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COMBINING PARTICLE FILTERING WITH CRICKET SYSTEM FOR INDOOR LOCALIZATION AND TRACKING SERVICES

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ABSTRACT

We describe the design, implementation and performance evaluation of a wireless sensor network based localization and tracking system, which can provide localization services in many of the pervasive computing applications. Our system uses non-linear Bayesian filtering to obtain accurate tracking results from noisy localization data. This allows high-accuracy tracking of non-linear motion even in the presence of non-Gaussian measurement noise, which is a significant improvement in generality compared to many state-of-the-art sensor network localization systems. Our prototype uses a combination of radio and ultrasound signals to obtain distance estimates necessary for the filtering process, although in principle any distance estimation technique can be used. We also describe improved outlier detection and post-calibration methods for enhancing the quality of the distance estimates obtained compared to earlier systems.

I. INTRODUCTION

Wireless sensor networking (WSN) research has had a major impact on the development of localization and tracking services in two ways. Firstly, WSNs can serve as providers of location context and mobility awareness especially indoors where the performance of other approaches is often unsatisfactory. Numerous solutions in this domain have been suggested in the literature, and several personal and shared location-aware applications benefiting from this kind of location context have been proposed by the pervasive computing community. Secondly, WSNs can themselves benefit from location information. For example, routing based on geographic addresses is in several applications a more natural choice than classical routing.

These considerations motivated us to develop an indoor localization and tracking system providing location context in real-time with low error bounds so that it can be used in a variety of pervasive computing applications for providing mobility and localization support. Our system provides a high degree of accuracy and is adaptable into a wide variety of location based services due to its flexible design.

The rest of the paper is organized as follows: In section II., we give state-of-the-art overview of the existing indoor localization and tracking solutions in relevance to pervasive applications. Section III. gives details on the design and implementation of our localization and tracking system. In section IV., we describe the experimental set-up and the results. Finally, we conclude the article in section V.

II. RELATED WORK

Localization techniques are mainly based on distance estimation, angle measurement, neighborhood proximity or hop-count methods. All the localization schemes rely on one or more physical signals and each of the techniques has its own parameters including hardware requirements, scalability aspects, performance metrics and constraints. The active RFID and IR based systems (e.g. [1]) have inherently limited indoor coverage and suffer from interference from environment. The ToF based systems require a strict synchronization of all the nodes and any offset between the clocks of the sender and receiver directly contributes to the ranging error. Synchronization is not only expensive but also requires a regular offset compensation thereby adding an undesired network overhead. Localization methods based on radio received signal strength [2, 3] are well-investigated. However, all the RF based localization and tracking systems require a pre-calibration or indoor radio propagation model, which in reality is not simple [4]. Bayesian estimators based on signal strengths and site maps have also been developed (see, [5] as a commercially successful example). Signal strength based schemes inherently suffer from fading and multipath effects and hence are not very reliable. Techniques based on time-difference of arrival (TDoA) require two types of transceivers but promise more accuracy [6].

M.I.T.'s Cricket system [7] is an indoor localization system, which uses TDoA between a radio and an ultrasonic signal (together termed as a beacon signal) for distance ranging. Trilateration based localization is applied after gathering enough beacon signals from pre-positioned nodes.

LaSLAT [8] combines the distance estimates from Cricket system with Bayesian filtering for simultaneous localization and tracking. LaSLAT uses Laplace's method instead of extended Kalman filter (EKF) for gaining computational and convergence advantages but assumes noise processes to be Gaussian.

Adam Smith *et al.* [9] developed a system for tracking moving objects using Cricket nodes. For this purpose, they employed a tracking scheme based on EKF. In real world, most of the mobile objects have non-linear dynamics and noise characteristics may not necessarily be Gaussian distributed. Thus EKF is not an optimal choice. Since only one beacon signal can be transmitted at a time, the beaconing mechanism performed by statically positioned nodes at different time instants introduces error when the listening object is moving. We have addressed this issue in our design.

Our localization and tracking framework makes use of a non-linear Bayesian filtering scheme (called Particle filters) in contrast to EKF. Particle filters (PF) have been observed advantageous in robotics community (e.g. [10]) and for classical target tracking applications [11]. This approach allows our WSN based tracking framework to handle non-linear motion even in the presence of non-Gaussian measurement noise, which EKF-based approaches are unable to do. The flexibility of the filtering framework allows our system to be tailored to a wide variety of applications simply by changing the models for measurements and target dynamics. The system is also able to incorporate location information from a variety of sources. If other types of location information is available (based on, e.g. site maps or received signal strengths from RF beacons), it can be incorporated to the Bayesian filtering framework with ease.

III. System Design and Implementation

In this section, we give a more detailed description of the hardware and software platform and the system design.

A. Overview

Our system uses a number of off-the-shelf Cricket nodes as beacon and listener nodes. A mobile object with a Cricket node periodically transmits an active beacon signal, which is received by referenced listener nodes. The listening nodes perform TDoA based distance ranging. The distance estimates are then routed to a computationally powerful machine, which is capable of executing localization and tracking algorithm in real-time. Trilateration is employed for $3D$ localization after processing the distance estimates as discussed later. As mentioned above, the system uses particle filtering [11] based tracking algorithm, which incorporates non-linear dynamics of the system and puts no constraints on the noise processes to follow Gaussian distribution. The basic functional framework of the system is illustrated in Fig.1.

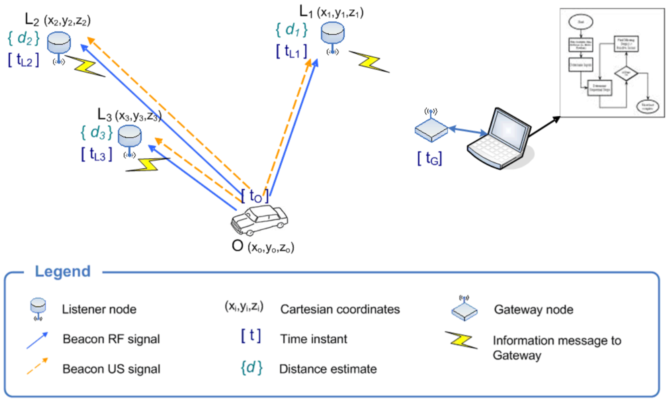

Figure 1: At time instant t_O, the mobile object O sends a beacon signal consisting of an RF signal and an ultrasonic (US) signal. When a listening node L receives the two signals, it computes the distance estimate d. The distance estimate is then transmitted to the gateway node G, which is attached to a PC. At time instant t_G, the gateway node receives the complete set of distance estimates from the listening nodes and passes it to the PC, which executes the localization and tracking algorithm.

B. Hardware and Software Platform

Cricket nodes are equipped with an on-board ultrasonic transmitter and an ultrasonic receiver circuitry, working at 40 kHz. The radio transceiver operates in 433 MHz ISM band, has a byte-level interface and provides an effective radio data rate of 19.2 kbps.

The embedded software application is implemented in TinyOS. The computationally intensive tasks (localization and tracking algorithms) are implemented on a PC in C/C++. In principle, some of the advanced PDAs and smart phones possess enough processing power to meet the computational complexity of PF based tracking algorithm in real-time.

C. Distance Ranging

The performance of trilateration based localization scheme is highly dependent on the quality of the distance estimates. The beacon node transmits RF and ultrasonic signals simultaneously. In order to avoid multipath effects, only the first ultrasonic pulse received (line-of-site component), is used for distance ranging. The time-difference measurement also includes the delay involved in the ultrasonic pulse detection and the interrupt handling duration, which are compensated by the system. The system also calibrates the speed of the ultrasonic pulse to the ambient temperature using the onboard temperature sensor readings. The ultrasonic pulse is detected based on a threshold, which depends on the received signal strength (RSS). Since RSS varies with the distance traveled, the system is expected to accumulate some error at higher distances. To compensate this, we apply a post-calibration scheme on the distance estimates for better accuracy. We obtained realistic calibration measures after extensive experiments. We observed that keeping the distance estimates "soft" (in millimeter scale) gives better accuracy. We also noted that using Cricket nodes, the reliable maximum distance ranging is approximately limited to 11 m and it gets even lower if the face angle between the transmitting and receiving nodes is increased.

D. Fault Tolerance

In order to localize an object in 3D space using trilateration, at least 4 unique distance measurements are required.[1]

We argue that despite using a lesser populated 433 MHz ISM band, radio packets still may lost due to fading effects and thus at a given instant of time, it is possible that no data is received at the gateway. Similarly, some of the distance estimates are simply identified as outliers. In order to produce a tracking update, the previously received distance measurement is used under the premise that the object has not changed its position much during the miss interval and that it represents the closest approximation. This is justifiable because indoor ubiquitous

[1] In a simplified framework, when the listening nodes are deployed in a coplanar fashion and the target object's presence on either side of the plane is known, we may even use three reference nodes to find a deterministic solution.

applications are people centric and so we do not expect high speed objects to be tracked. Furthermore, in the other case, the rest of the correctly received distance measurements and the dynamic filtering algorithm tend to keep the introduced error small.

E. *Bayesian Tracking Framework*

The tracking algorithm is based on a Bayesian filtering technique known as particle filtering that uses Sequential Monte Carlo (SMC) method to approximate the posterior probability densities of object locations. PF is a non-linear filtering algorithm that uses a large set of random samples (or particles) with associated weights to estimate the posterior probability of the state. The closeness of the discrete weighted-approximation to the actual posterior probability depends on the number of samples and the value of weights themselves.

In particle filtering context, the system maintains a set of parameters called the state vector. Using an appropriate system model, the state vector is used to predict the state vector at the next measurement time step. The filter uses a set of new measurements to correct the uncertainties in the predicted state vector.

The state vector selection is highly dependent on the dynamics exhibited by a moving object. The uncertainties are automatically incorporated by introducing suitable noise models. An object can also exhibit multiple kinds of motion. This can be coped with by introducing multiple models and appropriate switching from one model to the other. In the following, we describe the key concepts of the filtering framework in slightly more detail.

1) *State Vector*

A state vector $\mathbf{X}_n$ is maintained by the system at any discrete time instant T_n. In tracking literature, the state vector includes state variables like position, velocity, acceleration, turn-rate etc of the moving object. As an example for $2D$ motion of an object, if x_n and y_n represent the Cartesian coordinates and $\dot{x}_n$ and $\dot{y}_n$ represent the corresponding velocity components along the x and y axes, respectively, then $\mathbf{X}_n$ can be expressed as

$$\mathbf{X}_n = [x_n \; y_n \; \dot{x}_n \; \dot{y}_n]^T. \tag{1}$$

2) *System Model*

The system model describes the process of evolution of the state vector. The discrete time state expression of the system model can be written as

$$\mathbf{X}_{n+1} = \mathbf{F}_n \mathbf{X}_n + \mathbf{G}_n \mathbf{p}_n, \tag{2}$$

where $\mathbf{F}_n$ represents the transition state space matrix, $\mathbf{G}_n$ is the noise input matrix and $\mathbf{p}_n$ is the noise vector.

3) *System Noise Model*

The sources of errors in the system model are modelled by the system noise model. In target tracking applications, any unmeasured kinematic components in the system are modeled by the system noise process, $\mathbf{p}_n$.

4) *Measurement Model*

Particle filtering is a recursive prediction-correction cyclic process. In our case, the measurement cycle is repeated as a localization measurement is made. The measurement model is given by

$$\mathbf{Y}_n = \mathbf{H}\mathbf{X}_n + \mathbf{v}_n, \tag{3}$$

where $\mathbf{Y}_n$ is the measurement vector, $\mathbf{H}$ is the measurement matrix and $\mathbf{v}_n$ represents the measurement noise process. PF is able to handle arbitrary noise distributions unlike the conventional Kalman filter based techniques.

Based on these quantities, PF estimates the posterior probability $p(\mathbf{X}_n|\mathbf{Y}_n)$ by Monte Carlo integration. This is done using the system model (governing probabilities $p(\mathbf{X}_{n+1}|\mathbf{X}_n)$) and the measurement model (giving $p(\mathbf{Y}_n|\mathbf{X}_n)$) combined with standard Bayesian reasoning.

IV. Experimental Results

We conducted a number of experiments for the performance evaluation of our system ranging from various calibration tests to comprehensive object localization experiments both in static and mobile cases.

A. *Localizing a Statically Placed Object*

It was observed during the distance ranging tests that very few distances are found to be spurious and are highly uncorrelated with their neighboring estimates. These are identified as outliers and are simply discarded. We maintain a distance estimate window centered at the previous estimate. If the new estimate lies outside the window, it is simply rejected. We gathered over $10\,000$ samples of the position estimates after applying the outlier rejection heuristics and bias adjustments. The listener nodes were mounted on the ceiling at a height of 2.3 m from a beacon node in an office room of dimensions 3 m x 4 m. Fig. 2 shows the localization results obtained for a static object and its $2D$ position estimate histogram. A distinct high peak in the histogram suggests that the position estimation has a high degree of accuracy.

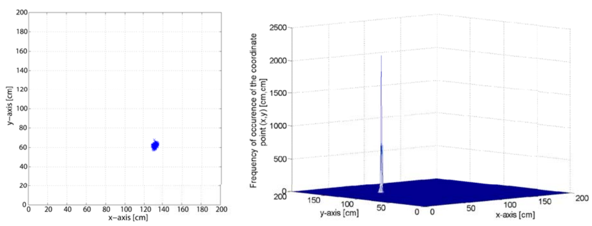

Figure 2: Localization of a statically placed object and its 2D histogram.

We also measured the true position of the object using a laser based range finder and computed the localization error in terms of Euclidean distance in the xy-plane. Fig. 3 shows the cumulative distribution function of the position error. It was found that the localization error, remains under 3 cm for more than 95% of the time.

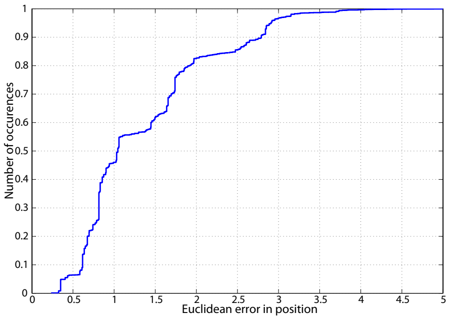

Figure 3: Cumulative distribution function of the position error in terms of Euclidean distance.

B. *Validation of the Tracking Framework*

The above described framework may be applied to a wide range of tracking systems by simply plugging-in the appropriate motion and noise models. However, in order to validate the results of our tracking algorithm, we tested the algorithm in a particular scenario, namely on a computer controlled train model. Since the trajectory is always confined to the rail-road, using a train model provides the ability to repeat the results many times in order to obtain statistically significant results. The experimental setup is shown in Fig. 4.

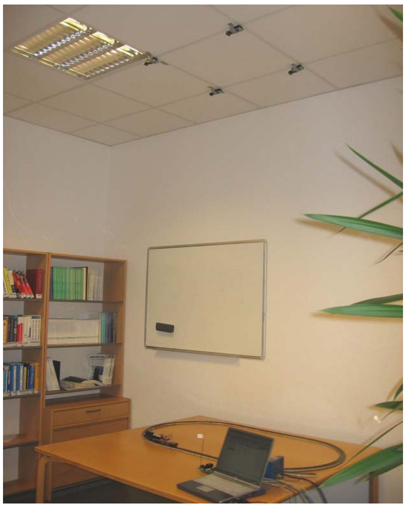

Figure 4: Experimental setup for measuring positioning accuracy of a moving object. Listening nodes are mounted on the ceiling, a beacon node is placed on the locomotive, while the gateway node is attached to the laptop.

The motion of the model-train is two-dimensional and thus the state vector in our scenario can be represented by Eq.(1). We use constant velocity (CV) [11] model and constant turning rate (CT) [12] to model the motion of the train along the straight and curved sections of the rail-road, respectively. (If we want instead to model the motion of an object with a different type of motion dynamics, we simply need to plug the appropriate motion model matrices and the noise models in the existing framework.) The state space matrices for CV and CT models are given by

$$\mathbf{F}_n^{(CV)} = \begin{bmatrix} 1 & 0 & T_n & 0 \\ 0 & 1 & 0 & T_n \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \text{ and } \tag{4}$$

$$\mathbf{F}_n^{(CT)} = \begin{bmatrix} 1 & 0 & \frac{\sin(\omega T_n)}{\omega} & \frac{\cos(\omega T_n)-1}{\omega} \\ 0 & 1 & \frac{1-\cos(\omega T_n)}{\omega} & \frac{\sin(\omega T_n)}{\omega} \\ 0 & 0 & \cos(\omega T_n) & -\sin(\omega T_n) \\ 0 & 0 & \sin(\omega T_n) & \cos(\omega T_n) \end{bmatrix}, \tag{5}$$

where the turn rate ω assumes opposite sign when the object is making a turn along clockwise direction to the case when it makes a turn along counter-clockwise direction.

The process noise $\mathbf{p}_n$ of dimensions 2×1 entering into the system is assumed to follow a zero mean Gaussian distribution. In our case, in Eq.(3), the noise matrix is expressed as:

$$\mathbf{G}_n = \begin{bmatrix} T_n^2/2 & 0 \\ 0 & T_n^2/2 \\ T_n & 0 \\ 0 & T_n \end{bmatrix}. \tag{6}$$

The measurement system provides the coordinate position (x_n, y_n) and the angle information θ of the model train. The bearing angle is measured using the digital compass CMPS03. Thus our measurement model can be written as $\mathbf{H}(\mathbf{X}_n) = [x_n \; y_n \; \theta]^T$.

In addition to the state-space matrices, we also need to choose the noise model to be used in the framework presented in section III.E. After performing calibration and outlier rejection, we measured the noise distribution in the distance ranging system. We gathered over 10 000 distance samples. The true distance was accurately measured and the error was computed. The histogram of the error in distance estimates is shown in Fig. 5.

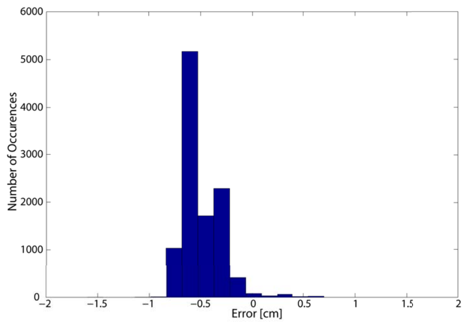

Figure 5: Noise distribution in the distance ranging system.

The narrow band histogram with a high peak suggests that the distance estimates have low variance and are quite accurate. It may however be noted that the mean value shows a bias of 0.48 cm. After extensive experimentation, we found that the bias is dependent on the node topology. It varied from 0.4 cm to 1.6 cm in most of the cases. We also tried using different sensor nodes as beacon and listeners in a particular topology, but a certain degree of bias was always observed. It originates mainly from the numerical approximations, sensor calibration errors and un-modeled environmental conditions. The localization noise in our system can be very well approximated as Gaussian $\mathcal{N}(0, \mathbf{Q})$ with zero mean and covariance matrix

$$\mathbf{Q} = \begin{bmatrix} 1.3560 & 0.7797 \\ 0.7797 & 1.0551 \end{bmatrix}. \tag{7}$$

We expected the noise in the (x, y) components to be correlated as both derive from the distance estimates. The noise characteristics in the (x, y) components depend on the noise in the distance estimates, the outlier rejection scheme, the calibration processes and the localization algorithm itself. There are some errors in the system that cannot be eliminated. The errors due to the miscalibrations in distance ranging, the abrupt temperature and humidity variations, the measurement bias depending upon the deployment of sensor nodes and the numerical calculation lead to noisy positions and, are modeled by the variance terms σ_x and σ_y in the measurement model. The noise in the digital compass is modeled by $U(-0.0083, 0.0083)$ and is augmented in the noise model.

After applying the above described framework on the train-model, we obtained the tracking results as shown in Fig. 6. The plus signs in the figure indicate the location measurements and the continuous line indicates the trajectory estimated by our tracking algorithm for repeated number of rounds. For 358 location estimates in three complete rounds, the average RMSE is found to be approximately 2.8 cm.

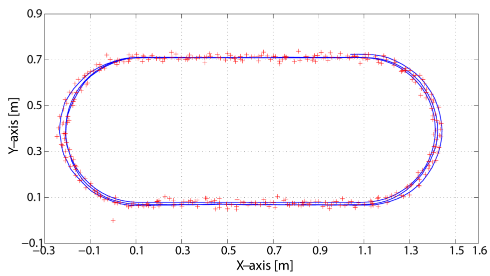

Figure 6: Tracking performance along elongated path.

V. Conclusions

From the obtained results, particle filter based approach to localization and tracking seems highly promising, and is certainly worth of further investigation to indoor pervasive computing applications especially with an implementation on smart phones. We have presented a flexible framework utilizing PFs that can easily be adapted into different types of scenarios and sources of localization data. Combining TDoA based localization with PFs yields superior performance compared to state-of-the-art approaches using the same hardware. While particle filters are commonly perceived as computationally intensive, our prototype shows that their use does not cause difficulties in common ubiquitous computing scenarios. Additionally, the improvements we have developed to TDoA based ranging are useful by themselves, and can be adopted in other systems even without the use of the overall filtering framework.

Acknowledgment

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