Wireless Inference-based Notification (WIN) without Packet Decoding

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Abstract

We consider ultra-energy-efficient wireless transmission of notifications in sensor networks. We argue that the usual practice where a receiver decodes packets sent by a remote node to acquire its state or message is suboptimal in energy use. We propose an alternative approach where a receiver first (1) performs physical-layer matched filtering on arrived packets without actually decoding them at the link layer or higher layer, and then (2) based on the matching results infers the sender's state or message from the time-series pattern of packet arrivals. We show that hierarchical multi-layer inference can be effective for this purpose in coping with channel noise. Because packets are not required to be decodable by the receiver, the sender can reach a farther receiver without increasing the transmit power or, equivalently, a receiver at the same distance with a lower transmit power. We call our scheme Wireless Inference-based Notification (WIN) without Packet Decoding. We demonstrate by analysis and simulation that WIN allows a sender to multiply its notification distance. We show how senders can realize these energy-efficiency benefits with unchanged system and protocols; only receivers, which normally are larger systems than senders and have ample computing and power resources for WIN-related processing.

1. Introduction

We consider a common sensor network scenario where remote senders, such as sensors, transmit notifications about event detected as well as their operational conditions (e.g., device operating normally, and remaining battery power) to some designated receivers over wireless channels. In such a scenario, it is often desirable that nodes draw only a small amount of power in transmitting such notifications. This would allow transmitters to survive for a long time like years even operating on a small coin battery, in applications such as industrial monitoring and home automation.

Under a conventional approach (e.g., [1]), we will adopt a low-power wireless network, e.g., Bluetooth or ZigBee, to send notifications. A sender will periodically transmit *normal packets* to report that it is in a *normal state*, and start transmitting *event packets* when it enters an *event state* upon noticing events of interest. A receiver will decode each received packet to determine if it is a normal or event packet, and in the latter case, may also examine packet payload to obtain further information about the event. In real-world applications, we expect that the bulk of the transmission is for normal packets and transmission of event packets is relatively infrequent. This means that it is especially important for the sender to minimize transmission energy for normal packets, while being able to quickly alert the receiver when events of interest occur.

We argue that for many sensor applications this conventional approach is suboptimal in terms of energy use. For example, there is no need for the sender to transmit at a relatively high transmit power to ensure all these normal packets transmitted can be decoded by the receiver, if the time series of packet arrivals can already reveal that the sender is in the normal state. Upon noticing events of interest a sender merely need to seek attention from the receiver about the new situation. To this end, the sender can just transmit packets with a different pattern in time series. The receiver can then use a robust inference method to classify the sender being in a normal or event state based on patterns in the time series of packet arrivals, without having to decode packets.

In this paper we explore such inference-based approaches where no packet decoding is required. This would enable the receiver to operate at a lower signal-to-noise ratio (SNR), and, in turn, allow the sender to reach receiver at the same distance with lower transmit power or, equivalently, farther receivers with the same transmit power.

A key issue with such approaches is their accuracy in classifying the current state of the sender in low SNR situations when the receiver is distance away, and/or the wireless chancel is noisy. We show in this paper how a two-layer hierarchical inference can be effective

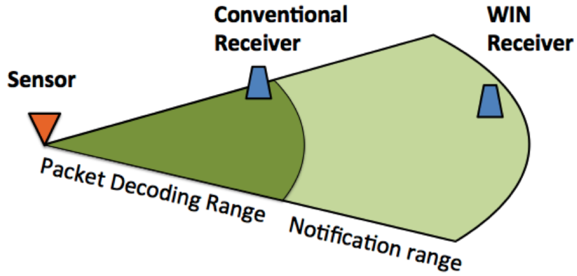

Figure 1. The WIN receiver can receive notification from

in providing robust and reliable classification based on the packet arrival patterns, even when some packets may have distorted symbols or may be completely lost. We call our approach Wireless Inference-based Notification without Packet Decoding, or for short, WIN.

2. Observations on Wireless Sensor Network Communications

We consider a wireless sensor network where the messages being sent are relatively stationary. For example: fire alarm sensors in a building or thermal sensors in an exhibition area routinely report their status through a wireless channel. In these scenarios where repeated traffic patterns are expected, a receiver can come to learn the probable patterns of incoming packets. As described below our approach has several advantages over the conventional packet decoding method.

2.1. Posterior Probability Estimation of Codewords

Conventional wireless communication assumes no prior knowledge of what we expect to receive. Therefore all codewords are considered equally likely. Let c_i be the message being sent and x be the received signal. Decoding algorithm makes decisions by maximum likelihood estimation (MLE):

$$p(c_i|x) = p(x|c_i)p(c_i) \propto p(x|c_i)$$

given that the prior $p(c_i)$ is assumed to be a constant. It is then the interest of channeling coding to design codes with efficient decoding algorithm that approximates MLE.

However, note that optimal decisions should be based on the real posterior probability $p(x|c_i)p(c_i)$. While this may be difficult to implement in general, simple solutions would suffice in the case were only a few codewords are likely to occur. In a stable sensor network environment, this may be a more fitting assumption than uniform prior. In this paper, we consider the case where c_i is restricted to $\{inactive, normal, event\}$, and demonstrate significant gains for utilizing this prior knowledge.

2.2. Multi-layer Inference

When a single packet provides insufficient evidence about the state of sender, the receiver can wait for other incoming packets for better inference results. A receiver can be a lot more powerful if is allowed to accumulate information overtime time. In WIN, we model packet arrival patterns in addition to just packet patterns, so that even undecodable packets can be useful.

2.3. Classification with Respect to False Negative and False Positive

Not all errors are equal. Sometimes it is safe to misclassify normal state as an event while mistaking event as normal could lead to more severe consequences. We can make decisions according to the posterior probability with respect to false positive/negative rates required by application. While this may not be possible for conventional wireless communication due to the complexity of applications, it is doable for many sensor scenarios and should not be overlooked.

3. Overview of the WIN Approach and Comparison with Conventional Methods

We describe the conventional approach of transmitting notifications, and then describe at a high level how our proposed WIN approach can accomplish the same task with lower energy consumption.

Conventional methods include wireless networks designed for energy-constrained applications, such as Bluetooth LE, ANT+ or ZigBee [2, 3, 4]. While hardware and protocols of these networks have been optimized for low-energy senders, they are still based on the conventional network-layering abstraction. In particular, packets must be decoded at the link or a higher layer in order to reveal packet load that contains notification messages. To be specific, in the rest of the paper, we will use Bluetooth LE [9] as our comparison target.

As depicted in Figure , under the conventional approach a sender periodically transmits normal packets (black) to a receiver to report that the sender is alive and it is in a normal state. Upon noticing events of interest, the sender enters the event state and starts transmitting event packets (red). The receiver will attempt to decode every received packet to determine the state of the sender.

Under a corresponding WIN approach, the sender in the normal state will periodically transmit normal packet like in the conventional approach. When the sender enters the event state, it will transmit event packets pe-

Figure 2. Conventional approach vs. WIN. Time slots labeled by time are shown at the bottom. Solid bars denote normal (black) and event (red) packets transmitted at various time slots.

riodically under a different arrangement about the length of packet burst or gap. Figure depict of an example of such a WIN scheme based on the following time series of packet transmissions:

Normal state: burst =1 and gap = 3
Event state: burst = 2 and gap = 6

Note that in supporting WIN, a conventional sender does not need to change its protocol stack; all it needs to do is to change packet transmission patterns during the event state. Thus existing sensor transmission systems are readily useable. This is an advantage over other approaches that also exploit physical layer signal properties [5].

The receiver employs physical-layer matched filters to determine whether each time slot has an arriving packet. Based on the matching results from multiple time slots, the receiver uses inference methods to infer the state of the sender (see Sections 4). By making use of aggregated matching results from multiple time slots and leveraging the designed-in separation between the time series of packet transmissions for the normal vs. event state, as we will show later, a WIN receiver can operate at a lower SNR. As a result, a distant receiver may still be able to infer the state of the sender even it cannot decode normal or event packets. This is illustrated in **Figure 1**. When a receiver determines that the sender is in the event state, should the receiver happen to be mobile, it could move itself closer to the sender to decode the event packet and learn about the event. Alternatively, the receiver may dispatch other agents for the task.

4. Inference Methods Used by WIN

WIN infers the state of the sender from physical layer measurements on arrived packets. The receiver matches arriving signals against a dictionary of patterns corresponding to the sender's states. Consider, for example, the scenario displayed in Figure , where the sender

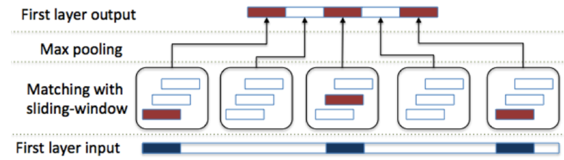

Figure 3. When detecting packets in the first layer, we use max-pooling with a sliding-window to address variations in packet delay due to multipath.

transmits one packet every four slots in the normal state, and 2 back-to-back packets every eight slots in the event state. No packets will be sent when sender is inactive. Hereafter, we refer these time slots as subintervals.

We use a two-layer hierarchical model to infer the state of the sender. In the first layer, we perform a filtering operation matching the observed signal with t, the target packet pattern, using sliding-window across all possible locations within a subinterval. The sliding-window allows us to detect the packet even with delays variances caused by multipath [6]. We then take the max of these values and call it m_i for subinterval i. This value reflects the likelihood of the target pattern t being present in subinterval i. See Figure 3 for an illustration.

In the second layer, we match m_i with arrival pattern, and classify according to the result, m. Figure 4 depicts a simulation result on the distribution of m conditioned on the three different states, at -15dB SNR. As shown in the figure, the distribution of m is fairly close to Gaussian distribution, which can be explained by central limit theorem. The inferred state s is selected according to:

$$s = \begin{cases} inactive, & m < t_n \\ normal, & m < t_e \\ event, & m \geq t_e \end{cases}$$

where thresholds t_n and t_e are chosen to satisfy a notification false positive rate R_n and an event false positive rate R_c.

Our method is a special case of a two-layer model that computes sparse representations of input in machine learning [7]. Our problem here is simpler because we can design the dictionary and assure that the dictionary entries are well separated to increase inference accuracy.

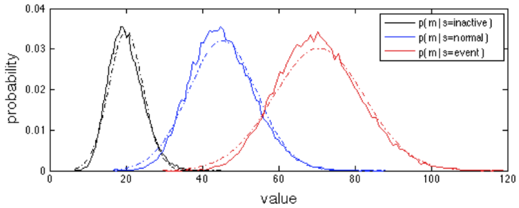

Figure 4. Probability distributions of the value of the matching metric $\boldsymbol{m}$ or state inactive, normal and event. Dotted lines are approximations with Gaussian.

5. Performance Analysis

We compare the conventional approach and WIN by computing their probabilities of successful transmission of notification. For both methods, the sender is allowed to transmit at most R packets, where each packet consists of n bits. A conventional transmission is successful if the receiver correctly decodes a packet with no CRC error. A WIN transmission is successful if the sender's state is classified correctly. For this analysis, we consider the AWGN (additive white Gaussian noise) channel with no packet delays.

Performance of Conventional Approach

A conventional method would only fail when none of the R packets pass the CRC. Thus,

$$p(fail) = \left\{1 - \left(1 - \frac{1}{2}erfc(SNR)\right)^{n}\right\}^{R}$$

where $BER = \frac{1}{2}erfc(SNR)$ for some $SNR = \frac{E_b}{N_0}$.

WIN Performance

In WIN, transmission fails if a state is misclassified. We will first find the distribution of detector z for each time slot, and then derive the distribution of the second layer detector m. Finally, we will estimate the probability of classification error by WIN.

Let t be the pattern of a packet in physical layer, and y be the sensed signal. We consider the hypothesis test on hypotheses H_0 and H_1:

$$y = \begin{cases} H_0: w \\ H_1: t + w \end{cases}$$

where $w \sim N(0, \mathbf{I})$ is noise from an AWGN channel. Then, a physical-layer detector based on matched filter can be expressed as $z = |t^H y|^2 = y^H t t^H y = yTy$ where $T = tt^H$ is a rank-1 matrix. We follow the analysis by Reed et al to compute false positive rates in detecting packets with matched filter, which gives the distribution of z as summarized in the following theorem [8]:

THEOREM 1 *If* $\mathbf{x}$ *is* $N_m(\mathbf{m}_x, \mathbf{I}_m)$ *and* $\mathbf{B}$ *is an* $m \times m$ *projection matrix of rank k then* $\mathbf{x}^H\mathbf{B}\mathbf{x}$ *has a noncentral* $\chi_k^2(\delta)$ *distribution where* $\delta = \mathbf{m_x}^H\mathbf{B}\mathbf{m_x}$.

By theorem 1, the distribution of z is

$$\chi_1^2(d) = e^{-z-|t|^2}\mathrm{I}_0\left(2\sqrt{z|t|^2}\right)$$

where I_0 is the modified Bessel function of the first kind. We have $d = d_0 = 0$, $d = d_1 = t^H t = |t|^2$ for the two hypotheses H_0 and H_1, respectively. The mean and variance (μ, σ^2) of z is (1,1) under H_0 and (d_1+1, 2d_1+2) under H_1. Given $SNR = \frac{E_b}{N_0}$ under unit variance Gaussian noise, we have $|t|^2 = |nSNR|^2$ where n is the number of bits per packet. Now, we have the distribution of matched filter detector z as a function of channel SNR.

Let Z_0 and Z_1 denote the random variables drawn from $p(z|H_0)$ and $p(z|H_1)$. The second layer detector m is then

$$m \sim \begin{cases} inactive: M = RZ_0 \\ normal: M = \frac{R}{2}(Z_0 + Z_1) \\ event: M = RZ_1 \end{cases}$$

where R is the max total number of packets to be transmitted. (Note that this particular distribution comes from the arrival pattern as shown in Figure 2, and it is possible to design other patterns to adjust the relative distance of these distributions). Since M is just a sum of random variables for which we know the mean and variance, we then approximate the distribution of m with normal distribution:

$$m \sim \begin{cases} inactive: N(R, R) \\ normal: N(\frac{R}{2}(d_1 + 2), \frac{R}{2}(2d_1 + 3)) \\ event: N(R(d_1 + 1), R(2d_1 + 2)) \end{cases}$$

Once we have the distribution of detector m, we can then select thresholds t_n and t_e to satisfy desired bounds on notification false positive rate R_n and an event false positive rate R_c using the quantile function of normal distribution:

$$t_n = R + \sqrt{2R}\ erf^{-1}(1 - 2R_n)$$
$$t_e = \tfrac{R}{2}(d_1 + 2) + \sqrt{2R(2d_1 + 3)}\ erf^{-1}(1 - 2R_e)$$

After selecting thresholds according to the false positive rates, we can derive the false negative rate for classifying normal and event states. For simplicity, we take the max of these two as the failure rate for WIN:

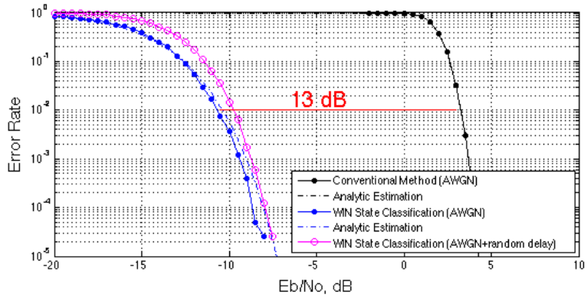

Figure 5. WIN exhibits approximately a 13dB gain over conventional approach under AWGN channel.

$$p(fail) = \frac{1}{2}\left\{1 + erf\left(\frac{t_e - R(d_1 + 1)}{\sqrt{2R(2d_1 + 2)}}\right)\right\}$$

We compare the WIN failure rate to that of the conventional approach derived earlier in Section 4 by evaluating failure rate at different *SNR*. As shown in Figure 5, WIN clearly outperforms the conventional approach.

6. Simulation

We present the simulation results on the error rate for the conventional system and the WIN proposal. The number of total packets (R) in a complete transmission is 20, and the number of bits per packet (n) is 80. Since CRC error becomes more likely when the packet size is larger, we select the smallest packet size for a wireless network to avoid bias against the conventional method. This size is 80 bits according to the specifications of Bluetooth LE [9]. We simulate with two channel models: AWGN channel and AWGN channel with uniform random packet delay.

The simulation results are shown in Figure 5. Under AWGN channel, WIN achieves error rates lower than 1% as long as the received SNR is greater than -10dB (see blue curve), while the conventional method has more than 1% error at 3 dB. In other words, there is roughly a 13 dB gain for WIN. Note that our analytic estimations match closely to the results obtained by simulation.

In the case where there are random packet delays due to multipath, WIN experience minor performance loss because of variations in the packet arrival pattern. In our simulation we assume a random delay up to 3 samples based on indoor environment, and the SNR loss is only about 0.5 dB (See magenta line in Figure 5). The conventional method process packets individually, and is therefore not affected by packet delays. Overall, WIN outperforms conventional method by a large margin.

7. Conclusion

Conventional network layering is provided to support modular design principles, but it is at the expense of losing information in each layer. For example, in the physical layer we loss information from demodulation and in the link layer we loss information when we toss the entire packet upon CRC errors. Furthermore, conventional design avoids utilizing prior knowledge because it is not always available. Such information loss and underutilization means a substantial drawback for applications that have stringent low-energy requirements. Via interference technology based on machine learning, WIN aims at making use of all information resulting from physical-layer matched filtering operations. In addition, WIN leverages designed-in separation between traffic patterns of different states of the sender, so the state classification can be tolerant to channel noise. For these reasons, we have shown that WIN can achieve 13 dB gains in terms of robustness against channel noise. Lowering the required signal strength at receiver by 13 dB translates to 4.5x range in free space. Our results may be useful for future ultra-low power designs for notification transmission over wireless channels.

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