Poster: Event-triggered State Estimation Meets Duty Cycling Protocol

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Abstract

Many event-triggered state estimation methods have been proposed to estimate the system state while reducing the communication rate of sensor nodes. Almost all of them measure the performance by how much transmission ratio can be compressed under a given reconstruction quality. This is too simplistic: the computation cost of the technique and the effects of the underlying network stack should also be considered. This paper investigates the performance of those techniques taking the average overall energy cost into account. The results indicate that: a) there is a mismatch between aperiodic transmission scheme and duty cycling protocols; b) the traditional metric is not always fair and there exists a region of transmission rate to ensure energy saving.

1 Introduction

State estimation using wireless sensor networks (WSNs) has gained much interest in the past decade. Due to the expensive wireless communication, limited bandwidth and redundant data, many event-triggered state estimation methods are proposed, where the communication happens only when certain events occur [4]. Almost all of them estimate the performance by the trade-off between transmission rate and reconstruction quality [3]. However, the gain by using such techniques in terms of energy saving is not fully investigated.

The node needs to use the underlying protocols to send the inaccurate estimate to the remote server. The radio duty cycling (RDC) layer plays a key role in such single hop communication. It regulates the access of multiple nodes to the shared wireless channel. To preserve the energy cost, they are typically designed to switch the nodes' radio on and off in a duty cycle manner. Among the existing protocols as summarized in [1], we believe that sender-initiated asynchronous protocols are more energy efficient, since the sender controls the transmission in event-triggered state estimation. To setup the communication link, the sender usually transmits a long preamble, or a series of short preambles or data packets to indicate the need for communication; the receiver periodically wakes up to detect the transmission and stops the communication with an acknowledgement.

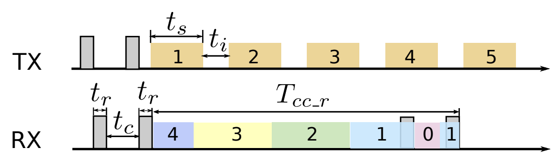


Figure 1. The duration of $Ns = n$ ($0 \leq n \leq N_{max}$) as the start sending position varies in T_{cc_r} of the receiver.

To reduce the number of transmission trials, N_s, for establishing the communication link, many protocols use some intelligence in the sender to memorize the wake-up period of the receiver. As the transmission becomes aperiodic after using event-triggered state estimation, these intelligence becomes infeasible. N_s becomes a random number and affects the overall energy consumption, while the analysis is missing in the literature. This paper analyzes the distribution of N_s and finds the effect of the radio duty cycling layer on the performance of the event-triggered state estimation methods.

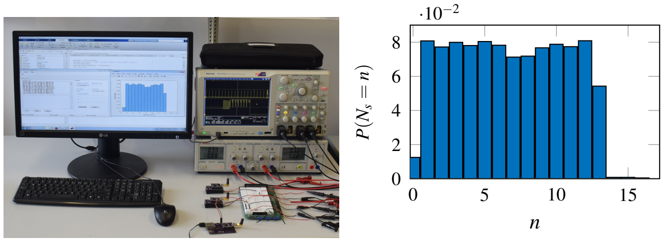
2 Probability Mass Function of N_s

As shown in Fig. 1, the wake-up period of the receiver is T_{cc_r}, the duration of each transmission trial is t_s, and the interval between two consecutive transmissions is t_i. The listening time of the receiver are slightly different when the sender transmits wake-up preamble and data packets. The former leaves the radio in receive mode long enough to detect the transmission and the latter uses clear channel assessment (CCA) to detect the channel activity. Here we focus on the later case, which is more efficient than the former [5], but the results can be easily extended to the former case by replacing $t_l = 2t_r + t_c$, where t_c is the interval between two CCAs and t_r is the time required for a RSSI to give a stable CCA indication. The starting position of the transmission within T_{cc_r} determines N_s. The maximum number of transmissions, N_{max}, happens when the receiver just misses the first packet and the transmission is detected in the following period. In Fig. 1, $N_{max} = 4$. Mathematically, N_{max} is a function of t_s and T_{cc_r} and can be calculated by:

$$N_{max} = \text{ceil}\left\{\frac{T_{cc\_r} - (2t_r + t_c + t_s)}{t_s + t_i}\right\} + 1 \qquad (1)$$

International Conference on Embedded Wireless Systems and Networks (EWSN) 2019
25–27 February, Beijing, China

ISBN: 978-0-9949886-3-8



(a) (b)

Figure 2. a) Experiment setup. b) The measured PMF of N_s when the receiver's CCR is 32 Hz with 2 hours of data.

We shift the starting transmission position to find the duration that the number of transmission trials is n ($1 \leq n \leq N_{max}$). As the starting position moves along the time axis, $n = N_{max}$ until that the end of trial No. 3 reaches the wake-up of the receiver. The duration is $t(N_s = N_{max}) = T_{cc\_r} - (2t_r + t_c + t_s) - (N_{max} - 3)(t_s + t_i)$. Similarly, the duration of $N_s = n$ when $1 < n < N_{max} - 1$ is $t(N_s = n) = t_s + t_i$. The duration for sending 1 trial is slightly different from others. It consists of two parts separated by the duration of sending 0 trial, which happens when the receiver detects the CCA of the transmitter. The first part corresponds to the duration that the first CCA detects trial No.1 with duration $t_s + t_r$. When we keep shifting, the first CCA of the receiver may detect the last CCA of the transmitter, which makes the number of transmitting trials equal to 0 with the duration $2t_r$. After that, the second CCA can detect No.1 with $t_c - t_r$ duration. Thus, the probability mass function (PMF) of N_s is:

$$P(N_s = n) = \begin{cases} \frac{2t_r}{T_{cc\_r}}, & \text{if} \quad \text{n=0} \\ \frac{t_s + t_c}{T_{cc\_r}}, & \text{if} \quad \text{n=1} \\ \frac{t_s + t_i}{T_{cc\_r}}, & \text{if} \quad 1 < n < N_{max} \\ \frac{t(N = N_{max})}{T_{cc\_r}}, & \text{if} \quad n = N_{max} \end{cases} \tag{2}$$

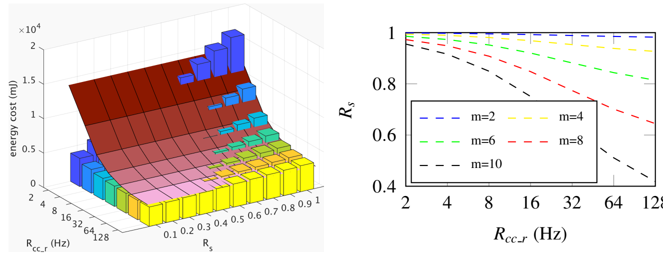
The average number of transmissions N_{avg} can be calculated by $N_{avg} = \sum_{n=1}^{N_{max}} nP(N_s = n)$. It is used to obtain the average energy consumption in Section 3.

3 Experimental Results

For the experimental implementation, we select PKF [2] as the event-triggered state estimation method, and ContikiMAC [5] as well as IEEE 802.15.4 as the network stack. The experimental setup is shown in Fig. 2a. It uses a PC for data reconstruction and OpenMotes for sending and receiving.

When the channel check rate (CCR) is $R_{cc\_r} = 1/T_{cc\_r} =$ 32 Hz, $N_{max} = 16$ calculated by Eq. (1). By adding a random time shift after each transmission to imitate different start transmission position in the experiment, we count the number of transmitted packets in 2 hours and obtain the PMF of N_s experimentally. The result is depicted in Fig. 2b. It is slightly different from Eq. (2), mainly caused by the limited memory of Matlab, which restricts the amount of measured data to find a more precise distribution. Nevertheless, the maximum transmitted packets are consistent and the overall trend matches with each other.

The measured sensing cost is 2.09 mJ and the computation cost of PKF is 0.62 mJ when the system order is $m = 10$.



(a) (b)

Figure 3. a). The overall average energy cost with and without using event-triggered state estimation; b) The transmission rate boundary to ensure energy saving.

By tuning the error threshold, we can obtain different transmission ratio R_s using PKF. The overall average energy cost without using event-triggered technique E_{no} combining the measured constants and the analyzed PMF function is shown in Fig. 3a by the red surface, which is a function of R_{cc_r}. The bars denote the energy consumption after using PKF, E_{with}, at different R_s and R_{cc_r}. Under the same R_{cc_r}, E_{with} increases as the transmission rate grows (the compression ratio decreases) and penetrates the surface of E_{no} denoting a minus gain. The intersection of E_{no} and E_{with} is depicted in Fig. 3b (the black line), which gives the minimum compression ratio that the technique should achieve in order to reduce the overall energy cost. The region of the transmission rate under the line ensures energy saving.

We have changed the system order, m, to further measure the energy cost to find the constraints. As m gets smaller, a lower reduction of the communication energy cost is enough to compensate the decreased computation energy cost. For example, R_s increases from 0.4182 to 0.9824 as m decreases from 10 to 2, when $R_{cc\_r} = 128$ Hz.

According to the explicit function between transmission rate and threshold for PKF as analyzed in [2], we can obtain the corresponding boundaries of the threshold τ for a given system. For example, when $m = 2$, τ should be smaller than 1.91, to make $R_s < 0.9824$ when $R_{cc\_r} = 128$ Hz.

4 Conclusions

The results are not only helpful for event-triggered state estimation techniques but also for general rate reduction methods, which are helpful to tune the parameters that determine the transmission rate in these techniques to ensure energy saving.

5 References

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