Pedro José Marrón
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Wireless Sensor Networks

8th European Conference, EWSN 2011
Bonn, Germany, February 2011
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Preface

This volume contains the proceedings of EWSN 2011, the 8th European Conference on Wireless Sensor Networks. The conference took place in Bonn, Germany during February 23–25, 2011. The aim of the conference was to discuss the latest research results and developments in the field of wireless sensor networks.

EWSN received a total of 87 paper submissions of which 14 were selected for publication and presentation, yielding an acceptance rate of about 16%. Paper submissions were received from 29 different countries in all parts of the world. EWSN adopted a double-blind review process, where the identities of the paper authors were also withheld from the reviewers. The selection process involved around 250 reviews with all papers being evaluated by at least three independent reviewers. In addition, the reviews where discussed by the Technical Program Committee in a virtual meeting after collecting all reviews and prior to making final decisions. The final program covered a wide range of topics which were grouped into five sessions: Routing and Mobility, Optimization Techniques, MAC Protocols, Algorithms for Wireless Sensor Networks, and Systems and Abstractions. It included theoretical and analytical approaches, together with empirical research and protocol/system design and implementation.

The conference included a keynote by Mani Srivastava with the title "System Issues in Wireless Sensor Networks," a demo and poster session, co-chaired by Luca Mottola and Daniel Minder, for which separate proceedings are available, and an industrial demo session, co-chaired by Herman Tuininga and Siebren de Vries, where companies working in the area of wireless sensor networks had the chance to exhibit their products throughout the conference. The conference also included a tutorial on "Machine Learning for Wireless Sensor Networks" by Anna Förster and a tutorial on "TeenyLIME" by Amy Murphy.

We would like to thank everyone who contributed to EWSN 2011. In particular, we would like to thank the Technical Program Committee for their reviews and input in forming the program. We also would like to thank the local administration at the University of Bonn for their help with the conference planing and last, but certainly not least, our sponsors: Networked Embedded Systems Group at the University of Duisburg-Essen (Gold Sponsor), CONET Network of Excellence (Gold Sponsor), Boeing (Bronze Sponsor), and Libelium (Bronze Sponsor).

February 2011

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Abstract. The accuracy of link-quality estimators (LQE) is mission-critical in many application scenarios in wireless sensor networks (WSN), since the link-quality metric is used for routing decisions or neighborhood formation. Link-quality estimation must offer validity for different timescales. Existing LQEs describe and approximate the current quality in a single value only. This method leads to a limited accuracy and expressiveness about the presumed future behavior of a link. The LQE developed in this paper incorporates four quality metrics that give a holistic assessment of the link and its dynamic behavior; therefore, this research is an important step to achieving a higher prediction accuracy including knowledge about the short- and long-term behavior.

1 Introduction

For most algorithms in wireless sensor networks (WSN) it is essential that each node has thorough knowledge about its direct neighbors. This information is collected and provided by neighborhood management protocols and is used, e.g., for routing decisions, group formation, or data sharing. The dynamic behavior over time of the wireless channel and the missing correlation between adjacency and possibility of communication—due to obstacles and multi-path propagation—render the definition of the neighborhood of a node a non-trivial task. One important criterion used by neighbourhood management protocols to determine the importance of a node is the quality of the communication between nodes, which in turn is provided by a link-quality estimator (LQE). Depending on the intended application, either the short- or long-term qualities of a link or a combination of both is preferred for choosing an appropriate node in the vicinity [2]. In the past many different approaches were investigated [14,6,4,7,2,11,3,1] or are currently used, e.g., in TinyOS [10,8].

In principle a LQE measures the quality based on logical (e.g., packet success rate) or physical (e.g., received signal strength) metrics. Newer proposals use a combination of these in order to improve the accuracy of the prediction [1]. However, common to these LQEs is that the measured quality is squeezed into a single value—e.g., a moving average—due to memory restrictions and for easier comparability. In doing so, the value represents only a snap-shot of the plain link-quality at a specific point in time without any additional information about variation and the current trend of the long- or short-term behavior in the past. The expressiveness of such a single-value metric is limited: This procedure is

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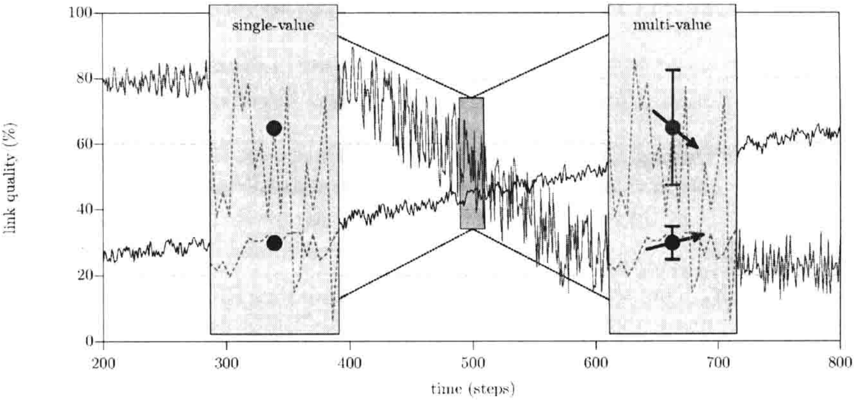

Fig. 1. Link-quality estimation of a deteriorating and an improving link with a single-value (left) and statistical multi-value (right) technique

comparable to a stock market, where a stock is described only by its current value or an average of its last values. Based on this limited information it is a game of luck to decide in which stocks to invest in the future. Furthermore, it is important to know which stock will perform better for a short-term profit and which is suitable for a long-term investment.

The same considerations are valid for judging the quality of a link. Figure 1 visualizes the problem of comparing two link-qualities. With a metric that reflects only the current quality, a comparison is nearly impossible even for a short-term projection. Based on a single-value prediction the deteriorating link appears superior, since its current link-quality is higher. When using multi-value prediction the dynamic behavior of links can also be incorporated into the decision, so that the improving link will be favored: Although its current link-quality is lower, its positive trend and low deviation lead to a better future perspective when compared to the large variation and negative trend of the deteriorating link. Furthermore, all existing LQEs are only capable of providing either a short- or a long-term prediction. Yet, an application often needs different prediction windows, e.g., a long-term prediction for forming a cluster and a short-term one for selecting the eligible next routing hop.

In this paper we present a LQE that effectively calculates for each link four quality characteristics: short- and long-term quality, variation, and an indicator of the current trend. This LQE is a general approach that can be easily adopted to various sources of link-quality metrics. Intensive simulations and experiments are undertaken in order to proof the advantages of the newly developed approach over existing ones. We compare and analyze the ability of link-quality tracking of modern and well-known LQEs with our new approach. In this context, we identify problems and benefits of the different estimators, and we also determine the correlation and average error with respect to empirical ground-truth measures. Moreover, we analyze the ability of the LQEs to select reliable links, which is commonly needed for routing decisions and cluster formation. The paper concludes with a discussion of the results and intended future research activities.

2 Link-Quality Estimation Techniques

Estimating link-qualities in WSNs is a nontrivial task. Many existing solutions for other wireless networks are not feasible for WSNs. Particularly, the lack of infra-structure, limited memory, energy constraints, and low-cost transceivers complicate possible solutions. Various approaches were proposed in the past to overcome these limitations and to provide a meaningful metric describing the actual link-quality and thus predicting its future behavior. In this section, a brief overview and discussion of general link-quality metrics is carried out, followed by a thorough view on already existing approaches employing them.

2.1 Link-Quality Metrics

Basically, there exist two different categories of link-quality metrics: physical and logical indicators. The former are provided by the radio hardware and are based on the signal strength of a received packet, such as the Received Signal Strength Indication (RSSI), the Link-Quality Indication (LQI), or Signal-to-Noise Ratio (SNR). The logical indicators estimate the link quality by keeping track of message losses. Examples of such metrics are: Packet Success Rate (PSR), Required Number of Packets (RNP) [4], or Expected Transmission Count (ETX) [6] for describing the effort needed to successfully transmit a packet.

Physical Metrics. Using physical metrics has several advantages. The metrics come without any additional costs, since the measurement is performed by the receiver hardware every time a packet is received, or can at least be calculated easily in the case of SNR. Also only a small number of samples is needed to get a first approximation of the link-quality. Additionally, the metrics can be measured by utilizing any traffic on the wireless channel without the need of periodical broadcasts if the application produces enough traffic.

However, several research activities on this topic have shown that the physical metrics are of shortened use [12]. First of all, the metrics are strongly dependent on the receiver hardware—e.g., in our experiments with the Atmel RF230 many links have a RSSI value close to the sensitivity of the transceiver, but provide reliable packet reception at the same time. Secondly, the RSSI and LQI are only available for successfully received packets, but not in the case of packet loss. There exist different attempts to improve the quality of the measurements—e.g., RSSI calibration [5]—but these introduce a higher computation-complexity not suitable for WSNs. Another disadvantage is the expressiveness of these metrics with respect to the application-related perception, i.e., the expected PSR. In [9] Lal et al. show that physical metrics cannot always predict the PSR, especially in case of long-range links with an RSSI near the sensitivity threshold of the radio chip. In those cases the SNR-to-PSR relation is not deducible at all.

Logical Metrics. The advantages of logical metrics are that they do not depend on specific hardware characteristics and correlate directly with an application point of view, i.e., the ratio of successfully transmitted packets. This however leads to the problem that a node needs to track the ratio between the number of successfully received packets versus packet loss in an efficient way. A window-based approach consumes too much memory, and counting received and lost packets does not incorporate that recent events should be weighted higher. Hence, most of the logical metrics are calculated with an Exponentially Weighted Moving Average (EWMA) [14]. In contrast to physical metrics, LQEs based on this method rely on frequent packet transmissions in order to keep the link-quality estimates up-to-date.

Periodic broadcast packets are often used to achieve this goal and are also the most commonly brought-up drawback of these approaches, since they waste energy and occupy the wireless channel. However, the measurements—even of the physical link-quality estimators—are conducted by the receiver, but the information must be available at the sender. To perform the necessary exchange of information for each neighboring node, piggy-backing this data on top of application packets is risky due to increased packet size, especially in dense networks. Moreover, the time of information exchange depends on the network traffic of each node, so that large delays may occur and nodes make decisions based on outdated link-quality data. Thus, a periodic information exchange using dedicated broadcasts is always necessary when link-quality estimation is needed. This mitigates animadversion on the periodical broadcasts.

2.2 Link-Quality Estimators for Sensor Networks

Woo et al. define the Window Mean with EWMA (WMEWMA) [14], one of the first LQEs for estimating the PSR. In a previous work they also investigate and compare WMEWMA with different existing approaches. Thereafter, EWMA-based estimators have been widely adopted in WSNs.

ETX introduced by De Couto et al. [6] tries to estimate the number of transmissions that are necessary to send a packet successfully. The number of received packets within a fixed window is counted and compared to the number of expected packets that are periodically broadcasted by each node. The disadvantage of ETX is that it is only updated at the end of each window. A short window thus leads to a high fluctuation of the ETX metric and a long window to an infrequently updated ETX. Cerpa et al. [4] introduce RNP that incorporates the distribution of losses within the window. They observed that a link with consecutive losses should be rated lower than links with discrete losses. Four-Bit (4B) [7] is based on ETX with several enhancements. They use an EWMA for estimating the ETX and a second one for smoothing the final 4B metric. Additionally, 4B uses additional information from the link and network layer.

The Link Estimation Exchange Protocol (LEEP) is based on 4B and part of the current TinyOS version [8]. LEEP constitutes a layer between the MAC protocol and the application or routing engine, respectively. Whenever a packet is sent, LEEP attaches additional information to that packet: a sequence number, a counter for the number of known neighbors, and the ID and in-bound link quality of these neighbors. If the space (left by the upper layer) in the packet is too small, a round-robin procedure is used. The main disadvantage of LEEP is that in case of consecutive packet losses the link-quality is not updated. In addition to the limited number of possible links, due to memory restrictions, this behavior can result in a full neighborhood table with nodes that no longer exist.

The Adaptive Link Estimator (ALE), introduced by Weyer et al. [13], is an EWMA filter of the measured PSR. Each node sends a beacon per time interval (a so-called round) and records received beacons from other nodes within this interval. At the end of each round, link qualities are recomputed. Upon reception of a beacon from a previously unknown node the associated link-quality is initialized with a value of 50% to achieve a shorter rise-time for new links. The weight of the EWMA is adapted to the quality of the link. For good links ALE uses a higher weight for more stable estimation, while links with a lower quality are estimated in an agile fashion for a faster reaction.

An approach using Kalman Filter Based Link-Quality Estimation is proposed by Senel et al. [11]. They filter the RSSI of successfully received packets with a Kalman filter and subtract the noise floor to obtain an estimation of the SNR. Finally, a PSR is derived by applying a hardware specific SNR-PSR mapping for the transceiver. This approach is very complex and suffers from the restricted correlation between SNR and PSR [9].

The Fuzzy Link-Quality Estimator (F-LQE) is proposed by Baccour et al. [1]. The idea is to combine four different metrics into a single quality indicator using Fuzzy Logic. These four metrics are SNR, PSR, link asymmetry level (ASL), and stability (SF). The SNR is calculated after each successful packet reception by subtracting the power on the channel directly after packet reception from the signal strength of the packet. An EWMA filter is used to obtain the PSR. From the latter, the asymmetry level is obtained by calculating the absolute difference between the unidirectional PSR values of a node pair. The stability is defined as the coefficient-of-variation of the most recent 30 PSR values of a link.

3 Holistic Packet Statistics

All of the approaches presented in Sect. 2.2 have in common that they squeeze link quality into a single value. We argue that there should be a multi-faceted representation of link quality. Hence, we have devised the concept of Holistic Packet Statistics (HoPS). HoPS is tailored to provide detailed information about the static and dynamic behavior of a link using four distinct descriptors of the link quality. Due to the troublesome nature of the expressiveness of SNR values and the corresponding PSR matches—as laid out in Sect. 2.1—we take a different course than recent approaches and focus on the development of a more sophisticated link-quality assessment using logical metrics.

HoPS allows for utilizing enriched link information by granting access to all four link-quality metrics rather than hiding information by compressing them into a single value. Yet, this does not imply that there is no way to combine the values of HoPS into a single link-quality estimate. In this section, we define the four quality metrics of HoPS and present two possible solutions for dynamic link-quality assessment.

3.1 Link-Quality Descriptors

The four link-quality descriptors used by HoPS are measured at the receiver side by monitoring the packet success rate. Thus, a packet should contain a sequence number for the detection of packet loss. Additionally, the metrics should be updated frequently in a constant interval. Many presented LQE implementations (cf. Sect. 2.2) update only after a packet is successfully received; this leads to a wrong estimation if no more packets are received from a node.

Short-term Estimation is realized using a first-order EWMA filter for retrieving the in-bound PSR of a link in the recent past:

$$h_\tau^{\mathrm{ST}} = \alpha \cdot h_{\tau-1}^{\mathrm{ST}} + (1-\alpha) \cdot q_\tau \,. \tag{1}$$

The choice of the coefficient α influences the sensitivity to short-term changes in link quality. In the straight-forward case, q_τ is a binary value indicating whether an expected packet at time τ was received. Another option would be using a windowed mean, if more than one packet is received from the same node within an update interval. This technique is comparable to WMEWMA.

Long-term Estimation is obtained by a second-order EWMA filter, i.e., the values of the first-order estimation in (1) are smoothed by

$$h_\tau^{\mathrm{LT}} = \beta \cdot h_{\tau-1}^{\mathrm{LT}} + (1-\beta) \cdot h_\tau^{\mathrm{ST}} \,. \tag{2}$$

To achieve a strong smoothing effect, choosing β larger than α is advisable.

The dynamics of a link are obtained by means of the lower and upper deviation of the short-term estimation from the long-term estimation. The sum of lower and upper deviation yields the average absolute deviation. Due to space constraints the detailed derivation is omitted. To track the time-variant changes of these deviations and to preserve memory, another EWMA filter is applied:

$$\delta_\tau^+ = \gamma \cdot \delta_{\tau-1}^+ + (1-\gamma) \cdot \varphi\left(h_\tau^{\mathrm{ST}}, h_\tau^{\mathrm{LT}}\right) , \tag{3}$$

$$\delta_\tau^- = \gamma \cdot \delta_{\tau-1}^- + (1-\gamma) \cdot \varphi\left(h_\tau^{\mathrm{LT}}, h_\tau^{\mathrm{ST}}\right) , \tag{4}$$

$$\text{with} \quad \varphi(x,y) = \begin{cases} x-y, & \text{if } x > y \\ 0 & \text{else} \end{cases} . \tag{5}$$

These two values are utilized as follows.

Absolute Deviation Estimation is the estimated average absolute deviation

$$h_\tau^\sigma = \delta_\tau^+ + \delta_\tau^- \,. \tag{6}$$

This value gives an impression of the stability of the link in terms of the variation of h_τ^{ST} around its mean h_τ^{LT}. Its calculation demands less computing power than the recursively determined standard deviation, while not being less expressive.

Trend Estimation is intended to reflect the course that a link is taking:

$$h_\tau^\theta = \delta_\tau^+ - \delta_\tau^- \,. \tag{7}$$

A floating link—i.e., its long-term quality has had no notable changes in the past and is therefore not likely to change in the future—can be identified by values of h^θ close to zero. In contrast, positive values indicate an improving link, whereas negative values expose a deteriorating link. The absolute value of the trend indicates the slope of the current trend.

3.2 Theory in Praxis

At this point, we give a brief introduction to the interpretation and usage of the four link-quality metrics of HoPS. There are many possible solutions for the utilization of the four link-quality indicators of HoPS. For instance, a routing protocol could favor a less varying link over one with the same long-term quality. Another possibility would be to use the variation and trend in order to compute a lower bound link-quality with a given confidence. Hence, there is no silver bullet for an enriched employment of these values. However, we want to present two examples of merging the four HoPS ingredients into a prediction value.

The first approach is a dynamically adjusted link-quality estimator:

$$H_\tau^{\text{dyn}} = h_\tau^{\text{LT}} + \frac{\left|h_\tau^\theta\right|}{h_\tau^\sigma} \cdot \left(h_\tau^{\text{ST}} - h_\tau^{\text{LT}}\right) \qquad \left(0 \leq \frac{\left|h_\tau^\theta\right|}{h_\tau^\sigma} \leq 1\right) \tag{8}$$

This estimator describes a floating link ($h^\theta \approx 0$) by its long-term behavior and a massively changing link ($\left|h^\theta\right| \approx h^\sigma$) by its short-term estimate. Intermediate assessment is achieved using the relative behavior of trend and variation.

Approach number two is a confident long-term predictor:

$$H_\tau^{\text{pred}} = \begin{cases} h^{\text{LT}} + h^\theta - \omega \cdot h^\sigma, & \text{if } h^\theta \geq \omega \cdot h^\sigma \quad (0 \leq \omega < 1) \\ h^{\text{LT}} + h^\theta + \omega \cdot h^\sigma, & \text{if } h^\theta \leq -\omega \cdot h^\sigma \\ h^{\text{LT}} & \text{else} \end{cases} \tag{9}$$

In contrast to the previous method, a link is classified by the difference between trend and variation. If a clear trend can be identified—i.e., a relative threshold ω is exceeded—the long-term value is shifted correspondingly. The goal is to improve the prediction of the link behavior by incorporating the trend.

4 Evaluation Methodology

To evaluate and compare HoPS with the LQEs introduced in Sect. 2.2, we conducted simulations based on a 13-day real-world experiment. The purpose of this experiment is to gather real-world data in terms of the PSR and channel information, which is used by the TinyOS Simulator (TOSSIM) to feed the different LQEs. The main benefits of this approach are (i) detailed information about node connectivity in a real-world scenario, (ii) an identical runtime situation for all experiments, and (iii) repeatable experiments under real-world conditions.

4.1 Data Basis

A sensor-node testbed, consisting of 15 IRIS nodes with distances between 1 m and 40 m, was employed in our University building. All nodes were USB-powered. Every node broadcasted beacon messages within a fixed interval of 4 s with a random jitter using a uniform distribution. The transmit power was 0 dBm on radio channel 22. Packets consisted of a virtual payload of 13 bytes—containing a beacon sequence number—and a 13 byte MAC header. Clear Channel Assessment (CCA) was performed with at most 5 retries. We have not deactivated this feature, as we are interested in realistic connectivity behavior of a sensor network; moreover, a failed CCA implies that the sender experiences a high radio signal, but it does not necessarily imply the inability of the receiver to correctly receive a packet. Upon reception of a beacon, the following data is logged on the connected computer: node ID of sender and receiver, the sequence number, LQI, and SNR. From this data, a detailed track of packet receptions and corresponding physical channel quality was produced. More than 280 000 packets were transmitted per node.

4.2 Methodology and Metrics

We adjusted the physical layer of TOSSIM to reproduce our office environment. This layer utilizes the data basis to decide if a packet sent at a given time is received by other nodes in the network. When a node puts a radio packet onto the channel, this physical layer checks for all other nodes in the network, if they have received the experiment beacon in that time slot. The packet is only delivered to the nodes, for which this is the case. The result is a realistic, repeatable, and fair simulation environment.

We obtained the PSR ground truth by applying Hamming windows of lengths from 30 s to 60 min. The different LQEs are compared in terms of their ability to correctly represent the current and future course of each link. For this comparison, we used a normed cross correlation function (CCF) and the mean absolute error (MAE). Quality values are in the range of 0 to 100% with an 8-bit resolution; EETX values are converted to PSR. In case of F-LQE, the raw value is used. The implementations of LEEP and RNP have a resolution of tenth. ALE and HoPS run with 16-bit integers. To achieve fair conditions, we also ran an adapted version of LEEP using double precision.

4.3 Parameters

The parameters of the LQEs have been chosen as proposed in the corresponding papers. LEEP and RNP use an EWMA coefficient of 0.9 and update the estimations every 3 packets. F-LQE uses the fuzzy membership functions from [1] and a fuzzy parameter of 0.6. ALE uses filter coefficients of 0.9 in agile and 0.987 in stable link state, where PSR estimates of 86% and 74% serve as the thresholds to switch states. The parameters for HoPS are $\alpha = 0.9$ for short-term and $\beta = \gamma = 0.997$ for long-term and deviation estimation. HoPS initializes