Demo Abstract: Field Deployable Real-Time Indoor Spatial Tracking System for Human Behavior Observations

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ABSTRACT

There remains an increasing interest in accurate indoor tracking; one such example is the study of human behaviors, especially to understand cognitive decline in older people. However, a solution that is capable of accurate tracking, easy to field deploy and freely available to the research community remains. Further, research studies often focus on localization or high accuracy as opposed to developing a field deployable solution. We demonstrate **bTracked**, a *field deployable* tracking system for mobile BLE device bearers using BLE beacon signals. In particular, we exploit, not only range estimations but also pose of the BLE device bearer for tracking. Together with a particle filter and the concept of *generic sensor models* for generalized indoor environments, we present an *online* and *real-time* tracking application of persons. We present a web-based Application for deployment and visualization of spatial tracking information across multiple remote deployment sites.

CCS CONCEPTS

•**Networks → Location based services;**

KEYWORDS

Indoor localization, Indoor tracking, BLE beacons, spatial tracking

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1 INTRODUCTION

There is an increasing interest in accurate indoor tracking systems not just for supporting indoor navigation [1] but also as a tool for understanding the behavior of people; especially older people, their cognitive decline and the effectiveness of interventions to prevent such decline [3, 4, 6, 7]. Although the problem of outdoor spatial tracking has largely been addressed by the Global Positioning System (GPS), accurate, easy to deploy, low cost, and accurate spatial tracking in indoor environments remains a challenging problem.

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In this demo, we consider the problem of developing technological tools and methods to replicate the success of outdoor environments for indoor environments in the context of a field deployable system for behavior observations and understanding of older people through fine grain spatial tracking–determining accurate traversal trajectories–in smart spaces [3, 4, 6].

In this demo, our system, **bTracked**, continuously performs online and real-time tracking using a recursive Bayesian filter by handling a continuous stream of beacon data collected from body-worn sensors. The sensor data are collected from low cost base stations on a messaging bus architecture capable of handling multiple data sinks and connecting data publishers—base stations—with data subscribers—tracking algorithms. In contrast to past research, we explicitly consider the deployability aspects of the system in our design. Thus, we consider how to best allow a user to set up a tracking system starting from off-the-self beacon technologies and to allow easy viewing of real-time trajectories. Figure 1 presents a high level view of the individual components of the system and their interactions. A complete description of bTracked is in [2].

2 PRINCIPLE

Our primary aim is to be able to actively track a moving target—a person wearing a SensorTag—within a given map. It is assumed that the system has knowledge of this map and the state space. This is achieved by defining the area that we are interested in using the *Deployment Plan Designer Tool* we developed for this purpose and overlaying this with an xy plane and coordinate system.

To accomplish our goal of deployability, we rely on generalized sensor models, which we develop offline, and can be easily adopted to fit into new unseen environments with minimal effort. To ensure our models from scene analysis are generic and cover all cases of common rooms types in an indoor house setting, we divide the rooms into three main categories: i) Empty Room: A room of arbitrary size that is primarily comprised of empty space, ii) Cluttered Room: A room of arbitrary size where there is 'clutter' in the form of furniture. iii) Corridor: A narrow room or walkway of width roughly around 100 cm. Given the similarities in the architecture of typical houses, we assume that all rooms will fall into one of the above categories.

For each of the environments we developed a parameterised RSSI-pose-distance models. To estimate the parameters of these models, we record RSSI measurements at regular distances from a beacon up to a distance of 200 cm across four different poses $\theta = 0^\circ, 45^\circ, 90^\circ, 180^\circ, 275^\circ$. We collect multiple readings at each point to record the distribution of RSSI values at each point and for a given orientation. We can represent the mean (1) and standard deviation (2) of RSSI as:

$$\mu(d) = A - 10n\log(d) \tag{1}$$

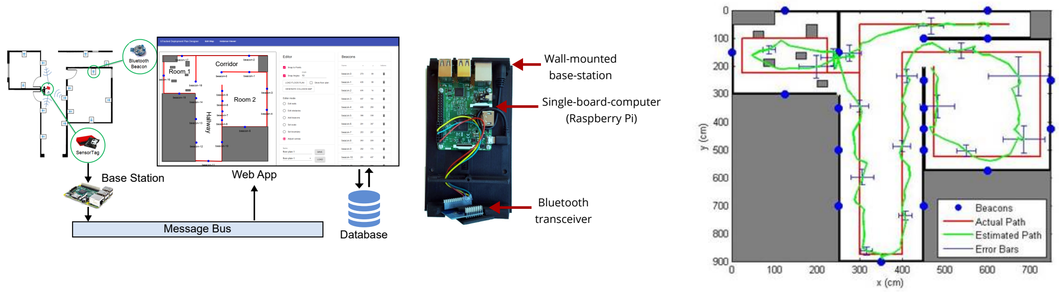

Figure 1: (left) Overview of the system with the *Deployment Plan Designer Tool*, (center) a base-station (BLE transceiver and single board computer), (right) Experiment showing estimated path trajectory. We achieve a mean path estimation error of 23.5 cm

$$\sigma(d) = ld + c \tag{2}$$

where d is distance from transmitter to the receiver. In deriving the model for the standard deviation (2) of RSSI, we assume that noise $\sigma(d)$ increases linearly with distance. Using a least squares fit we estimate the parameters A, n, l and c for each of these environments summarized in the table below:

Room type	A	n	l	c
Empty Room	-14.52	2.54	0.77	0.02
Cluttered Room	-9.77	2.66	4.59	0.01
Corridor Room	-41.58	1.24	2.91	0.01

We use the model described above to implement a particle filter based tracking algorithm. To implement this, we need to compute the observation or measurement likelihood, $p(z_k|\boldsymbol{x}_{m,k})$, for each particle m, and then assign weights based on this likelihood. This likelihood describes the probability of receiving an RSSI measurement $\mathbf{R} = \{r_1, r_2, ..., r_b\}$ from the set of beacons $\mathbf{B}$, where r_b is the RSSI measurement from a single beacon $b \in \mathbf{B}$, given state $\boldsymbol{x}$. Now, the likelihood of an RSSI reading, r_b, from beacon b can be described by:

$$p(r_b|d_{m,b}) \sim N\Big(\mu(d_{m,b}), \sigma(d_{m,b})\Big)$$

where $\mu(d_{m,b})$ is the mean RSSI obtained using the log-normal model and $\sigma(d_{m,b})$ is the standard deviation—see Equations 1 and 2, respectively. Then, assuming the independence of individual RSSI measurements, the likelihood is given by:

$$p(\mathbf{R}|\boldsymbol{x}_{m,k}) = \prod_{b \in \mathbf{B}} p(r_b|d_{m,b})$$

3 DEMONSTRATION

We use Texas Instruments (TI) BLE Beacons based on the CC2541 chip as the emitter of the beacon signal. They are configured to advertise 10 times per second at a transmit power of -23 dBm. Each beacon has a unique MAC (Media Access Control) address, that can allow it to be uniquely identified by the rest of the system. Their small size and low cost allows them to be deployed very densely around a tracking area.

A TI SensorTag CC2650 is used as the receiver of the BLE signals from the beacons. The SensorTag is small, can be worn around the neck with a simple lanyard and, thus, does not obstruct user activities. We configure the SensorTag to continuously scan for beacon signals, extracting the RSSI from each of these signals, and subsequently broadcasting a packet containing the detected beacon IDs along with their RSSI to a base-station—see Figure 1—which then forwards this data to a central server. Each SensorTag has a unique MAC address allowing it to be *uniquely* identified and associated with a specific user—see [2] for a complete description.

End-user interaction with the system is by way of a web application. The web app consists of a *Deployment Plan Designer Tool* that allows the user to reconstruct the environment in which the tracking system is to be deployed. The user configures the dimensions of the rooms and positions and IDs of the beacons used, and optionally the location and sizes of any immovable obstacles within the environment. This is linked to a database that stores different maps. The second part of the web app is the *Real Time Trajectory Visualization Tool*, which shows the movement of the person in real time. Upon receipt of a new RSSI packet, the server executes the tracking algorithm, and then renders the display with the updated position of the person. *We will demonstrate the system while allowing users to wear the SensorTag in the exhibition area as well as experience ease of deployment of the tracking application (demo video [5]).*

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