Event Detection Using Phenomenon Models

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Wireless sensor networks can use their monitoring sensors to detect if and when an event is happening by monitoring secondary effects on the physical environment. However, it is often difficult to separate the effects of the event from the intrinsic properties of the monitored environment, especially since the effects will likely diminish with distance.

A naive approach to event detection is to set a threshold, and signal an event if any sample is higher than it. This particular approach suffers from a number of problems. If the event effects fade quickly with distance, the sample may be very close to normal conditions unless it is taken close to the event. The design choices for a successful threshold-based approach are either to have a very dense network, such that there is always at least one sensor close to the event, or set the threshold low enough, in which case noise in the readings would result in frequent false positives.

Moreover, a large class of interesting events is transient. A system has a limited time to analyze the environment and decide whether an event has occurred. For this class of events, energy constraints introduce an additional challenge. In a threshold-based approach the sampling frequency must be high enough to guarantee that at least one sensor that is close to the event will be awake during it. Such high frequency sample rates are not only very expensive, but are often unrealizable. Recent work [1], [2] focused on optimizing the distribution of sensors to maximize the accuracy of the system (i.e., maximize the number of events detected while minimizing the number of false positives) or synchronizing the sleep schedule. Our system, TotalSense, aims to achieve the same goal by making smarter use of the sampled information, through *a priori* knowledge of the propagation model of the physical event that is being monitored.

Our approach enables more accurate detection without the need for high duty-cycles or high spatial densities. In TotalSense, sensors farther from the event can still contribute to the decision process. A bit of information that would be meaningless by itself could make the difference when integrated with all the other samples. Such cooperation can provide a good accuracy even if no sensor is physically close to the event. Any sample, taken at anytime, contributes to an analysis to determine whether the collection of samples can fit a scenario where the event has occurred. Our analysis algorithm is based on the *likelihood-ratio test* [3], which is used to make a decision between two hypotheses based on which one fits better the observed scenario. Given a set of samples we compute the likelihood function for spatial position and time instant of the event. We then integrate it over all possible spatial locations and over a time interval ending at the current time and lasting the length of the event. Finally, this result is compared with the same integral based on the hypotheses that the event did not happen. An alternative implementation of TotalSense, enables a distributed computation of this integrals.

The main benefits of TotalSense are twofold. First, if the duty-cycle and sampling frequency are the same, TotalSense can provide a better accuracy compared to a threshold-based approach. Furthermore, since TotalSense can base its decision on samples that a traditional approach would consider meaningless, we can enable longer sleep intervals without affecting our accuracy. An active sensor far from the event location can still contribute to the detection.

We evaluated the performance of TotalSense through simulations considering a model whose response in time is that of a *first order linear system* and with a polynomial fading in distance (e.g., inverse square law). This model is used in control theory to describe the behavior of several physical systems [4]. The poster includes results of our simulations in a variety of scenarios obtained by changing the parameters of the model. It is important to note that the general approach of TotalSense can be applied to different physical models.

We simulated a physical environment characterized by stationary conditions. We then perturbed these conditions according to the physical model of the event. All measures are affected by a Gaussian noise. A grid of sensors takes samples at different rates and we applied TotalSense and the threshold-based approach on the collected data.

The benefits of using a coordinated approach appear when comparing the number of false positives that we must tolerate to identify a certain fraction of the simulated events. When the event is barely distinguishable from noise, TotalSense is still able to correctly identify 100% of events with a no false positives while to achieve the same goal the threshold-based approach signals a false-positive occurrence in 70% of simulations. Also, TotalSense is able to identify events even when the sampling frequency is low. When the sampling interval is 1.5 times the duration of the event, there is a chance that no sensors near the event will be able to sense its effects. Our integration enables a correct detection of more than 70% of the events with no false positives. If the system detection requirements are higher, TotalSense can detect more events with a presence of false positives always lower than that achieved by the threshold-based approach.

In the poster, we will provide a complete description of our system, of the simulations and a more comprehensive set of simulated results which compared the two approaches in a large set of scenarios.

References

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