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Doppler effect on target tracking in wireless sensor networks

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ABSTRACT

This paper presents a new detection algorithm and high speed/accuracy tracker for tracking ground targets in acoustic wireless sensor networks (WSNs). Our detection algorithm naturally accounts for the Doppler effect which is an important consideration for tracking higher-speed targets. This algorithm employs Kalman filtering (KF) with the weighted sensor position centroid being used as the target position measurement. The weighted centroid makes the tracker to be independent of the detection model and changes the tracker to be near optimal, at least within the detection parameters used in this study. Our approach contrasts with previous approaches that employ more sophisticated tracking algorithms with higher computational complexity and use a power law detection model. The power law detection model is valid only for low speed targets and is susceptible to mismatch with detection by the sensors in the field. Our tracking model also enables us to uniquely study various environmental effects on track accuracy, such as the Doppler effect, signal collision, signal delay, and different sampling time. Our WSN tracking model is shown to be highly accurate for a moving target in both linear and accelerated motions. The computing speed is estimated to be 50–100 times faster than the previous more sophisticated methods and track accuracy compares very favorably.

1. Introduction

Recent advancements of micro sensors technology have allowed a wide range of wireless sensor networks (WSNs) implementations to be realized. WSNs are used in monitoring and detecting specific events in many types of industrial and military environments. They are especially useful in such situations as tracking emergency rescue workers, tracking military targets in modern battlefield scenerios, and monitoring traffic in transportation systems [1].

WSNs, in general, are composed of a large number of micro sensors and a base station. Each micro sensor is battery powered and is constructed using analog sensor, microcontroller, memory, and communication component subunits. A WSN acoustic tracking system, the main subject of this paper, includes two parts. One consists of acoustic sensors which are distributed in a uniform grid (or some other known configuration) to detect target sound. The other is the fusion center where target detection information from the sensors is processed to track the target. In general, these sensors are not capable of performing complicated computation and communication because of the limited power and computing resources that are present at each node. Each sensor uses a single bit to indicate that a target had been detected. When the sensor detects target sound power that is higher than a predetermined threshold value, it sends the detection information bit along with its ID and sound power information to the fusion center, otherwise it sends no information. The fusion center receives the signals from the sensors and records the receiving time along with the sensor ID and sound power information. Based upon the particular sensor layout, each sensor ID is translated into a corresponding target position that can be used along with the sound power information for tracking the target using a wide range of tracking methods.

1.1. Previous studies

A number of tracking methods for a single target tracking have been proposed in the literature for WSN type applications. Mechitov et al. [1] and Kim et al. [2] used a path based approach that used the detection duration of each sensor as a weight and performed line fitting in a time window to estimate target position at each time step. The requirement of using detection duration information from each sensor may be a hindrance for real time application of the algorithm and reliable line fitting may require a high sampling rate by each sensor. Both methods also need time synchronization and information exchange between neighboring sensors and thus tend to further impose computing and communication loads to each sensor. Wang et al. [3,4] used a similar geometric method for target position estimation which requires each

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sensor to store neighbor node identifier, intersection points of sensing circle of the node and its neighbor and an angle corresponding to the arc defined by these intersection points of the sensing circle. In noisy real-world environments accurate estimation of these parameters may be challenging. Also the applicability of the method to a target with a short sensing range covering only one or zero sensor or with a long sensing range covering many sensors is to be seen.

Ribeiro et al. [5] developed Kalman filter (KF) based recursive algorithms for distributed state estimate based on the sign of innovations (SOI). Running the SOI-KF requires each sensor to detect the target sound, compute the state and observation predicted estimate, obtain SOI and send the information to all other sensors for computing the updated state. As each sensor has limited power and limited computing and communication resources, this algorithm may give too much load to each of the sensor nodes.

Recently, a number of authors [6–8,11] chose the particle filters (PFs) over KF for target tracking in WSN environments. They claim that KF is not an optimal filter as the system and measurement process are not linear and Gaussian in real environments. PFs have become one of the most popular methods for stochastic dynamic estimation problems and the PFs can handle nonlinear/non-Gaussian measurements and dynamics of target with high accuracy but at the expense of computational complexity [10]. For the application of PF to WSN, PFs with lower computational complexity were proposed [22,23] but the error propagation through the sensor network was regarded as the main drawback of the methods [9]. Similar results are reported by other authors [12–19]. As an improvement over PF, Teng et al. [9] applied a variational filter (VF) for target tracking. The filter uses a Monte Carlo method for a set of weighted samples to approximate the posterior distribution and adapts the variational approach. The authors claim that the algorithm is able to track targets in near random motion with high accuracy.

All the previous studies mentioned above use the power law for simulating target sound power detection by the sensors and use the same power law for modeling the detection in their trackers. Their use of power law excludes the Doppler effect so that their detection model and track results are applicable only for very low speed targets. The power law model also makes the detection model in their tracker susceptible to mismatch with the detection by the sensors deployed in real environment [8]. Even though their choice of trackers yields high track accuracy in their simulation, their trackers do not guarantee the same accuracy when it is used for real WSN environments because of the mismatch. Furthermore, their computational complexity, especially for PF and VF, is too high that their trackers may be costly for real world WSN system.

1.2. Contribution of this paper

The main contribution of this paper is to develop a realistic detection algorithm where the Doppler effect appears naturally depending on the target speed. For our tracker, we use the KF with the weighted centroid of detecting sensor positions as target position measurement, which makes KF near optimal. None of the previous studies used KF for acoustic WSN tracking systems, except the case of distributed state [5,24], by reasoning that KF is not optimal in a variety of real world situations. The weighted centroid also allows the tracker to be independent of sound detection models so that there is no detection mismatch between the tracker and the sensors in the field.

With our realistic detection model incorporated into KF, we can track high as well as low speed targets accurately with very low computational complexity. The tracker also enables us to study various environmental effects on track accuracy, including Doppler effect, detection message delay and message collision at the fusion center, and different sampling time steps. Our simulation study of these environmental effects demonstrates that the track accuracy is sensitive to these effects.

Using our KF, our track accuracy is comparable to the accuracy of PF and VF and the computing speed is estimated to be nearly 100 times faster than the speed of those filters. The high computing speed and high track accuracy are critical factors for implementing the system in real world. This study is meant to lay the groundwork for more detailed systems study for implementing a WSN tracking system in real world scenarios.

This paper is organized as follows: Section 2 describes the detection framework. It gives a detailed description of Doppler effect in the sensor detection simulation. In Section 3, we describe the tracking framework demonstrating that KF becomes near optimal. An algorithm for tracking a target in acceleration is also presented. In Section 4, we show the simulation results for track accuracy of target in linear and accelerated motions, and different environmental effects. Section 5 compares our results with those of previous works. Section 6 concludes the paper.

2. Detection framework

We assume that the wireless sensors are simple passive sensors without range measurement capability. Each sensor has its own unique integer ID that translates into its position. Each sensor has own internal noise and also encounters ambient noise from the sensing region. A threshold value for the noises is set for each sensor before the deployment. Target sound over the threshold value will be detected by the sensor as a signal from a target and the detection information will be sent to the fusion center.

2.1. Model for target sound propagation with Doppler effect

Most of previous studies modeled the received target sound power using the following simple power law equation.

$$P_{s,t} = P_{0,t}/d_{s,j}^{\alpha} + \nu_{s,t} \tag{1}$$

where $P_{0,t}$ is the target sound power at time t, $P_{s,t}$ is the target sound power detected by the sensor, s, at time t, and $\nu_{s,t}$ is the detection noise at the sensor s which is assumed to be a zero mean Gaussian distribution. The distance from the sensor, s, to a target position at a time index j is expressed as $d_{s,j}$ in Eq. (2) and α is an attenuation parameter that depends on the environment of the sensing region.

$$d_{s,j}^2 = \left(x_s - x_j^t\right)^2 + \left(y_s - y_j^t\right)^2 \tag{2}$$

Here, (x_s, y_s) is the sth sensor position and (x_j^t, y_j^t) is the target position at a time index j. If the detected target sound power, $P_{s,t}$ is one of measurement vector, the relationship between the measurement, $\vec{z}_{s,t}$ and target state vector, $\vec{x}_t$ is a non-linear function as

$$\vec{z}_{s,t} = h(\vec{x}_t) + \nu_{s,t} \tag{3}$$

Eq. (3) causes the Kalman filter (KF) to be suboptimal and then the PFs are appropriate for target tracking in WSN.

We note that Eq. (1) is not an accurate detection model for high speed targets as the equation does not take into account the Doppler effect. As the sound speed is 340 m/s, target speed can be a non-negligible fraction of the sound speed and the Doppler effect is important for high speed targets. Below, we are going to derive an equation of target sound propagation in which the Doppler effect is included and estimate the maximum target speed that allows us to use Eq. (1) as an accurate target sound detection model.

Fig. 1(a) shows the target position moving from left to right with a constant speed at times t_0, t_1, t_2, and t_3 and the sound wave propagation from respective target positions in the time step, Δt.