(i)) + (1 - \beta_2) mean(\mu_{PRR}(i), \mu_{SA}(i), \mu_{ASNR}(i), \mu_{ALQI}(i)) \quad (31)$$

where the smoothing factor β_2 is 0.6.

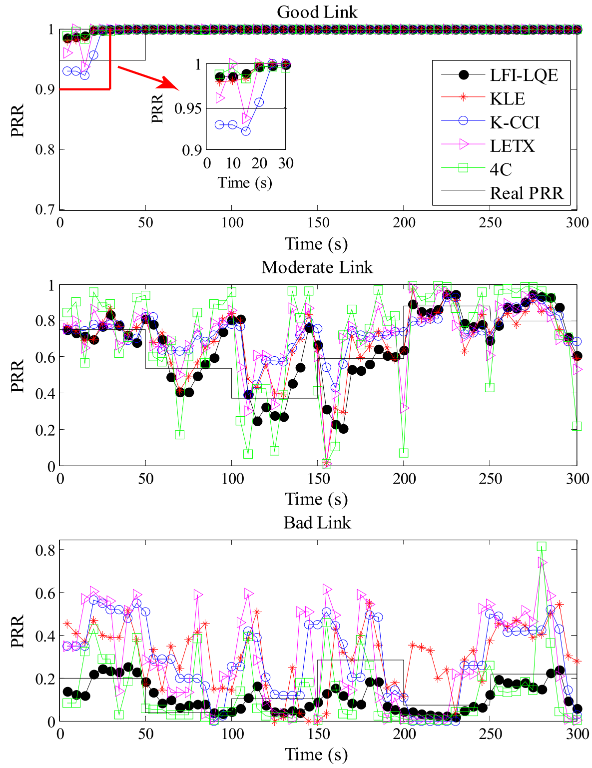

FIGURE 14. **Performance comparison with single-parameter estimators under different link quality.**

As multi-parameter fusion estimators based on machine learning algorithms are too complicated for WSNs which have limited computing power, they are not chosen for comparison. Although 4C also uses machine learning algorithms for link quality prediction, the mapping model between LQI and PRR that it ultimately uses is obtained by offline training. As a result, it will not increase too much computation overhead when the estimator is in the actual running. Time windows of above estimators are all set to 5s. Since the short-time statistical PRR could not truly reflect the link quality [3], PRR counted every 50s is used as the evaluation criterion for accuracy.

D. PERFORMANCE COMPARISON UNDER DIFFERENT LINK QUALITY

Performance of the estimators is compared under different link quality, as shown in Fig. 14 and Fig. 15. The same good link, moderate link and bad link as in Section V-II are used. Other good, moderate and bad links are also tested and similar results are obtained. For the sake of space, corresponding charts are omitted. Fig. 14 shows the comparison between LFI-LQE and single-parameter estimators, and Fig. 15 shows the comparison between LFI-LQE and other multi-parameter fusion estimators. It can be seen that LFI-LQE and single-parameter estimators all perform well under the good link, while the estimated values of other multi-parameter fusion estimators are quite different from the real PRR, although they are very stable. Under the bad link, estimated values of

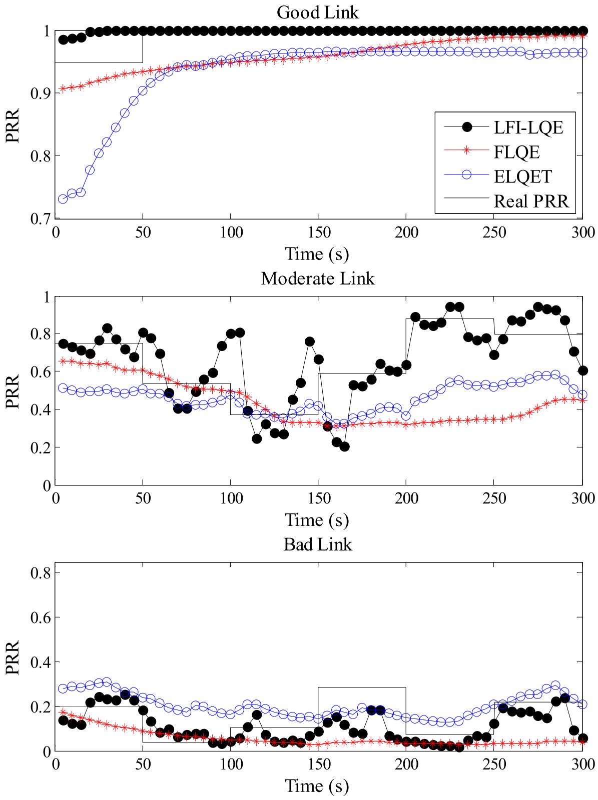

FIGURE 15. Performance comparison with other multi-parameter fusion estimators under different link quality.

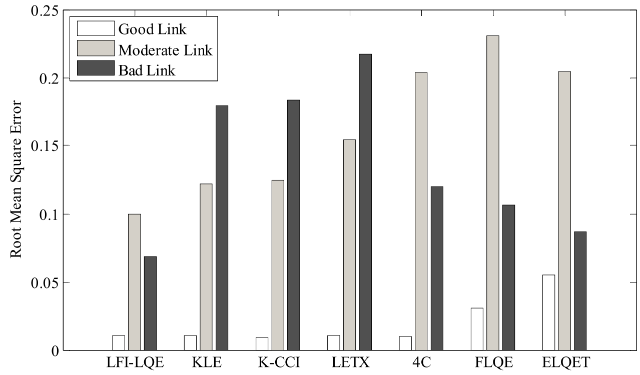

FIGURE 16. RMSEs under different link quality.

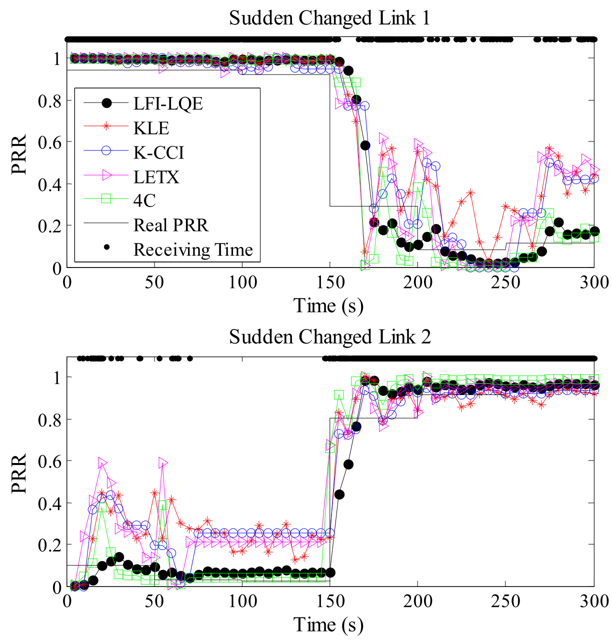

FIGURE 17. Performance comparison with single-parameter estimators under sudden changed links.

single-parameter estimators fluctuate greatly and are inaccurate, because little information could be obtained by single-parameter estimators in bad links. However, estimated values of LFI-LQE and other multi-parameter fusion estimators are more accurate and stable. Under the moderate link, although more information could be obtained than the bad link, estimated values of single-parameter estimators still fluctuate greatly due to the large fluctuations of physical layer parameters themselves. Estimated values of other multi-parameter fusion estimators are still stable, but their estimate errors are fairly large. Benefiting from the fusion of SNR and LQI and more effective preprocessing, estimated values of the proposed estimator are stable and accurate under different link quality. ELQET and FLQE are too stable, so they are unresponsive when the link changes. For example, under the moderate link, ELQET and FLQE could not keep up with link changes accurately after 150s as LFI-LQE does. The reason is that the fuzzy logic of ELQET and FLQE would select the most pessimistic parameter as part of their final estimations, which inevitably results in too pessimistic estimations.

In order to evaluate the accuracy of LFI-LQE quantitatively, RMSEs under different link quality are calculated, as shown in Fig. 16. It is obvious that RMSEs of LFI-LQE and single-parameter estimators are all very small under the good link, while RMSEs of FLQE and ELQET are relatively larger. Under the moderate and bad link, RMSEs of LFI-LQE are both the lowest. Compared with other estimators, estimate error of the proposed one is reduced by 18.32% to 60.11%.

E. PERFORMANCE COMPARISON UNDER SUDDEN CHANGED LINKS

In addition to fluctuations, there are also sudden changes in actual links [9]: changes of environmental conditions may cause the link to suddenly change from good to bad, or from bad to good. The estimator should respond quickly and accurately when sudden changes arise. Two sudden changed links both with length of 300s were chosen from the long-time experiments for performance comparison of the estimators, as shown in Fig. 17 and Fig. 18. Among them, the sudden changed link 1 represents a sudden change from good link to bad link, and sudden changed link 2 represents a sudden change from bad link to good link. The changes both occur at 150s of two links. Other sudden changed links are also tested and similar results are obtained. For the sake of space, corresponding charts are omitted. Fig. 17 shows the comparison between LFI-LQE and single-parameter estimators, and Fig. 18 shows the comparison between LFI-LQE and other

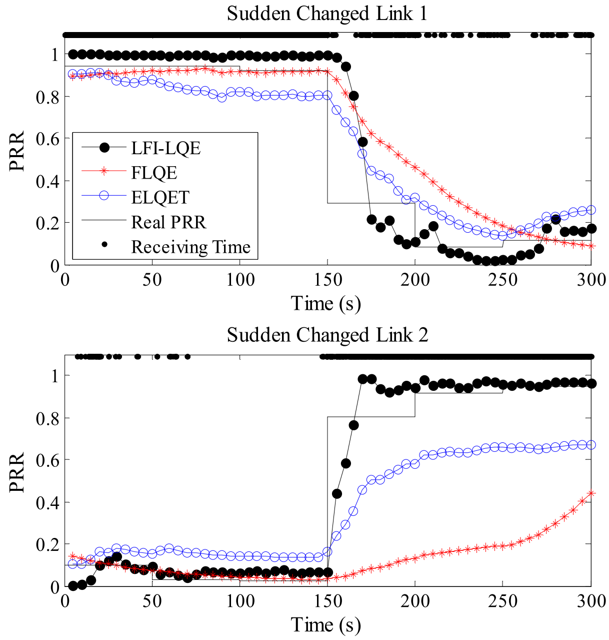

FIGURE 18. Performance comparison with other multi-parameter fusion estimators under sudden changed links.

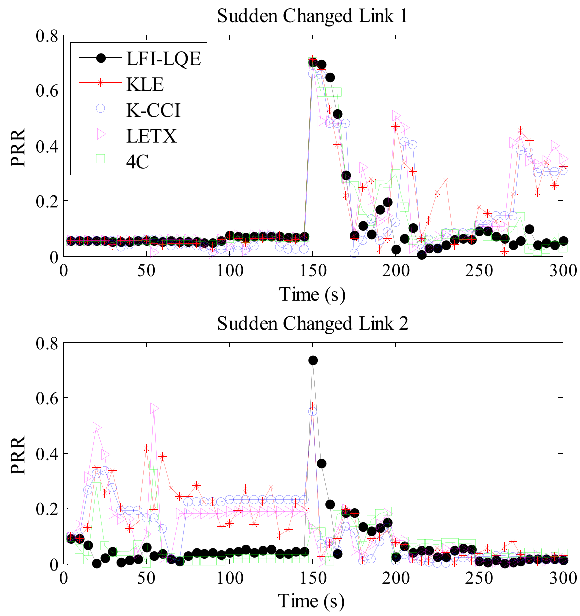

FIGURE 19. Difference curves of single-parameter estimators under sudden changed links.

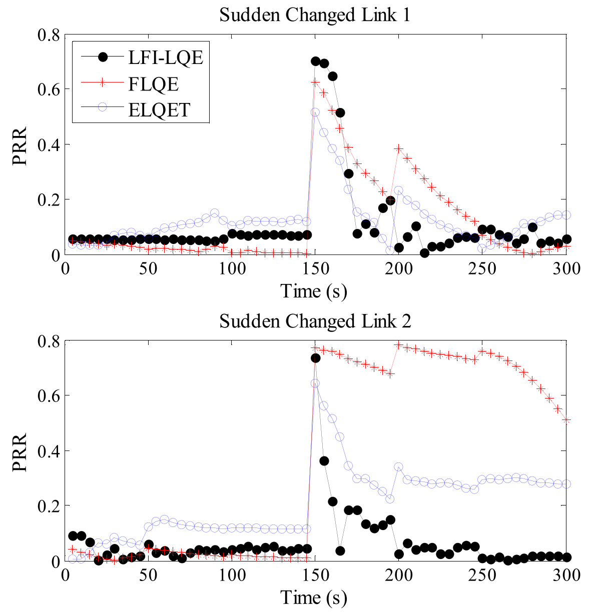

FIGURE 20. Difference curves of multi-parameter fusion estimators under sudden changed links.

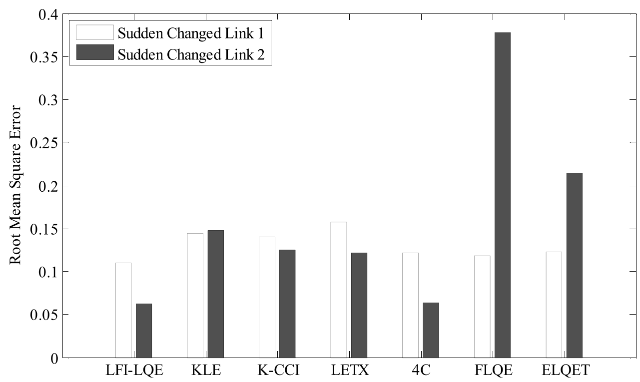

FIGURE 21. RMSEs under sudden changed links.

multi-parameter fusion estimators. In order to demonstrate the reaction speed of each estimator more intuitively, whether data packets are received or not is also marked at the top of Fig. 17 and Fig. 18.

Due to different preprocessing methods employed by the estimators, there are differences between response times to the sudden changes. It can be seen from Fig. 17 that there are few packets received for a period after the sudden change arises in link 1. Therefore, estimators do not have enough information to react. LETX and 4C, which use mean values of physical layer parameters, are the fastest. However, their responses are excessively fierce and the following estimations fluctuate greatly. That is to say, although LETX and 4C react more quickly, their estimations are not reliable.

Response times of LFI-LQE, KLE and K-CCI are essentially the same, but large fluctuations also appear for subsequent estimations of KLE and K-CCI. Unlike them, LFI-LQE is still stable after reaction. Therefore, it could describe link quality more accurately. It can be seen from Fig. 18 that reactions of FLQE and ELQET are too slow, which lead to considerably large errors.

For the sudden changed link 2, there are quite a lot of packet losses at the beginning. In this stage, estimated values of single-parameter estimators are inaccurate. Unlike them, LFI-LQE could get stable and accurate estimations. When the sudden change arises in link 2, LFI-LQE and single-parameter estimators all react quickly. However, reaction speed of LFI-LQE is not as fast as single-parameter estimators due to its more stable preprocessing. On the other hand,

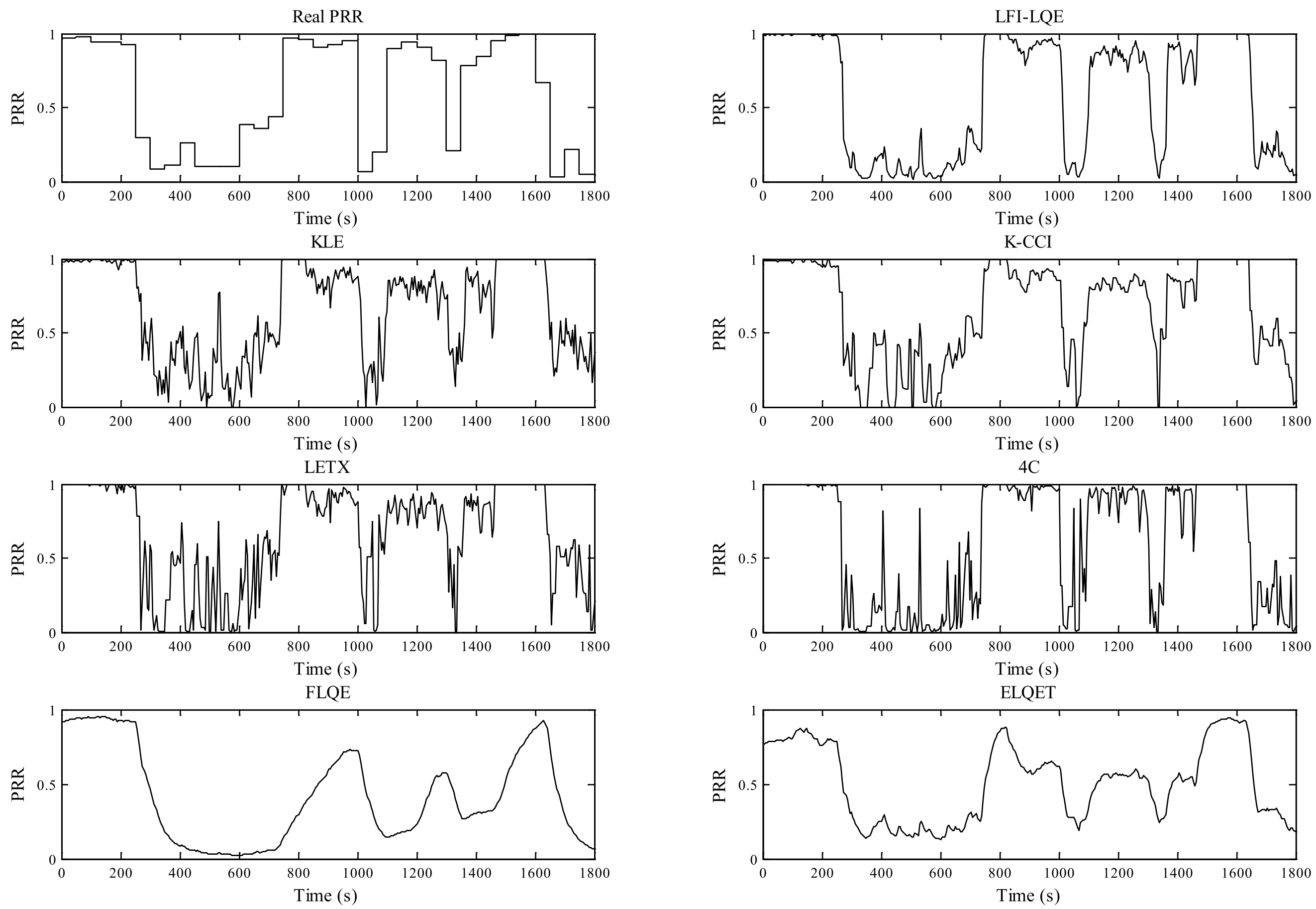

FIGURE 22. Performance comparison under a long-time link.

reactions of FLQE and ELQET are still very slow, which makes them much worse than LFI-LQE.

Although single-parameter estimators react quickly when the link suddenly changes, their estimated values fluctuate greatly when the link quality is not good. To analysis the time points when estimators generate accurate estimated values, differences between estimated values of each estimator and the real PRR were calculated, as shown in Fig. 19 and Fig. 20. The time point when the difference is less than 10% for the first time is taken as a standard. From Fig. 19, it is shown that under sudden changed link 1, LFI-LQE is one of the fastest estimators to generate accurate estimated values, all at 175s. However, as sudden changed link 2 is from bad link to good link, all estimators could acquire enough information within one time window after the sudden change arises to make accurate estimation. Hence, LETX and 4C, which use window averaging, generate accurate estimated values within only one time window, both at 155s. KLE and K-CCI, which use Kalman filtering, also generate accurate estimated values at 155s, while LFI-LQE that uses exponential weighted Kalman filtering generates accurate estimated values at 160s. As can be seen from Fig. 20, reactions of ELQET and FLQE, which use fuzzy logic to fuse multiple parameters, are very slow, and could not generate accurate estimated values even for long time.

In order to describe the accuracy of LFI-LQE quantitatively, RMSEs under sudden changed links are calculated, as shown in Fig. 21. It is obvious that RMSEs of LFI-LQE are the smallest under sudden changed links. Compared with other estimators, estimate error of the proposed one is reduced by 1.42% to 83.43%.

F. PERFORMANCE COMPARISON UNDER A LONG-TIME LINK

Fig. 22 shows the performance comparison under a long-time link, which length is half an hour. This link is composed of different link conditions, including good links, moderate links, bad links, and sudden changed links, which can be used to evaluate estimators under complicated conditions. Among the single-parameter estimators, LETX and 4C, which use mean values of physical layer parameters, perform rather badly. Fluctuations of their estimated values are quite large. Estimated values of KLE and K-CCI, which are based on Kalman filtering, fluctuate less than LETX and 4C. Thanks to exponential weighted Kalman filtering and multi-parameter fusion, LFI-LQE is more stable than

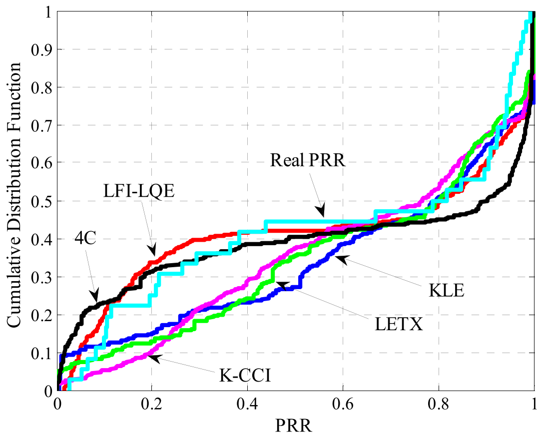

FIGURE 23. CDFs of the estimated values for single-parameter estimators under the long-time link.

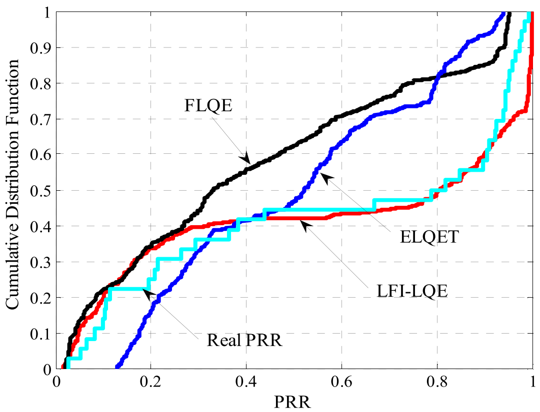

FIGURE 24. CDFs of the estimated values for multi-parameter fusion estimators under the long-time link.

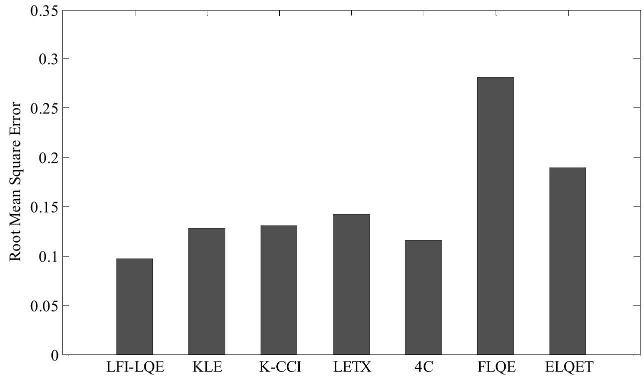

FIGURE 25. RMSEs under the long-time link.

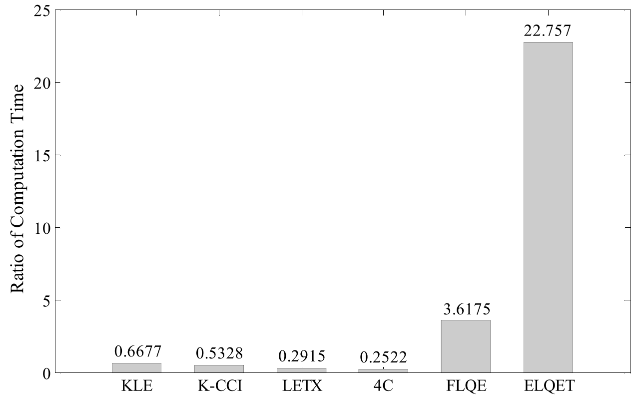

FIGURE 26. Relative computation overheads of the estimators.

single-parameter estimators. Although FLQE and ELQET are more stable than LFI-LQE, their estimated values are quite different from the real ones. As a result, they could not truly reflect the link quality.

Fig. 23 and Fig. 24 show the Cumulative Distribution Functions (CDF) of the estimated values under the long-time link. It can be seen that estimated values of FLQE and ELQET are almost evenly distributed. However, it can be seen from the distribution of real PRR that the proportion of moderate links under this long-time link is quite small, which means that FLQE and ELQET could not describe link quality accurately. Since LETX, K-CCI, KLE, and 4C only use the link quality information carried by single physical layer parameter, the distributions of estimated values for LETX, K-CCI, and KLE under bad links and moderate links are quite different from that of real PRR. Similarly, the distribution of estimated values for 4C under good links is quite different from that of real PRR. Unlike them, the distribution of estimated values for LFI-LQE is very close to that of real PRR.

In order to describe the accuracy of LFI-LQE quantitatively, RMSEs under the long-time link are calculated, as shown in Fig. 25. It is obvious that RMSE of LFI-LQE is the smallest under the long-time link. Compared with other estimators, estimate error of the proposed one is reduced by 16.64% to 65.61%.

By comparing and analyzing the performance of candidate estimators under different link quality and sudden change links, it can be seen that single-parameter estimators would fluctuate greatly and get inaccurate estimations under bad links with few packets received and moderate links with large fluctuations. Estimators using fuzzy logic to fuse multiple parameters are too stable, which could not keep up with link changes accurately in time. Additionally, these estimators are apt to underestimate the link quality. Benefiting from the fusion of SNR and LQI and more effective preprocessing, the estimator proposed in this study could not only achieve stable and accurate estimations under bad links and moderate links, but also generate accurate estimations quickly under sudden change links. Therefore, its performance under the long-time link is the best.

G. COMPUTATION OVERHEAD

In order to compare the computation overheads, the time that candidate estimators take to generate 10000 estimated values is counted. 20 times were repeated under the same condition to eliminate the error that may occur in single run. Then, average time of 20 runs was taken as the time of each estimator. In order to show the difference in computation overhead more clearly, the ratio of computation time relative to the proposed estimator was calculated, as shown in Fig. 26. Platform parameters used in this test are as follows: 3.5GHz Intel Pentium processor, 8GB memory; Windows 10 operating system; Matlab 2013a.

It is shown that relative computation overheads of single-parameter estimators are all smaller than the proposed one. Among them, 4C and LETX, which preprocess physical layer parameters by window averaging, are the fastest, while KLE and K-CCI using Kalman filtering are the second. LFI-LQE takes slightly longer time than single-parameter estimators, but much less time than other multi-parameter fusion estimators. Compared with KLE, computation overhead of LFI-LQE increases by 49.77%. However, it decreases by 72.36% and 95.61% respectively compared with FLQE and ELQET.

VI. CONCLUSIONS AND FUTURE WORKS

Accurate and agile link quality estimation is necessary for efficient routing in wireless sensor networks. Using the mapping models between physical layer parameters and packet reception ratio, link quality can be estimated with advantages of high agility and low overhead. However, these physical layer parameters are usually very unstable. Existing estimators typically use window averaging or Kalman filtering to preprocess these parameters. Unfortunately, the processing effects are not satisfactory. Additionally, existing estimators either take only one physical layer parameter into consideration, which makes them difficult to describe real link quality accurately, or employ too complicated multi-parameter fusion methods, which could not offer a good balance among accuracy, agility and low overhead.

In this study, a lightweight, fluctuation insensitive multi-parameter fusion link quality estimator is proposed. In order to get more stable estimations, exponential weighted Kalman filtering is utilized to preprocess two physical layer parameters, SNR and LQI. Then, lightweight weighted Euclidean distance is used to fuse these two parameters to fully utilize link quality information carried by them, which would not introduce excessive computation overhead. This lightweight multi-parameter fusion method combines the advantages of SNR and LQI under different link quality, so it could achieve more accurate estimations. On this basis, link quality is estimated quantitatively with the mapping model of the fused parameter and packet reception ratio, which is constructed by logistic regression.

Experimental results show that the proposed estimator could reflect link quality more realistically. Compared with similar estimators, estimate error of the proposed one is reduced by 18.32% to 60.11% under moderate and bad links, by 1.42% to 83.43% under sudden changed links, and by 16.64% to 65.61% under a long-time link. More importantly, computation overhead of the proposed estimator is equivalent to those of single-parameter estimators, but much less than other multi-parameter fusion estimators. Compared with the later, computation overhead is reduced by 72.36% to 95.61%. In the future, the proposed estimator would be integrated to existing protocols of wireless sensor networks.

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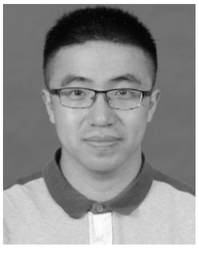

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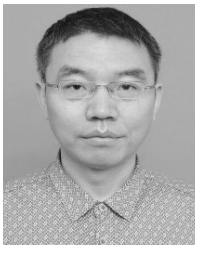

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