Wireless Sensor Networks for Battlefield Surveillance

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ABSTRACT

In this position paper, we investigate the use of wireless sensor network (WSN) technology for ground surveillance. The goal of our project is to develop a prototype of WSN for outdoor deployment. We aim to design a system, which can detect and classify multiple targets (e.g., vehicles and troop movements), using inexpensive off-the-shelf wireless sensor devices, capable of sensing acoustic and magnetic signals generated by different target objects. In order to archive our goals, we intend to design a system, which is capable of automatic self-organization and calibration. Such a system would need to be capable of performing detection and tracking of targets as well as sending the real time enemy mobility information to a command centre.

Real-time tacking with WSN is extremely challenging since it requires high system robustness, real time decision making, high frequency sampling, multi-modality of sensing, complex signal processing and data fusion, distributed coordination and wide area coverage. We propose a Hybrid Sensor Network architecture (HSN), tailored specifically to meet these challenges. We investigate data fusion technologies such as particle filters, to handle both environmental and sensing noises of inexpensive sensors.

1.Introduction

Research in Wireless Sensor Networks (WSN) is widespread and pervasive in many disciplines because of the potential to embed tiny, inexpensive, low-power sensors in many environments to provide a wide range of surveillance and monitoring applications [1-4]. A key advantage of WSN is that the network can be deployed on the fly and can operate unattended, without the need for any pre-existing infrastructure and with little maintenance. Typically, sensor nodes are deployed randomly (e.g., via aerial deployment), and are expected to self-organize to form a multi-hop network. A sensor node is capable of sensing some physical phenomenon (e.g., detect tank vibrations or sniper gun noise [1]), processing the sensed data and communicating the observed measurements to fusion nodes, also called micro-servers. The sensor nodes may also perform data aggregation/compression to reduce the communication overhead in the network.

In this paper, we investigate the design tradeoffs for using WSN for implementing a system, which is capable of detecting and tracking military targets such as tanks and vehicles. Such a system has the potential to reduce the casualties incurred in surveillance of hostile environments. Our goal is to develop a distributed tracking and detection system based on a Hybrid Sensor Network (HSN) architecture [22], which consists of a large number of low-power micro sensor nodes with limited capabilities and a few powerful cluster-heads called micro-servers. Our system will estimate and track the target based on the spatial differences of the target object signal strength detected by the sensors at different locations.

The proposed system is made up of several components for detecting and tracking moving objects. Figure 1 shows the logical view of these components. The first component consists of inexpensive off-the-shelf wireless sensor devices, such as MicaZ motes [5], which are capable of measuring acoustic and magnetic signals generated by different target objects (e.g., vehicles). The second component is responsible for the data aggregation and dissemination algorithms. It includes local micro-servers, where the measurements are transferred. The system tracks the target based on the spatial differences of signal strength measurements produced by the target object and collected from sensors at different locations. Therefore, the third component of the system is responsible for data fusion algorithms. This component will also be capable of handling noise introduced by the environment as well as by the sensors themselves. A data fusion algorithm performs various computationally and memory intensive tasks. Consequently, these tasks are carried out by the micro-servers, which have significantly more resources than the tiny sensors.

In order to detect and classify the moving object we are planning to investigate the possibility of using the **Particle Filter (PF)** approach [6]. PF is a recursive Bayesian **Track-Before-Detect (TBD)** target state estimator. It does not require threshold values to operate, which make it suitable for low Signal to Noise Ratio (SNR) systems such as WSN. However, PFs typically involve many resource-intensive computation tasks. Due to the resource limitations of the sensor devices, implementing a PF in a WSN system is a challenging task. We will investigate how to use PFs to improve the tracking accuracy of WSN while addressing the resource constraints of these devices.

The rest of this paper is organized as follows. In the next section, we discuss related work, which has focused on developing tracking solutions using WSN. In

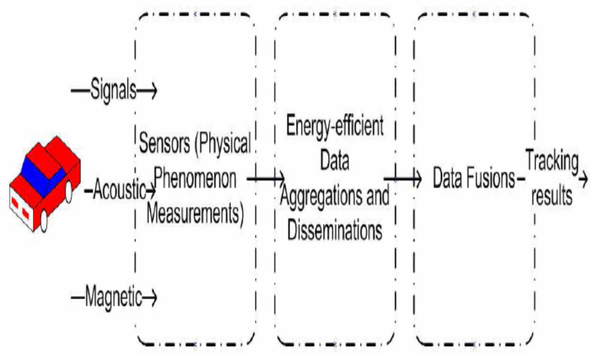

Figure1. Logical view of the architecture

particular, we concentrate on the collaborative signal processing algorithms and their applications in WSN. In Section 3, we describe our hybrid sensor network architecture. Finally, Section 4 concludes this paper.

2.Related Work

In this section, we will discuss previous work, which has explored the use WSN for tracking and detection of objects. We also provide an overview of collaborative signal processing algorithms that have been implemented in WSN.

2.1 Wireless Sensor Networks for Tracking and Detection

Detection and tracking of moving objects has been identified as a well-suited application, which would benefit from the use of WSN. One of the earliest attempts to use tiny acoustic sensor devices for tracking proposes can be found in [7]. In this work, the target is estimated via triangulation, i.e., by comparing the differences in the sound propagation delays from the sound source to different acoustic sensors. The major limitation of this work is that sensor readings are assumed to be not influenced by noise, which is quite unrealistic for real world deployments.

In [8], the authors developed a lightweight multi-modal detection algorithm for mote level micro sensors. They found out that simple fusion algorithms such as moving averages with thresholds are useful in object detection using WSN. However, this work suffers from the same limitation as [7]. In order to design a system, which can be readily deployed in real scenarios, it is imperative to account for noise and interference, especially given that such networks are likely to be deployed in hostile environments. Apart from the environmental noise, sensor readings are inherently noisy due to the small form factor and unsophisticated nature of the sensors. Hence, most of the WSN applications have low SNR. The authors in [6] have demonstrated that the threshold-setting algorithms do not perform well for low SNR data because the signal data below the threshold are interpreted as noise. Such loss of information is potentially dangerous for applications where the SNR is low, such as our tracking application, where inexpensive tiny sensors collect the data.

In [9], Duarte et al. evaluated different machine learning algorithms in the context of vehicle detection. They propose a two level detection architecture to increase the reliability. Different target detection algorithms, such as K-nearest neighbor, Maximum Likelihood and support vector machine classifier, were evaluated at local nodes level. Then, the results of local nodes level evaluation are passed to group level where data fusion is performed. Four data fusion algorithms, Maximum A Posterior (MAP) decision fusion, Maximum Distance, Nearest Neighbor, and Majority Voting, are evaluated to show the effectiveness of proposed Maximum A Posterior Decision Fusion. However, in the proposed scheme, resource-intensive tasks such as Fast Fourier Transfer (FFT) need to be performed at local nodes level; therefore, it is not suited for mote level sensors.

In [10] Ledeczi et al. designed and implemented a sniper localization system based on acoustic signal processing and triangulation. However, special hardware (Digital Signal Processing board) has been exclusively designed for the resource-intensive acoustic signal processing tasks. Similarly, in [11] He et al. designed and implemented a WSN which consists of magnetic, acoustic, and motion sensors. This system is able to classify a moving target such as a walking person or a vehicle. In this work, the motion sensor used is an expensive high-end micro-power impulse radar (MIR). Hence, it is not a suitable choice for cost-effective WSN systems, where the deployment consists of hundreds of sensors.

2.2 Collaborative Signal Processing in Sensor Networks

In [12], the authors built a framework to study the trade-offs between energy consumption and the quality of tracking for different tracking strategies. In [13], Coates compared the performance of two methodologies, the distributed parametric approximation and the more advanced distributed particle filter using adaptive encoding, which implements particle filtering in WSN. It was shown that the second algorithm can reduce wireless data communications significantly but requires substantially more computations. Under some simplifying assumptions, e.g., zero-mean Gaussian distributed noise model and linear sensor measurement model; it was shown that the performance of particle filter using 4-bit adaptive encoding was comparable to the particle filter using 16-bit fixed encoding. In their later work [14], parallel particle filters were run in multiple nodes to further reduce wireless transmissions. These parallel particle filters were used to quantize vectors of measurements. As a result, thousands of motes are needed to achieve reasonable tracking performance as shown in simulations. Further, the authors assumed that the motes have a fix sensing range of 8 meters, a fixed detection probability of 0.7 within this sensing range, and did not consider communication errors. The lack of realistic assumptions renders it difficult to apply the proposed algorithm in a real-world system.

Ihler et al. purposed a Nonparametric Belief Propagation (NBP) algorithm, whish is a generalization of particle filtering, to localize the positions of sensors based on the time delay or received signal strength between sensors [15]. Simulations have shown that NBP algorithm converged significantly faster than other non-linear optimization algorithms, while still providing comparable performance. Further, NBP is a distributed algorithm, which inherently leads to the reduction of wireless transmissions. However, in this work, the sensors are static, which makes the estimation tasks simpler compare to the task of tracking moving targets.

In [16], Sheng et al. proposed a maximum likelihood (ML) algorithm with expectation maximization for the purpose of tracking object based on acoustic energy source localization method. Evaluations by simulations have shown that the performance of ML algorithms is comparable to non-linear least square algorithms, with significant reduction in the number of wireless transmissions. In their later work [17], the authors proposed two distributed PFs with Gaussian Mixer Model (GMM) approximation to track moving objects. It was shown that by approximating the local sufficient statistic with GMM, the communication burden could be dramatically reduced, while it is possible to maintain comparable tracking performance. Both of these works [16-17] used a simplified acoustic energy based source localization measurement model where path-loss-factor is 2, which is not always true in realistic environments. Distributed implementation of PFs and re-sampling algorithms has also been explored in [18]. However, the focus was on distributing computation, and the communication overhead of the proposed approach.

In summary, previous experimental work on tracking, using WSN either used simple threshold-setting algorithms or required extra hardware on each tiny sensor device to perform resource intensive signal processing tasks. Threshold-setting algorithms have the potential of disregarding useful sensor data and thus not suitable for low SNR WSN systems. Additional special-purpose hardware is typically financially and energy expensive, which is not suitable for low-cost and self-powered WSN systems. Most of the performance analysis in previous work on collaborative signal processing was conducted using theoretical analysis and simulations, with the focus on exploring the design space and trade-offs under specific constraints and assumptions. The constraints and assumptions used in this analysis are simplified, which makes it difficult to apply these proposed algorithms in real world WSN systems.

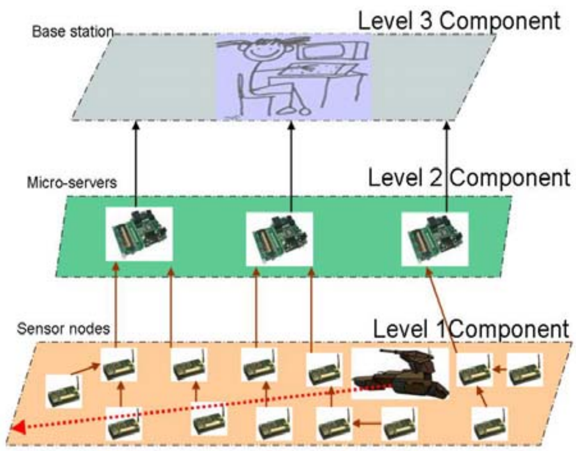

Figure 2. HSN architecture (The arrows indicate the data flow between different enteties)

Our goal is to design and implement a hybrid sensor network based system for the detection, classification and tracking of moving targets. Our system will use a large number of inexpensive tiny sensors to increase network coverage and a limited number of micro-servers, which will perform the resource-intensive tasks. The system will be implemented using off-the-shelf sensor and micro-server nodes.

3. Hybrid Sensor Network Architecture

In this section, we provide a detailed overview of our proposed HSN architecture. As was outlined in the introduction, our architecture consists of several logical components (Figure 1). Figure 2, shows the physical architecture of the three major components. Each component consists of different types of hardware and is responsible for executing different tasks.

The first level components consist of the tiny sensor devices. We intend on using inexpensive off-the-shelf wireless sensor devices (e.g. Crossbow MicaZ motes [5]), which are capable of measuring acoustic and magnetic signals generated by the target objects (e.g. tanks).

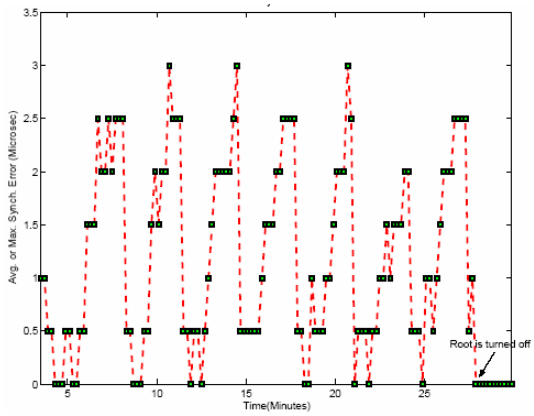

Figure 3A. Average synchronization error in a single hop environment

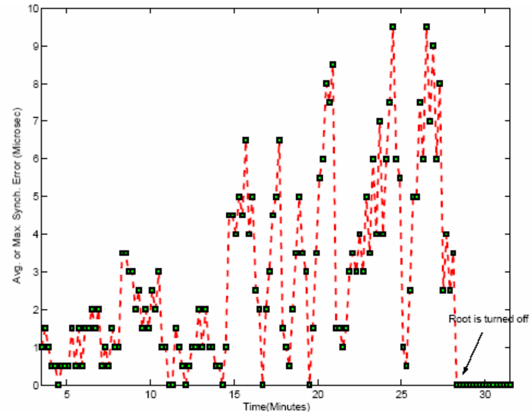

Figure 3B. Average synchronization error in a mutihop environment.

We have carried out some initial experiments to evaluate the suitability of these motes in measuring the required signals. In these experiments, several off-the-shelf MTS 310 sensors were placed along the roadside and used to detect signals from vehicles that drove along the road. Our initial experience with these sensors indicates that they can clearly identify the signature of a vehicle. Figure 4 plots the acoustic and magnetic measurements (X and Y axis) of one sensor over a period of 160 seconds during, which three vehicles passed by the sensor. The graph depicts that the sensor can correctly detect the presence of these three vehicles as evidenced by the larger amplitude of the senor readings, which corresponds to the presence of a vehicle. Although the figure shows the signature of three vehicles very clearly, we can also observe significant level of noise. This confirms our initial hypothesis that simple threshold based detection algorithms can potentially cause the WSN to generate false alarms. Moreover, the noise makes it difficult for the system to locate the target using ranging algorithms based on the signal strength.

Apart from the environmental noise, noise in the sensor readings can also be present due to the calibration errors in the sensors. The IEEE has recently drafted a standard, IEEE 1451.4 [19], to deal with the calibration errors. This standard incorporates mechanisms for plug and play capabilities of analog transducers based on Transducer Electronic Data Sheet (TEDS). One of the main advantages in using TEDS is that it contains the information needed by an instrument or measurement system to identify and properly use the signal from an analog sensor. TEDS information can be stored in EEPROM of a sensor and it contains all the necessary information for sensors calibration. Future sensors will adhere to this new standard, reducing the effect of calibration errors on our system.

In order to achieve reliable target tracking, sensor nodes need to be time-synchronize, localize and forward sensor data to the higher level components (Level 2). For the purpose of time-synchronization, the Flooding Time Synchronization Protocol (FTSP) proposed in [20] will be used. The FTSP achieves time synchronization between a sender and multiple receivers by means of a single radio message, time-stamped at the both ends (the sender and the receiver sides). It estimates the clock drift using linear regression. In order to support a multi-hop synchronization a dynamically elected node, called the root of the network, maintains the global time and all other nodes synchronize their clocks to the local clock of the root. We implemented the FTSP component in TinyOS environment, specifically targeted for MicaZ and Mica2 motes. Figures 3A and 3B show the average synchronization error after the FTPS is applied for single hop (Figure 3A) and multihop (Figure 3B) environments. As can be seen from these figures, the average error in both cases is small (order of microseconds). However, the average error in multihop environment is larger.

Localization of sensor nodes is a well studied area of research and algorithms such as the one proposed by Bulusu et al. [21], can be leverage in our work. It is also important that a sensor can construct and maintain a path to the closest micro-server. To enable this, we are planning to use the **Anycast** protocol, proposed by Hu et al. [22].

The second level component consists of the more capable hardware, such as the Stargate type devices [5]. These components are responsible for the aggregation of data from the sensor nodes located in the lower level component. Once the data is aggregated, it is a responsibility of the micro-server to perform computationally and memory intensive tasks, such as data fusion algorithm. In this work, we intend to investigate the feasibility of using the **PF based on the Bayesian TBD estimator [6]** algorithm. The basic idea is based on the work introduced in [6, 23]. There are several advantages of using the PF, namely:

- The possibility of a target to be present is modeled by the probability function and explicitly available from the filter.
- The method can track targets moving randomly in the field of the deployment. It is not limited to tracking targets that only move in a straight line.
- Non-Gaussian noise in sensor readings can be incorporated into the filter. We will need to estimate the distribution function of this noise.
- It permits us to detect targets with variable levels of intensity.

In order to use the PF, we begin by assuming that the sensors deployed in a plane, which corresponds to a square region of dimension NxM. Next, we randomly generate $\overline{N}$ number of particles in the format of:

$$p_k = \{x_i, y_i, v_i^x\ , v_i^y, I_k, E_k\} \qquad (1)$$

Where k is a discrete time-step, $x_k = (x_i, y_i)$ and $v_k = (v_i^x, v_i^y)$ denote the position and velocity of a target, I_k corresponds to the intensity of the target and E_k is an indicator whether the target is present or not. The variable, E_k can take on two values, namely $E_k = 0$ indicating the absence of the target and $E_k = 1$ denoting its presence. The target can appear at any place and at any time-step. Following its appearance the target proceeds on a trajectory until it disappears, i.e., the intensity of the target signal strength falls below the sensor's sensitivity level. Hence, we can model the transitional probability of the target birth (P_b), and death (P_d) as follows:

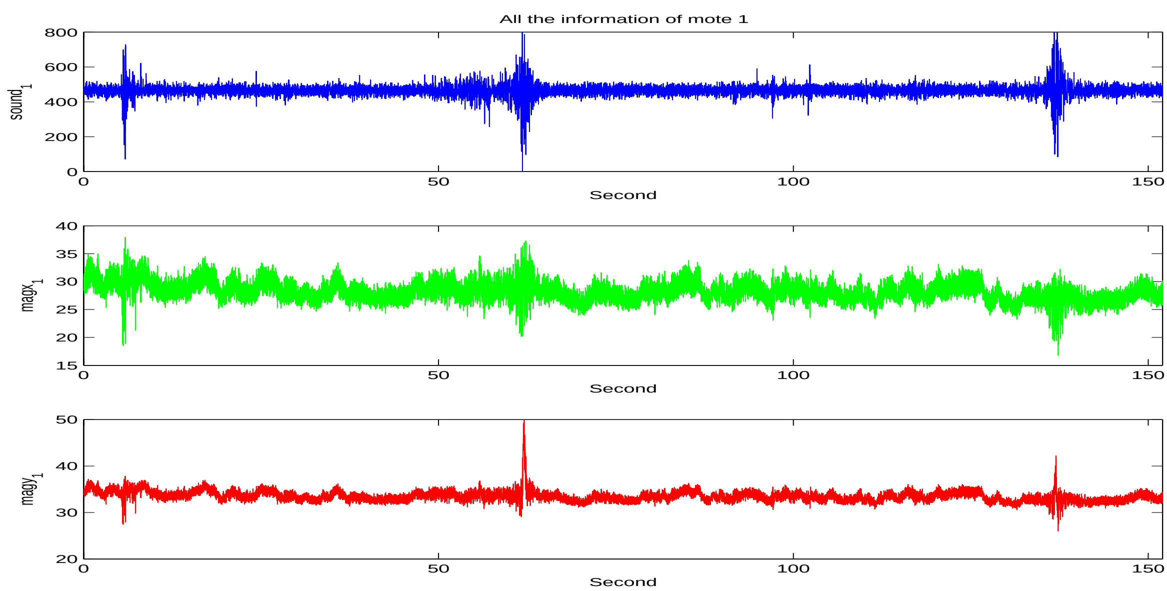

Figure4. The acoustic and magnetic measurments (X and Y axis) for a MTS310 sensor

$$P_b = P(E_k = 1 | E_{k-1} = 0)$$
$$P_d = P(E_k = 0 | E_{k-1} = 1) \quad (2)$$

In previous work, it was assumed that these probabilities are known a priori. However, if they are not known they are usually assigned a very low value (e.g., 0.1). Each sensor provides a measurement at a discrete instance of time k, and each of these measurements can be modeled as follows:

$$z_k^{(i,j)} = \begin{cases} h_k^{(i,j)} + w_k^{(i,j)} & if\ E_k = 1 \\ w_k^{(i,j)} & otherwise \end{cases} \quad (3)$$

Where, $w_k^{(i,j)}$ is the amount of noise in a measurement and $h_k^{(i,j)}$ is the contribution of the target intensity to the measurement. In general, the background noise function is assumed to follow the Gaussian model, which is not necessary true in real world deployments. In this work, we are planning to derive the characteristics of the background noise function by making use of some training data.

The contribution of the target intensity to the measurement can be estimated as follow:

$$h_k^{(i,j)} = \frac{I_k}{(\sqrt{(x_i - x_j)^2 + (y_{i-}y_j)^2})^{\varepsilon}} \quad (4)$$

Here, (x_i, y_i) is the position of the sensor, (x_j, y_j) is the position of the target and ε is the path loss exponent of the signal strength. Note that the initial values of I_k and (x_j, y_j) are unknown. They are recursively estimated over time using equation (4) and the matrix Z_k of complete measurements recorder at a time k:

$$Z_k = \{z_k^{(i,j)} : i = 1...N, j = 1...M\}$$

The goal of the PF is to compute recursively the posterior density of target presence/absence E_k and the target state (position, velocity, intensity) using all previous measurements:

$$p(x_k, E_k = 1 | Z_{k-1}) =$$
$$\int p(x_k, E_k = 1 | x_{k-1}, E_{k-1} = 1, Z_{k-1}) p(x_{k-1}, E_{k-1} = 1 | Z_{k-1}) dx_{k-1}$$
$$+ \int p(x_k, E_k = 1 | x_{k-1}, E_{k-1} = 0, Z_{k-1}) p(x_{k-1}, E_{k-1} = 0 | Z_{k-1}) dx_{k-1}$$

4. Conclusion

In this position paper, we outlined hybrid sensor network based architecture for the tracking of moving targets. We provided a detailed overview of the related work in this area emphasizing their limitations. Previous experimental work on tracking with WSN either uses simple threshold setting, which has the potential of disregarding useful sensor data and is hence not suitable of low SNR systems, or requires costly specialised hardware in each tiny sensor to perform resource intensive signal processing tasks. Our goal is to design and implement a hybrid sensor network system, which consists of several tiny inexpensive sensors and a limited number of powerful micro-servers. The sensor nodes, which are deployed over a wide area use acoustic and magnetic sensors for detecting the presence of the moving objects, while the resource-intensive tasks, such as the data fusion algorithms are offloaded to the micro-servers.

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