An Empirical Study of Link Quality Estimation Techniques for Disconnection Detection in WBANs

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ABSTRACT

Sensor nodes in many Wireless Body Area Network (WBAN) architectures are supposed to deliver sensed data to a gateway node on the body. To satisfy the data delivery requirements, the network needs to adapt itself to the changes in connection status of the body nodes to the gateway. As a prerequisite, Link Quality Estimation (LQE) needs to be done to detect the connection status of the nodes. The quality of links in WBANs is highly time-varying. The LQE technique should be agile to react fast to such link quality dynamics while avoiding frequent fluctuations to reduce the network adaptation overhead. In this paper, we present an empirical study on using different LQE methods for detecting the connection status of body nodes to the gateway in WBANs. A set of experiments using 16 wireless motes deployed on a body are performed to log the behavior of the wireless links. We explore the trade-offs made by each LQE method in terms of agility, stability, and reliability in detecting connection changes by analyzing the experimental data. Moreover, different LQE methods are used in an adaptive multi-hop WBAN mechanism, as a case study, and their impact on the Quality-of-Services (QoS) are investigated.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design; C.4 [**Performance of Systems**]: Modeling Techniques; Performance Attributes

Keywords

Link Quality Estimation; Wireless body area network; Disconnection detection; Quality-of-service.

1. INTRODUCTION

In a Wireless Body Area Network (WBAN), several small-scale wireless sensor devices are deployed on a human body to sense and transmit biological signals of the body. In common network architectures, one node plays the role of a gateway node to gather data from all nodes in the WBAN and transmit it to a higher level network (e.g., a central station).

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Thus the body nodes are supposed to deliver their sensed data to the gateway node. There are several approaches for data delivery to the gateway nodes, from a one-hop star architecture to multi-hop data forwarding mechanisms.

Regardless of the used network protocol for data delivery to the gateway, applications have specific Quality-of-Service (QoS) requirements that should be satisfied by the networking protocol. In particular, Data Delivery Ratio (DDR) to the gateway node and energy consumption are important parameters. The network protocol is responsible for meeting the data delivery requirements of the application while minimizing the energy consumption of the nodes to prolong the life-time of the sensor nodes.

WBANs are very dynamic and the network topology and the quality of wireless links varies over time (due to posture changes and body movement). The protocol needs to adapt itself to these dynamics to continuously meet the QoS requirements. This can be done by data retransmission, data forwarding through nodes with good wireless links to the gateway as relay nodes, or transmit power adaptation, for instance. An adaptation mechanism is triggered when the connection status of some nodes to the gateway changes. A node is connected to the gateway node if it is able to properly reach the gateway directly to satisfy the data delivery requirements; otherwise, it is disconnected.

The connection status of the body nodes to the gateway is detected by monitoring the quality of wireless links to the gateway. Thus, Link Quality Estimation (LQE), aiming to quantify the quality of the wireless links, is a prerequisite for (dis)connection detection. Several LQE techniques for Wireless Sensor Networks (WSNs) exist, each with specific features [1]. Accuracy, agility to follow link quality dynamics, stability, energy efficiency, and computation overhead are characteristics that should be taken into account for selecting an LQE method for a specific network. WBANs are a special kind of networks with frequent topology changes and link quality variations. Thus an LQE method for WBANs needs to be firstly agile to react fast to such frequent link quality variations. Link quality directly affects DDR for the nodes that experience a change in their connection state. As the LQE result is going to be used for triggering the adaptation mechanism of the underlying network protocol, it should be stable enough to avoid frequent fluctuations. In addition, the method needs to be energy efficient with as little as possible required computation and hardware support to be used by ultra-low power body sensor devices.

The main contribution of this paper is to experimentally study the performance of different LQE methods presented for WSNs for (dis)connection detection in WBANs. We deployed 16 wireless nodes on a human body and performed several experiments with different network configurations (such as different transmit power levels of the nodes). The status of the links was logged during each experiment. This experimental data is then used to investigate the characteristics of various LQE methods and also to explore the trade-offs made by each method and its configurations in terms of agility, stability, and reliability. Although there are several work in the literature that investigate the performance of LQE methods for WSNs and ad hoc networks, to the best of our knowledge, this is the first effort to experimentally study these techniques in WBANs. We also present an LQE method, Smoothed Link Likelihood Factor, which is able to make a very good trade-off for various performance metrics in many WBAN scenarios. Finally, we use different LQE methods in an adaptive WBAN mechanism [2], as a case study, to investigate the impact of using each method on the WBAN performance (i.e., energy consumption and DDR).

The paper is organized as follows. The next section describes the problem of disconnection from the gateway in WBANs. Sec. 3 discusses the classification of LQE methods for WSNs from [1] and their suitability for WBANs. In Sec. 4, our experimental setup and the used metrics for investigating the characteristics of different LQE methods are described. Sec. 5 presents data analysis results for various LQE methods and different configurations, and gives an impression of the characteristics of each estimator. In Sec. 6, the use case is presented and the achieved QoS by using different LQE methods are compared. Sec. 7 concludes.

2. PROBLEM STATEMENT

We consider $S = \{s_1, s_2, ..., s_N\}$ as the set of N Body Sensor nodes (BSNs) deployed on a body, forming a WBAN. One of these nodes, say s_N, plays the role of a gateway (hub) to gather sensed data from all nodes in the WBAN. As the nature of various body signals being sensed is different, there is usually a high diversity in data sampling and also data delivery requirements for different BSNs. This implies that each sensor needs to be treated considering its own specifications.

$\mathcal{R}^t(s_i)$ is defined as the Data Delivery Ratio (DDR) of node s_i at time t that shows the percentage of the $\mathcal{H}$ last data items sampled by node s_i before time t that reached the gateway, calculated by Eqn. 1.

$$\mathcal{R}^t(s_i) = \frac{1}{\mathcal{H}} \sum_{k=1}^{\mathcal{H}} D^{t,k}(s_i) \tag{1}$$

where $D^{t,k}(s_i)$ is a 0 or 1 valued parameter that shows whether the k^{th} data item sampled by node s_i before/at time t (starting to count backward from time t) has reached the gateway; a value of 1 indicates a successful delivery. The application may specify a constraint $\mathcal{RC}(s_i)$ for DDR of each node s_i. It means that the application expects the value of $\mathcal{R}^t(s_i)$ to remain above this threshold ($\mathcal{R}^t(s_i) \geq \mathcal{RC}(s_i)$). However, because of the stochastic nature of the network, this may not be 100% satisfiable during the network operation. Therefore, the application needs to have tolerance to a certain percentage of violations of its constraint $\mathcal{RC}(s_i)$. As an example, an application may require the DDR for a node s_i to be higher than 80% in 95% of the time.

All nodes are initially supposed to send their data directly to the gateway. This is a common communication approach (e.g., [3, 4, 5]) because of the small scale of WBANs. However, the direct link to the gateway may fail because of body influence on the wave propagation, or the very low transmission power of some nodes. Each node has a certain packet transmission period and each data packet has some retransmission budget to be delivered to the gateway. The data packet gets lost if it cannot be delivered using the available (re)transmission opportunities.

Definition: *A body sensor node s_i is said to be disconnected from the gateway iff it cannot satisfy the required data delivery ratio $\mathcal{RC}(s_i)$ by sending its packets directly to the gateway node within the available transmission budget.*

Taking this definition, disconnection of a node depends on the quality of its wireless link to the gateway, data sampling and transmission rates, and the DDR requirements for that node. This means that we may have two nodes with the same link quality, where one is considered connected and the other is considered disconnected, because of different sampling specifications and DDR requirements. When a node goes to a disconnected state, the network protocol should adapt itself to improve data delivery for the disconnected node and to bring the DDR of the node within the acceptable range. The protocol should also adapt when a node reconnects to the gateway to optimize the consumption of network resources.

Here we consider two common solutions that may be used to deal with this disconnection problem. The first one is to provide multi-hop data routing, by getting help of other BSNs that have currently good links to the gateway (e.g., [2], [6]). The second approach is to adapt the transmit power of the node (e.g., [7] and [8]), hoping to improve the link quality to the gateway and getting out of the disconnection state. This method resolves the issue as far as a higher transmit power is available for the BSN. A combination of these two approaches may also be applied.

Regardless of the method that the networking protocol uses to deal with disconnections, a mechanism for detecting connection changes should be in place to trigger the adaptation mechanism. As the data sampling and transmission period, and DDR constraints ($\mathcal{RC}(s_i)$) are known, we only need to measure the quality of the wireless link between the BSNs and the gateway to detect connection state of the nodes. The speed and accuracy of the LQE method influence the performance of the WBAN protocol. Because of very frequent topology and link quality changes in WBANs, the LQE method should react fast enough to follow the changes in the quality of links. Late disconnection detection may lead to data loss or even violation of DDR requirements for the BSNs. Late reconnection detection is also expensive, because the protocol may be performing unnecessary data forwarding or the BSN uses unnecessarily high transmit power. The method should not be very sensitive to incidental link failures or connections. It needs to be stable enough to avoid frequent fluctuations in order to to keep the overhead of the adaptation mechanism low and to make it robust.

There are several LQE methods in the literature of WSNs. In [9], the performance of prominent software-based LQE techniques are compared by applying them in simulating static WSNs. The quality of wireless links and the kind of network dynamics in WBANs substantially deviate from typical WSNs. In this paper, we investigate the performance of LQE methods for detecting connection changes in real-world WBANs. This is done by performing comprehensive experiments using wireless motes deployed on a body, logging the status of the wireless links, and applying different LQE methods on the logged data. It allows us to explore the trade-offs in terms the agility, stability, and reliability of the estimators in detecting connection changes. These performance metrics and the method for measuring them are described in Sec. 4.2.

3. LQE FOR WSNS AND WBANS

3.1 Classification of LQE Techniques

Techniques for estimating the quality of wireless links in WSNs are firstly categorized as *hardware-based* and *software-based* methods [1]. Link Quality Indicator (LQI), Received Signal Strength Indicator (RSSI), and Signal-to-Noise Ratio (SNR) are hardware-based LQE methods provided by many radio devices. The hardware-based link quality values are directly given by the radio device and no further computation is necessary in software. However, these techniques suffer from some limitations. First, the provided values are only for successfully received packets and the lost packets are not taken into consideration. This may lead to overestimating the link quality. Second, the hardware-based LQE techniques are only suitable for classifying the links as very good or very bad and are not accurate enough to provide a fine-grained estimation of the link quality [10]. Another fact that further limits the use of hardware-based techniques is that not all radio chips are equipped with a link quality estimator (e.g., Nordic nRF24L01[11]).

Software-based LQE methods are done in software base on the ability of the links to deliver the whole packets (data packets or beacons). These estimators are classified into *sender side* and *receiver side* methods. Sender side techniques compute or approximate the average number of times a data item should be (re-)transmitted until it is correctly received by the receiver. This is done by the sender of the packets and uses the acknowledgment that is sent by the receiver. Thus, asymmetric links degrade the accuracy of these methods. Required Number of Packet transmissions (RNP) [12], the Link Inefficiency metric (LI) [13], Expected Transmission Count (ETX) [14], and four-Bit [10] are examples of sender side LQE techniques.

In this work, we investigate the behavior of *receiver side LQE methods* for estimating the quality of links toward the gateway node in WBANs. Sender side methods rely on acknowledges from the receiver (gateway here), which is costly for energy constrained BSNs, and it is not done in many WBAN scenarios. Moreover, the main flow of data in typical WBANs is from BSNs to the gateway. So the gateway can use the existing data traffic for LQE without the need for beacon transmission by BSNs. In the following, the receiver side LQE techniques under investigation are described.

3.2 Receiver-side LQE Methods for WBANs

Assume that each BSN periodically transmits packets to the gateway node with round sequence numbers denoted by τ. $Link^{\tau}$ is a logical value (0 or 1), which is 1 if the packet transmitted at round number τ is directly received by the gateway; otherwise, it is 0. In fact, $Link^{\tau}$ shows the reception status of the packet at round τ. Based on this knowledge, the gateway is able to quantify the quality of its incoming links using the following estimators.

Packet Reception Ratio (PRR) at any time is the ratio of last w transmitted packets that are successfully received by the receiver, given by Eqn. 2.

$$PRR^{\tau} = \frac{1}{w} \sum_{k=0}^{w-1} Link^{\tau-k} \tag{2}$$

Actually, PRR is a moving average of link status and parameter w is the window size of the moving average. A smaller window size leads to more agile estimation at the cost of less stability (more fluctuations). Especially when the quality of the link is not on the extreme good or bad sides, a greater window size is required to accurately quantify the link quality [12]. PRR can be used as an LQE itself, but it is also the basis for some other LQE techniques. Fig. 1 depicts a block diagram of calculating the LQE techniques that are mostly based on PRR, and the involved parameters.

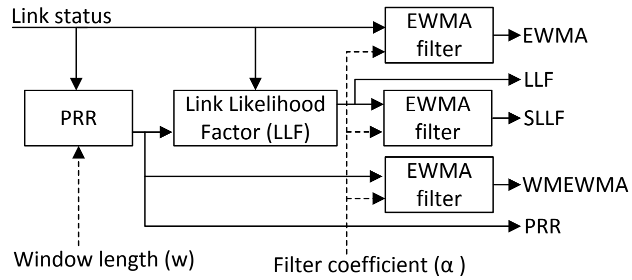


Figure 1: Block diagram of link quality estimators.

Time Weighted Moving Average (TWMA) calculates a moving average over a window of size w using a linear weighting function. It places heavier weight on more recent samples to make the quality estimation more reactive to temporal dynamics comparing to PRR. Eqn. 3 calculates this estimate.

$$TWMA^{\tau} = \frac{\sum_{k=0}^{w-1} \left((w-k) \times Link^{\tau-k}\right)}{\sum_{k=1}^{w} k} \tag{3}$$

Exponentially Weighted Moving Average (EWMA) is a type of infinite impulse response filter that applies exponentially decreasing coefficients (infinite window with exponential weights). Calculating this estimate is simple and memory efficient as a recursive calculation, given in Eqn. 4, only requires storage of the previous estimate.

$$EWMA^{\tau} = \alpha \times Link^{\tau} + (1-\alpha) \times EWMA^{\tau-1} \tag{4}$$

The coefficient $0 < \alpha \leq 1$ represents the degree of weighting decrease. A higher value of α discounts previous link states faster, which leads to a more agile LQE. In general, the technique has the property of being reactive to small dynamics of the link quality even for very intermittent link fluctuations. However, it severely suffers from frequent fluctuations, which cause an unstable estimation.

Window Mean with EWMA (WMEWMA) is proposed in [15] to smooth the PRR estimate using the EWMA filter aiming to make the estimation more stable, but still agile. It is a generalization of both PRR and EWMA. It is sometime referred to as Smoothed PRR (SPRR) [9]. The recursive calculation of the estimation is given by Eqn. 5.

$$WMEWMA^{\tau} = \alpha \times WMEWMA^{\tau-1} + (1-\alpha) \times PRR^{\tau} \tag{5}$$

WMEWMA has two control parameters, which are the window size w in calculating PRR and the history control coefficient $0 \leq \alpha \leq 1$. A higher value of coefficient α leads to a filter that passes lower frequency fluctuations on PRR, which means a more stable estimate. Setting $\alpha = 0$ converts WMEWMA to the base PRR estimate. In [15], it is claimed that this metric performs best overall because it provides the most stable estimate and is simple to calculate. However, the slow reaction of the estimator to link dynamics is a weakness of the estimator.

Link Likelihood Factor (LLF) is also a PRR-based LQE method, which is proposed in [6], specifically for estimating the quality of wireless links in WBANs. This metric tries to represent the likelihood for the link to be connected at any given time. The main point is to differentiate incidental link status from long-term behavior of the link taking the history of the link into account. Eqn. 6 gives the recursive calculation of LLF estimation. The only control parameter of the estimator is the window size w for calculating PRR on which the LLF estimate is built.

$$LLF^{\tau} = \begin{cases} LLF^{\tau-1} + (1 - LLF^{\tau-1}) \times PRR^{\tau} & Link^{\tau} = 1 \\ LLF^{\tau-1} \times PRR^{\tau} & Link^{\tau} = 0 \end{cases} \tag{6}$$

If the receiver successfully received the last transmitted packet ($Link^{\tau} = 1$), the metric is increased towards 1 with a rate determined by the history of this link (PRR) and the deviation of the previous value of the metric from its maximum value (i.e., one). Notice that if the link has shown a good connection in the recent history of length w, LLF will converge to one very fast. On the other hand, if the link has a poor PRR, the last successful reception is considered as a likely temporary connection and so LLF increases with a lower rate. In the second case, in which the last packet is lost ($Link^{\tau} = 0$), the metric is decreased, again with a rate proportional to the history of the link (PRR). If PRR is high, the last link failure is supposed to be an intermittent disconnection and the metric decreases with a low rate. The main idea behind this is that if the link has shown a good record, incidental disconnections do not decrease the metric too much and vice versa. Based on this, the LLF estimator is expected to respond fast to real dynamics of the link quality and tolerate intermittent link states. However, experiments show that for medium quality links, this estimator suffers from frequent fluctuations.

Smoothed Link Likelihood Factor (SLLF) is proposed in this paper to alleviate the stability problem of the LLF method. Experimental evaluations show that LLF is very agile in detecting connection changes in WBANs, but it suffers from frequent fluctuations. We use an EWMA filter to smooth the LLF estimate, similar to the filter which is used to smooth the PRR in the WMEWMA estimator. This filter is able to improve the stability of LLF at the cost of low degradation of the speed of detections. Eqn. 7 shows the calculation for SLLF.

$$SLLF^{\tau} = \alpha \times SLLF^{\tau-1} + (1 - \alpha) \times LLF^{\tau} \tag{7}$$

where $0 \leq \alpha \leq 1$ is the history control coefficient. Actually, this technique is expected to trade off the high agility of LLF for acquiring more stable estimations.

3.3 Disconnection Detection using LQE

To find out if node s_i is disconnected from the gateway, a threshold ℓ_i is considered for the estimated quality of the link from s_i to the gateway. This threshold is given individually for each node based on particular DDR requirements and sampling rate of that node. In [2], we presented a method for determining this threshold based on the DDR requirement $\mathcal{RC}(s_i)$, the transmission and sampling rate of node s_i

Note that for disconnection detection using any LQE method, hysteresis is introduced to prevent too frequent switches when the value of the LQE is around the threshold. A link moves from a connected to disconnected state when the LQE drops below the given threshold $\ell_i - \Delta\ell$. Accordingly, for moving to connected state from disconnected state, the quality factor should go higher than $\ell_i + \Delta\ell$.

4. EXPERIMENTS

Comparison of some LQE methods are previously presented in [15], [9], and [12]. Authors in [15] use a stochastic link data generation for static WSNs. In [9], wireless link models [16] available in the TOSSIM simulator [17] are used to generate link behavior data for static WSNs. Considering high node mobility and frequent topology changes in WBANs due to body movements and postural changes, simulation radio models fail to mimic near-realistic link behavior in these mobile networks. Although in [12] real experiments were performed to evaluate LQE techniques, it is done for static WSNs. The behavior of wireless links in WBANs substantially deviates from their behavior in static WSNs. This makes performing experiments for measuring the links in WBANs very important. Moreover, we aim to compare the described LQE techniques specifically for detecting disconnection from the gateway in WBANs.

We performed extensive experiments to record the behavior of wireless links from all nodes to the gateway node ($Link^{\tau}$) in a real WBAN. Then different LQE techniques are applied on the links' status records to check the performance of the estimators.

4.1 Setup and Performed Experiments

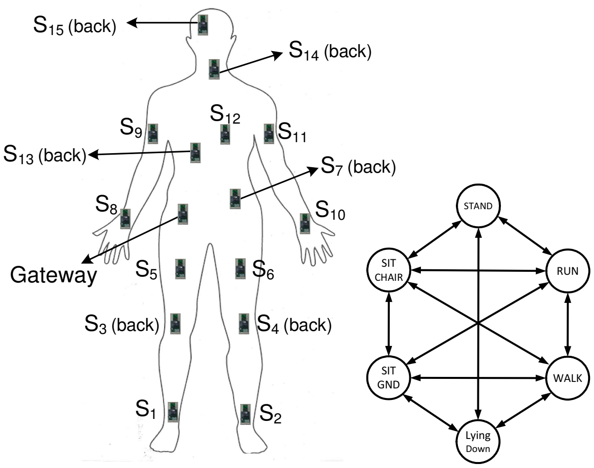
We deployed 16 *MyriaNed* [18] wireless nodes on various positions of a body. Fig. 2(a) depicts the node placement in the experiments. *MyriaNed* uses the *Nordic* nRF24L01 radio chip [11] as transceiver. This works in the 2.4GHz ISM band, which is one of the proposed carrier frequency bands in IEEE 802.15.6 for WBANs. The data rate is 2Mbps and packets have a fixed size of 32 bytes. Four transmit power levels (-18, -12, -6, 0dBm) are available for the radio. This allows us to test the links in various link conditions.

A TDMA-based mechanism is exploited for communication of the BSNs. Each node is given an exclusive time slot for packet transmission. Therefore, links behavior is not influenced by collisions. The TDMA frame length is set to $100ms$. Thus every node periodically transmits 10 packets per second. All body nodes including the gateway listen to all slots and record packet receptions from all other nodes at each TDMA round in their 4MByte flash memory. This way full traces of all links between all pairs of nodes are logged. All experiments were done in an indoor environment.

Body posture is a determining factor in the quality of the radio links in WBANs. We consider 6 postures in our experiments, namely *running*, *walking*, *standing*, *sitting on a chair*, *sitting on the ground*, and *lying down*. As the posture transitions are very important to evaluate the reaction of LQE methods upon link dynamics, we have all possible transitions between different postures during each experiment (Fig. 2(b)). Therefore, we performed a posture pattern of 36 postures having all possible combinations in which each posture was repeated 6 times. The duration of each posture is 2 minutes. Thus each experiment lasts 72 minutes. We performed four different experiments with four available transmit power levels. During one experiment, all nodes use a uniform transmit power level. In total, we gather link behavior of 15 BSNs to the gateway in 288 minutes of experiments with packet transmission period of $100ms$.

4.2 Metrics for LQE Characterization

To investigate the characteristics of LQE methods in detecting connection changes, we first need to have a *reference connection state* for each node. We use the future link states to calculate the packet reception rate of the link at each packet transmission round. At any round τ, we compute the packet reception ratio in a window of size $\mathcal{H} = 50$



(a) (b)

Figure 2: a) The position of 16 MyriaNed nodes on the body for the experiments. Nodes $s_{3,4,7,13,14,15}$ are deployed on the back side of the body. b) The postures of the person wearing the WBAN during the experiments. All possible posture transitions are performed in each experiment.

around τ. The calculated reception rate is then compared to a threshold ℓ to determine the reference connection state of the link at round τ. Fig. 3 illustrates the calculated PRR using future link states and the reference connection state using $\ell = 0.3$ and $\ell = 0.7$ for a time period of one of our experiments. This connection detection is then compared with the connection state produced by using the LQE techniques under investigation (described in Sec. 3). Note that the LQE methods do not have access to future information online during network operation. For each experiment, we run the analysis for 7 different values of the threshold (i.e., $\ell = 0.2$, 0.3, 0.4, 0.5, 0.6, 0.7, and 0.8), applying a margin $\Delta\ell = 0.1$ for hysteresis. High threshold values indicate that the data losses are hardly tolerable and the links are tagged as disconnected with low number of packet losses. Lower values of threshold allow higher rate of packet losses before the link is tagged as disconnected. Accordingly, the link is reconnected with showing lower rate of successful receptions. By applying various threshold values, we evaluate the LQE metrics with various application requirements. The same values of the threshold and its hysteresis margin ($\Delta\ell = 0.1$) are used in detecting connection status using each LQE method. In presenting the results, we show the average of the results over all experiments with different transmit power levels and various values of the threshold ℓ.

We investigate *agility*, *stability*, and *reliability*, as three metrics for characterizing the behavior of different LQE techniques. Agility aims to show how fast an estimator detects a connection change, once it happens. To measure it we compute the delay (in terms of rounds) from occurring a change in the reference connection status and the detection using the particular LQE method.

Stability shows the fluctuations in announcing a link as connected or disconnected. It actually aims to reveal the ability of the estimator in ignoring short-term link quality variations, which are very common in WBANs. To measure this metric, we count the average number of switches of (dis)connection detection using each LQE method. When comparing different LQE techniques, higher number of changes is a sign of less stability of the method, as all methods are applied on the same data set. This metric is in

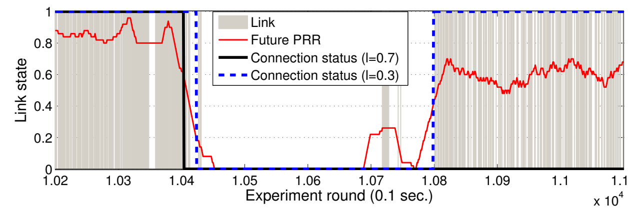


Figure 3: Reference connection status of the link from node s_1 to the gateway for a certain time period using two threshold values of $\ell = 0.3$ and $\ell = 0.7$.

conflict with the agility of the estimator and we target to explore the trade-off that each LQE method is able to make between agility and stability.

The reliability of the method measures the ratio of changes in the reference connection status that is detected by an LQE metric. If an estimation is overestimating or underestimating the quality of the links, it may fail in detecting a change in connection status. Moreover, a high delay in detection for slow estimators may lead to failure in detecting short duration disconnections or connections.

5. ANALYSIS OF LQE CHARACTERISTICS

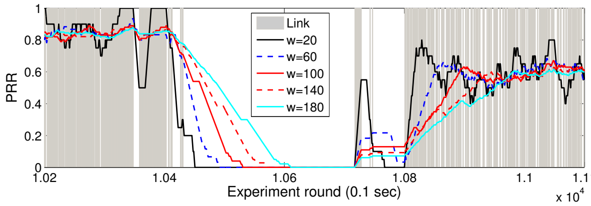
In this section, we first investigate the impact of the configuration parameters of the estimators on their performance and go through some detailed behavior of the metrics for a certain period of time. Then we show the trade-offs made by each estimator to compare them and investigate the best fitting estimators for WBANs from various points of view.

5.1 Configuration of the LQE Methods

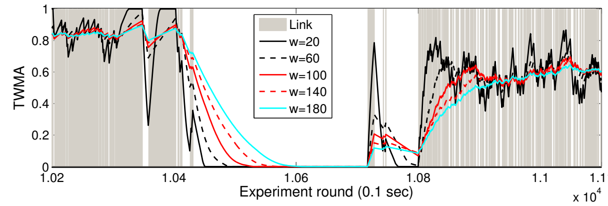
To show the response of the estimators to variations of the link quality, we zoom into the status of the link from node s_1 to the gateway over a short period of time (between rounds 10200 and 11100) in an experiment with the lowest transmit power level. In this time period shown in Fig. 3, there are some changes in the connection status of the link. Note that the reference connection status depends on the used threshold value (ℓ) for disconnection and reconnection detection. Using $\ell = 0.3$, for instance, the link goes from connected to disconnected state around round 10400 and vice versa at round 10800, whereas the link is not considered reconnected around round 10800 when using $\ell = 0.7$. There are also transient receptions and intermittent link failures in this time period, which are useful to observe the reaction of the estimators to these phenomena. Fig. 4 shows the link status ($Link^\tau$) at all rounds together with the estimated link quality. For each estimator, several settings are applied to depict its behavior with different parameter configurations.

Fig. 4(a) shows the PRR of the link for five different values of averaging window length. As expected, increasing the window length w increases the delay in detecting connection changes. TWMA (Fig. 4(b)) has smoother curves with faster reaction compared to PRR with the same window length.

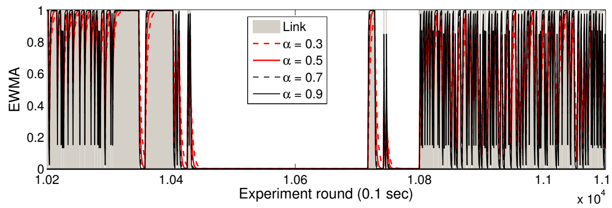
EWMA (Fig. 4(c)) reacts very fast to any change in the link connection status. The estimated link quality in this figure is not properly visible because of many fluctuations. When the value of parameter α is closer to one, the estimator reacts faster, but it is more fluctuating. Note that parameter α in EWMA has an opposite effect of the same parameter in other estimators (WMEWMA and SLLF). In EWMA, α is the coefficient for the new value of $Link^\tau$. Therefore, increasing it puts higher weight on the state of the link in the last round and puts lower weight on the previous estimate.



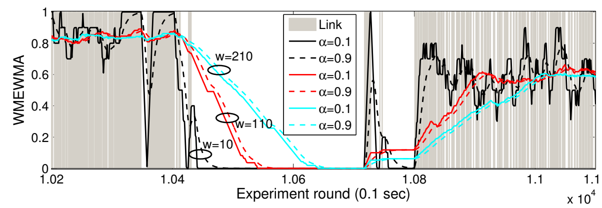
(a) PRR using different lengths of averaging window.



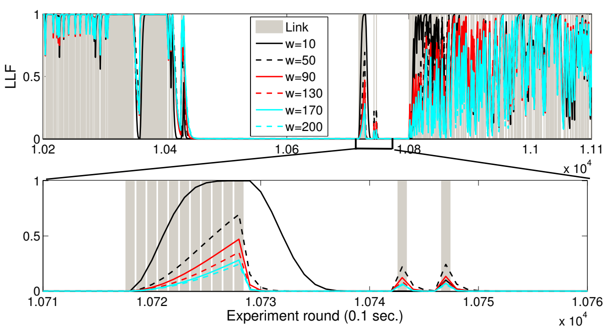
(b) TWMA using different lengths of averaging window.



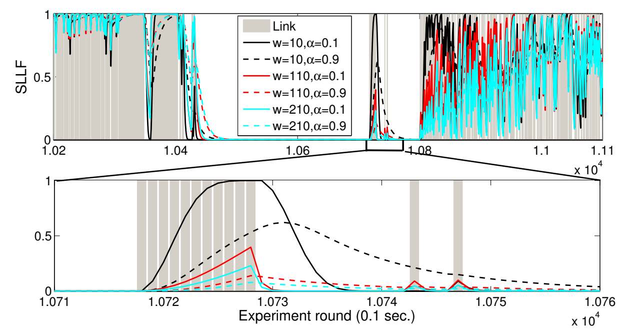
(c) EWMA using various values of last round control coefficient (α).



(d) WMEWMA using different values of w and history control coefficient α.



(e) LLF using different values of averaging window length (w). The lower graph zooms into a short period of time from the upper graph.



(f) SLLF using various values of w and α. The lower graph zooms into a short period of time from the upper graph.

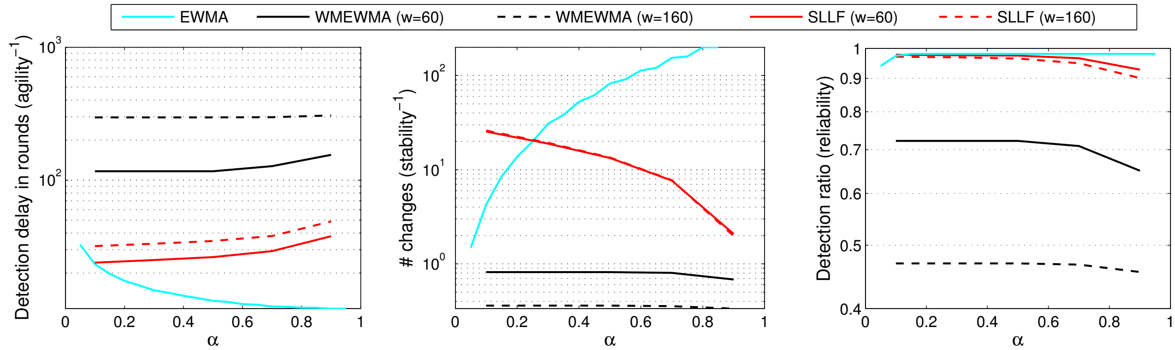
Figure 4: The quality of the link from node s_1 to the gateway for a certain time period estimated by various settings of different LQE techniques.

Fig. 4(d) shows the value of the WMEWMA estimator using some values of window length and history control coefficient. Results of using two values of $\alpha = 0.1$ and $\alpha = 0.9$ are shown as two (near-)extreme behaviors for each window length. One observation here is that the parameter w has a major impact on the delay and stability of this estimator. For each value of w, having a bigger α smoothes the curve more, which leads to slightly more stable estimation at the cost of slower reaction. Decreasing the value of α makes the performance of the WMEWMA estimator more similar to that of PRR.

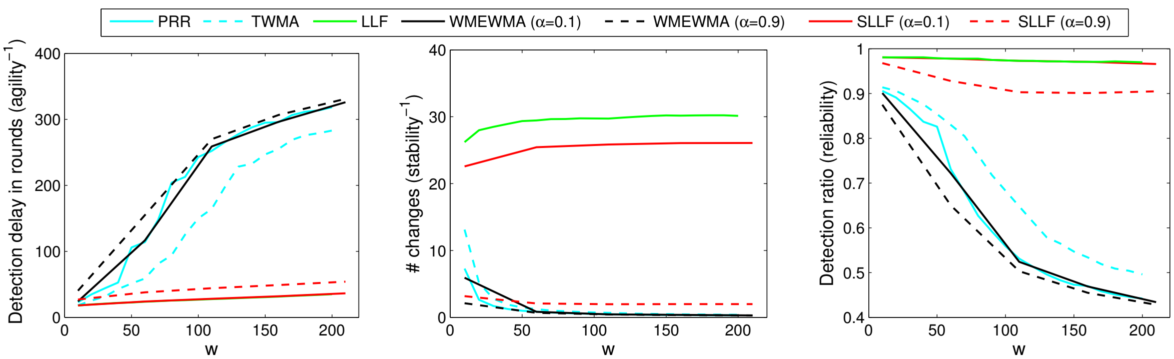
The relation between the behavior of the LLF method and the averaging window size is more complicated than that of other estimators. When w is lower, a link is considered faster as a good or bad link according to the PRR value with the given window size. The lower graph in Fig. 4(e) zooms into a time period (between rounds 10710 and 10760) with short-term receptions. Around round 10720 in this graph, some successful receptions are observed, the curve for $w = 10$ goes up earlier than others as the PRR quickly gets higher values. After this short period of successful receptions, it goes down later than others as the PRR with $w = 10$ has become one in this short period. For the LLF with $w = 90$, for instance, the link is not considered good any time during this period since the PRR value is low after this time period. Therefore, with observing the link failures starting from round 10730, the estimate goes down quickly (multiplication with a low PRR value in Eqn. 6).

SLLF in Fig. 4(f) smoothes LLF, which results in a slightly slower reactions, but less fluctuations. Transient receptions do not make a visible change on the value of SLLF, especially for higher values of α. Thus SLLF is better able to avoid transient link states than the base LLF estimator. The SLLF curve with $w = 110$ and $\alpha = 0.9$ in Fig. 4(f) makes a good balance in reasonably fast reacting to real changes in link quality and bypassing intermittent link behaviors. Such transient behavior is very common for wireless links in typical WBANs.

Fig. 5 depicts the relation between the average performance of different LQE methods in detecting link connection changes and the configuration parameters of these techniques. Lower delay and lower number of changes are considered better as they show more agile and stable estimators, respectively. Higher detection ratio is better as it reveals more reliable detection. Fig. 5(a) shows the dependencies on the value of α in the estimators that have this parameter. Among all, the performance of EWMA substantially varies with changing the value of α. Values of α close to one make the metric very unstable. Considering the high link fluctuations in WBANs, the results strongly recommend to avoid using values above $\alpha = 0.5$ for EWMA. Overall, EWMA shows the most agile estimator with the lowest sta-



(a) The effect of the history control coefficient (α) on agility, stability, and reliability of LQE methods. *The vertical axis is logarithmic.*



(b) The effect of averaging window length (w) on agility, stability, and reliability of LQE methods.

Figure 5: The effect of configuration parameters on the performance of different LQE techniques.

bility among all investigated metrics. Another observation is that both the WMEWMA and SLLF estimators perform better for high values of α. According to the results shown in Fig. 5(a), increasing the value of α improves the stability of the WMEWMA and SLLF estimators at the cost of a limited worsening of the delay. Thus increasing the value of α up to a value around 0.9 improves the overall performance of these metrics.

Fig. 5(b) shows the effect of the averaging window size w. For the LQE techniques having parameter w (all methods except EWMA), the agility decreases when increasing the window size. Among all, the agility of LLF-based estimators depends least on the window size. WMEWMA with $\alpha = 0.9$ shows to be overall the least agile estimator. The stability of the estimators shows in general a weaker dependency on the value of w, comparing to agility. Increasing the window size considerably decreases the detection ratio (reliability) except for the metrics that are based on LLF. The reason is the high reactivity of these techniques to link dynamics. One important observation in Fig. 5(b) is the behavior of the SLLF method with $\alpha = 0.9$. It has a good agility, high stability, and a detection ratio close to that of LLF (the most reliable one in Fig. 5(b)). In particular, setting the window size around 100 for this estimator seems to be a proper choice to balance different performance metrics.

5.2 Concluding LQE Characteristics

Fig. 6 show the achieved performance of different estimators and their configurations to show the trade-offs made by each estimator and to help in making decisions about using an LQE method. Note that almost all metrics make trade-offs in terms of different performance metrics, in particular, in terms of agility and stability. In the following, we sort the estimators according to the overall achieved results and detailed observations in our experiments for disconnection and reconnection detection in WBANs.

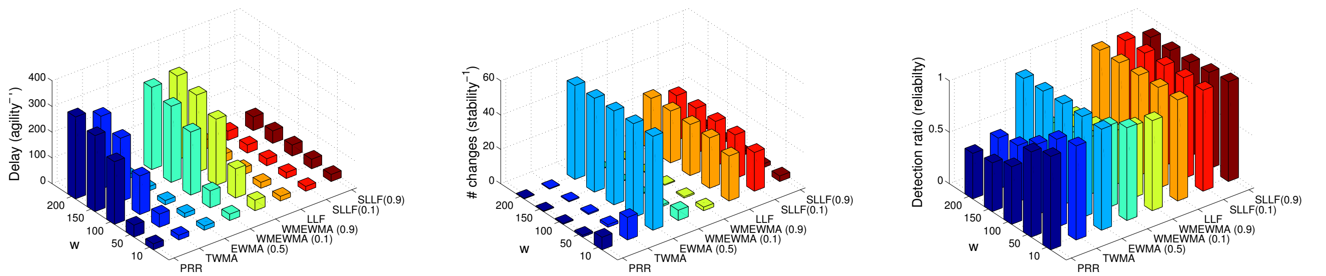
Agility: The EWMA method is found to be the most agile estimator that can exactly follow any link quality variation. Setting α very close to one makes the estimation equal to the link state at each round. The following ordered list presents all investigated LQE metrics from most agile to least agile, based on the results presented in Fig. 6(a). The slowest estimator in detecting connection changes is WMEWMA.

$$\textit{Agility}: \{\textit{EWMA},\ \textit{LLF},\ \textit{SLLF},\ \textit{TWMA},\ \textit{PRR},\ \textit{WMEWMA}\} \tag{8}$$

Stability: Again EWMA and WMEWMA are on both extremes for stability. WMEWMA shows to be the most stable estimator. This result conforms with the conclusions made in [15] and [9], although their evaluation of stability is based on the coefficient of variations of the estimate (the ratio of the standard deviation to the mean). EWMA is overall the most fluctuating estimator. The following list shows the investigated estimators from best stable to worst stable estimator.

$$\textit{Stability}: \{\textit{WMEWMA},\ \textit{PRR},\ \textit{SLLF},\ \textit{TWMA},\ \textit{LLF},\ \textit{EWMA}\} \tag{9}$$

Reliability: The reliability of the estimators in detecting the connection changes conforms to the agility of the estimator. EWMA (with $\alpha = 0.5$) can detect 98% of the connection changes. The ratio is around 97% and 95% for LLF and SLLF (with $\alpha = 0.9$), respectively. PRR, TWMA, and WMEWMA show a low detection ratio (sometimes even



(a) The agility of the estimators in detecting connection changes. A lower delay value shows a more agile estimator.

(b) The stability of the estimators in detecting connection changes. A lower number of fluctuations is a sign of a more stable estimator.

(c) The reliability of the estimators in detecting connection changes. Higher detection ratio means more reliable detection.

Figure 6: Comparing the trade-offs made by different LQE methods for disconnection detection in the performed experiments for WBANs.

less than 50%). To have a good detection ratio using these methods, we need to decrease the window size, which leads to very slow estimation.

6. IMPACT ON WBAN PERFORMANCE

So far in this paper, we investigated the characteristics (agility and stability) of the receiver-side LQE techniques using real WBAN link traces. In this section, the relation between the characteristics of the LQE techniques and the QoS of a WBAN application is investigated. We first present a qualitative discussion of the impact of the estimators' characteristics on the performance of a WBAN such as data delivery behavior and energy consumption. Then we use various estimators in an adaptive WBAN protocol as a case study, and investigate their impact on the achieved network performance. Finally, some guidelines for decision making about the most appropriate estimator based on the requirements of a WBAN application are provided.

6.1 Qualitative Discussion

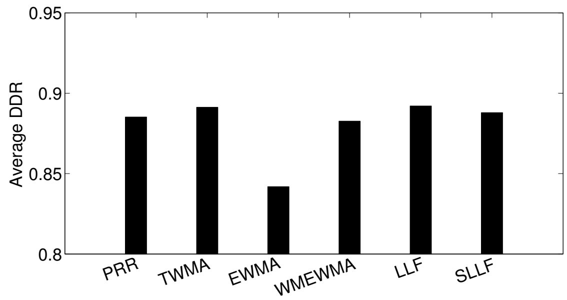
Suppose that the quality of the link from a body node, say s_i, to the gateway is very good, with sporadic intermittent failures. Due to a posture change, for instance, this link may go to a low quality state. A more agile estimator detects such a transition faster and hence, the network protocol adapts itself earlier to avoid data losses from the node s_i. Agile estimators such as EWMA, LLF, and SLLF perform the best and provide the least data losses during such transitions. It takes some time for a slow estimator like WMEWMA to detect these transitions. Also in a reverse transition (from a poor link quality to a very good state), more agile estimators cause less unnecessary usage of network resources (e.g., energy). Therefore, more agile estimators perform better for detecting the transitions between extreme link quality states from perspectives of both data delivery performance and energy consumption. Among the three aforementioned most agile estimators, LLF and SLLF are also able to ignore intermittent link behavior, while EWMA may unnecessarily react to such transient changes. Failure in ignoring intermittent link states leads to both data losses and energy wastage.

When a link is in a medium quality state, we may face frequent interchanging link successes and failures. Such link states are common in WBANs especially for the nodes that are deployed on mobile parts of the human body such as legs and hands. Empirical measurements in [5] show periodic variations of the quality of the link between a node on a hand and the gateway installed on the belly while walking. The period of such changes from good to bad quality and vice versa is measured as 1.2 second, which matches the duration of the walking steps. Depending on the frequency of such periodic quality changes and also the frequency of link measurements, we may decide to track the changes by using an agile estimator or to have a stable average estimation by using a stable LQE method. The time that a network adaptation takes to be accomplished and become effective is an important factor. The period of link quality changes should be much higher than the adaptation time; otherwise, it does not make sense to trigger an adaptation. Using a stable estimator like WMEWMA or PRR can provide an overall sense of link quality and avoids too many network adaptations, while an unstable estimator such as EWMA and LLF for the links with frequent quality changes triggers frequent network adaptations without giving the network enough time to perform adaptations. Tracking frequent quality changes using an unstable estimator also leads to data losses in many cases. When the estimator tags the link as connected with observing few link successes, the network stops supporting that node. Soon after that, because of fluctuating link quality, several failures may happen resulting in data losses.

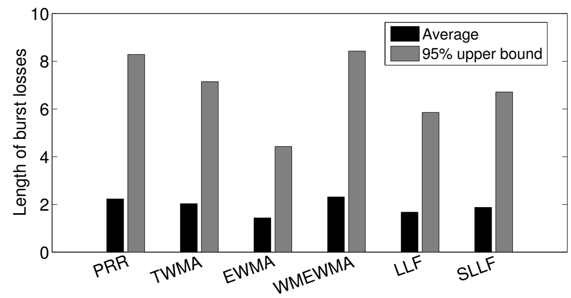
This qualitative analysis reveals that it may be the best to use different LQE techniques for different links in the WBAN, based on the behavior of the links. To provide an overall best performance trade-off, a certain level of agility and stability is necessary for an estimator. This inspires that an estimator such as SLLF, which balances between agility and stability, makes the best compromise. This way, this estimator can make a fast detection of the transitions between extreme link quality states ignoring intermittent link behaviors, and also a stable estimation for the links with high quality fluctuations.

6.2 Case Study

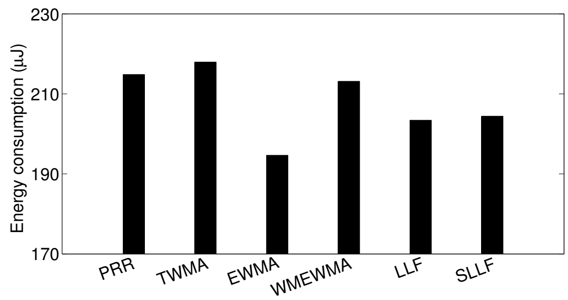
In [2], we developed an adaptive on-demand listening and data forwarding (ODLF) mechanism for WBANs. All nodes use a star architecture to directly send their data packets to the gateway. At the same time, the gateway estimates the quality of all its incoming links. Using this LQE and taking the sampling specification and DDR requirements of individual nodes into account, the gateway checks if some nodes are disconnected. Then the gateway requests the body nodes to listen to the disconnected nodes and forward their data. Thus an adaptive multi-hop data forwarding is established when it is necessary. We simulate the ODLF mechanism using various receiver-side LQE methods using the link traces



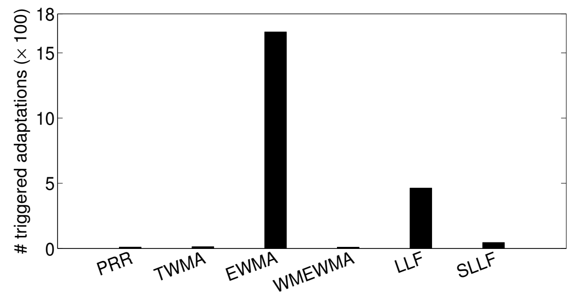
(a) Average data delivery ratio over nodes with low quality links to the gateway.



(b) Average length of burst data losses and the upper bound of the length of 95% of burst data losses.



(c) Radio energy consumption of nodes per TDMA frame (100 ms).



(d) Average number of triggered adaptations in the WBAN protocol using different estimators.

Figure 7: Achieved quality-of-services in the WBAN experiments that run the adaptive ODLF [2] protocol, using different LQE techniques for detecting disconnection from the gateway.

of the experimental setup of Fig. 2. Because we are using real logged link traces of the experiments, the behavior of the ODLF mechanism is the same to that of running ODLF on wireless body nodes.

Fig. 7 presents the achieved performance results of the ODLF mechanism in the WBAN experiments, when using different LQE techniques for (dis)connection detection. Fig. 7(a) shows the average DDR over nodes s_2, s_3, s_4, s_{10}, s_{11}, s_{13}, and s_{14}. These nodes have shown to have poor wireless links to the gateway in the experiments. By using different LQE techniques, the achieved DDR values vary. EWMA led to the worst DDR. As discussed in the previous subsection, this is expected because the EWMA estimation fluctuates frequently, especially when the link quality is highly dynamic. Considering overall DDR performance, LLF performed the best in this case study.

The distribution of data losses over time is also an important aspect of data delivery performance. Loss of several subsequently generated data samples may lead to a failure of the WBAN application even if the overall DDR lies in the acceptable range. To evaluate this, we calculate the length of burst data losses (the number of subsequent losses of data samples) during the experiments. Fig. 7(b) shows the average length of burst data losses, on average over the aforementioned nodes. We also show the upper bound of this length when considering 95% of the occurrences of data losses. WMEWMA shows the worst performance in this sense. Considering the low agility of this estimator, this result is expected. Because of very fast reactions, EWMA is able to avoid long burst data losses. The LLF and SLLF estimators are the next estimators in the row for providing the best performance in this aspect.

Nodes running the ODLF mechanism consume energy for listening to the disconnected nodes from the gateway. When the network connectivity is poor and more nodes are detected as disconnected, average energy consumption increases due to the need for more on-demand listening and data forwarding. Fig. 7(c) shows the average energy consumption of body nodes per TDMA frame using the ODLF mechanism, which differs when using different LQE techniques. EWMA causes less energy consumption compared to the other estimators. The reason is that with observing a very few link successes, EWMA quickly tags the link as connected and hence, other nodes stop listening to that node. However, in many cases, it leads to degradation of data delivery performance, as it is shown in Fig. 7(a) that this estimator provides the least overall DDR among the examined LQE techniques. LLF and SLLF are the next estimators that cause less energy consumption.

As the last performance observation, we count the number of triggered network adaptations in the ODLF by different LQE techniques. Each adaptation may be costly for the protocol. Behaviors of different estimators substantially differ from each other in this aspect. EWMA, the most agile estimator, triggered a very high number of adaptations. This number is also quite high for LLF compared to the other estimators. This limits the applicability of the unstable estimators for many WBAN applications and protocols, when the network adaptation is time- or energy-costly. In this case study (ODLF mechanism), the overhead of network adaptation is low. Otherwise, very fluctuating metrics such as EWMA would have been less convincing.

Considering all performance metrics, SLLF provides good DDR and energy consumption close to those of LLF, but with much fewer triggered adaptations. This is because of the balance that SLLF is able to make between agility and stability.

6.3 Guidelines for Decision Making

In Sec. 5, we observed the conflicts between different LQE techniques in terms of agility and stability. This leads to a trade-off between different network performance metrics, as some were explored in the previous subsection. Because of that, it is not straight-forward to suggest an estimator as the best choice for all WBAN applications. Network specifications and application demands should be then taken into account to select the most appropriate estimator.

In a WBAN scenario for which the stability of disconnection and reconnection detection is the only objective, WMEWMA with $\alpha \approx 0.9$ is the most appropriate LQE technique. When the protocol adaptation after a disconnection or reconnection has a very high overhead, this approach may help to have as little as possible adaptations. However, this estimator provides such stability at the cost of very slow detection with a high chance of missing the connection changes. On the other extreme, if the WBAN scenario needs to deal with every connection change very fast, the EWMA estimator with $\alpha \approx 0.4$ can be the best solution. However, the overhead of the protocol adaptation should be very low. Otherwise, a very high number of announced connection changes by this estimator causes a high overhead.

The above two scenarios are extreme cases. In other WBAN scenarios, we need to make an appropriate trade-off between different performance metrics. Thus a reasonably fast, stable, and reliable detection of the connection changes is preferred. In those scenarios, SLLF is the best fitting estimator for detecting connection changes. A configuration of SLLF with $w \approx 100 - 150$ (10-15 seconds) and $\alpha \approx 0.9$ provides the best performance. On the one hand, the agility of SLLF is very close to that of EWMA and LLF, and substantially deviates from the low detection speed of PRR and WMEWMA. On the other hand, SLLF is very stable, very close to the stability of WMEWMA. These mean that SLLF is able to make the best trade-off between the different performance metrics.

7. CONCLUSIONS

This paper investigates using Link Quality Estimation (LQE) techniques for detecting connection changes in Wireless Body Area Networks (WBANs). A node is connected to the gateway node in the WBAN, when it can properly reach the gateway to satisfy the data delivery requirements. Otherwise, the link is said to be disconnected. Detecting connection changes is of great importance to adapt the network protocol and node configurations during the network operation. The paper reviews the existing receiver-side LQE techniques and proposes a new method called Smoothed Link Likelihood Factor (SLLF). A set of experiments using 16 nodes deployed on different positions of the body are performed to log the behavior of the wireless links to the gateway node. Different estimators are applied on the logged data and their characteristics (agility, stability, and reliability) in detecting connection changes are investigated. Then the relation between different characteristics of the estimators and the WBAN performance is explored. The estimators have been used in an adaptive WBAN protocol as a case study and their impact on the performance of the network is studied.

Based on the detailed analysis of the results, the trade-off between the three mentioned criteria made by each estimator is explored and the best and worst estimators from the point of view of different characterizing metrics are discussed. No estimator is able to perform the best in terms of all performance metrics or in all WBAN applications. However, the SLLF method is able to balance different aspects and provides the best trade-off between the different performance metrics for many WBAN scenarios.

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