VoroLoc: Location Estimation Using Particle Filters, Voronoi Graphs and Ambient Sensor Data

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***Abstract*—In this paper we describe the design, implementation and evaluation of an indoor-tracking system that performs the estimation of user's location using an approach based on Particle Filters (PFs) [1], Voronoi graphs [2] and ambient sensor data gathered by an infrastructure of wirelessly-connected sensors. The system is currently under test in an independent-living environment composed on four apartments with 15 users. The system has been tracking users' movement with accuracy and precision that depends on the users' behavior.**

***Index Terms*—Wireless Sensor Networks, Independent Living, Particle-Filter-based Localization, Voronoi graph, Context-Awareness, Indoor Localization.**

I. Introduction

In this paper we describe the design, implementation and evaluation of an indoor-tracking system that performs the estimation of user's location using an approach based on Particle Filters (PFs) [1], Voronoi graphs [2] and ambient sensor data gathered by an infrastructure of wirelessly-connected sensors.

In this approach to the indoor position estimation problem, we want to address those situations in which users *do not want* or *cannot wear a transmitting device* in order to be localized. This situation arises in particular when it would be obtrusive to ask to wear a tag, e.g. at night, with non-cooperative patients or people suffering from mild cognitive dementia, etc.

Therefore, this approach is particularly suitable for home or independent living environments leading to minimally invasive and potentially inexpensive indoor-tracking systems.

The main idea of our approach is to use a particle filter (PF) to estimate the locations of people, exploiting the data gathered through an infrastructure of wirelessly-connected sensors; and using, when available, contextual data in order to disambiguate the situations of uncertainty.

Therefore, in order to continuously track the movement in the environment, every person has an associated instance of a PF. This may cause issues in term of efficiency given that one of the most important problems when using PFs is to correctly size the space where the particles can move. In order to overcome this issue, we decided to constrain the possible positions of particles using the Voronoi graph of the environment.

This idea about limiting the environment has been originally proposed in [3] and it leads to two important advantages. Firstly, this constrained version of PFs is far more efficient than an unconstrained one. Secondly, the usage of Voronoi graphs provides an efficient, and completely automated, discretization of the environment that can be easily integrated into a PF motion model.

The main drawback of the approach proposed in [3] is that it works only partially when more than one person is present in the environment. In this situation, there exists a data association problem caused by the fact that there is no way to identify with absolute certainty which user is causing the activation of a particular sensor.

Our contribution addresses this drawback: using PFs and proper motion models it is possible to track more than one user at the same time under some conditions using, when available, information about the particular context in which the system is deployed, e.g. all the users are detected in known areas and then they start to move, etc. For a more detailed description of this data association problem see Section III.

In order to verify our approach, we implemented it and deployed it in a test setting and in an independent-living environment composed on four apartments with a total of 15 users. The system has shown interesting results especially during particular times of the day (e.g. at night-time), and it is tracking users' movement with a good accuracy and precision.

The remainder of the paper is organized as follows. Section II describes the approach giving an architectural overview and detailing the components used for its implementation. Section III details the data association problems and the usage of contextual information. Moreover, Section IV describes the evaluation environment and finally Section V draws the conclusions.

II. The VoroLoc Indoor-Tracking System

The VoroLoc system is based on two main components: a data-gathering infrastructure and a filtering and fusion component. We will give more details about these components in the remainder of this Section.

A. Data-gathering Infrastructure

The Wireless Sensor Network (WSN) [4] used for data gathering is based on the IEEE 802.15.4 protocol with a tight synchronization between energy-aware nodes.

The sensor nodes are custom-built based on the Jennic JN5148 transceiver [5]. They are typically battery-operated and each node has four sensors that measure: movement, temperature, humidity and ambient light.

The movement sensor is based on the very common passive-infrared devices (PIR) typically used to automatically open doors. The nodes are installed in the environment on the walls at a height of 2.5 meters. The particular PIR sensor we used (Panasonic AMN42122) can detect slight movements between 0.3 m/s and 1.0 m/s. The PIR sensor is mounted in the node so that it is pointing downwards and covers a cone of about 2 meter radius at pavement level.

The infrastructure is very energy-thrifty because most of the nodes are normally off and turn-on only if the PIR is activated or, periodically with a very low duty cycle, to communicate the value measured by the other sensors. The turn-on time is also very short (~10 ms).

The network is organized as a tree hierarchy whose leaves are zones (typically rooms) with many slave nodes and one coordinator. In some cases it is necessary to operate the coordinator with a power supply but this is not strictly necessary. Coordinators report to a single "gateway" node that interfaces the WSN with other networks. The gateway is the only node that has to be always turned on. Given this network organization, the gateway receives all the data regarding the movement and the environment in a matter of a few milliseconds.

For more details about the data-gathering infrastructure see [6].

B. Filtering and Fusion. A Voronoi-based Particle Filter.

In the VoroLoc system, the filtering and fusion component is used to aggregate the localization data and to compute the user position.

This component implements the common Sequential Importance Sample with Resampling (SISR) algorithm [7]. Apart from the modifications described later in this Section, the implementation is quite common and it is a standard approach in several other fields (e.g. robotics, for robot tracking).

The SISR approach, when used in the tracking context, involves the prediction of the movement of each particle using a motion model that implements its Prediction Sampling step. Therefore, for the prediction step of the VoroLoc system, we implemented a human motion model specifically tuned for elderly people [8]. In this way, the behavior of the filter adapts better to the end-user behavior.

As previously outlined, in order to efficiently implement our PFs approach we decide to constrain the possible position of the particles using the Voronoi graph of the environment.

For our approach, and according to [3], we can define the Voronoi graph $G = (V, E)$ as a set V of vertices v_i and a set E of edges e_j. The set V is obtained in a completely automated way, starting from the known positions of the infrastructural sensors. The set E is used to represent the possible path between vertices and it can be computed using the information about the specific environment. For example, Figure 1 shows the resulting undirected Voronoi graph for a testing environment in which we (mostly automatically) pruned several edges that represent impossible connections, e.g. a passage through a wall.

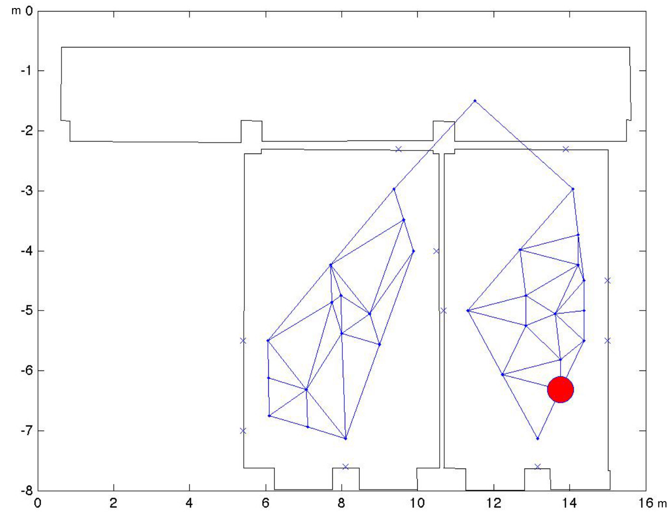

Fig. 1: The Voronoi graph of a testing environment. The Figure also shows the position of the infrastructure of data-gathering devices and walls. The red circle represents the detected user position.

Using this discretization method, it is easy to represent in VoroLoc the state s_t of each particle at a certain time t as a tuple $s = \langle e, d_e, p_m, v, h \rangle$, where e denotes the current edge on the Voronoi graph, d_e is the distance in respect to the starting vertex on the edge. Moreover, in this model, the state of every particle includes parameters used for the modelling the motion. In particular, the state includes the movement probability p_m, velocity v and heading h parameters.

During each prediction-sampling step of the SISR algorithm, the VoroLoc Particle Filter updates the velocity v and heading h of every particle as follows.

During the update step, every particle can be moved or left in the previous location. The probability p_m of moving a particle is proportional to the time elapsed since the last measurement received from the PIR sensors.

A particle is more likely moved if, given the proper movement data, the user is currently moving or a movement was detected in a previous step. After a fixed time (e.g. 10 s) without receiving movement data the particle filter is stopped and no update steps are performed (mainly because the user is no longer moving).

For every particle, if the particle is moving, the velocity parameter v is updated drawing a random value from a normal distribution $\mathcal{N}(\mu, \sigma^2)$ where μ = 1.25 and σ = 1.0. These parameters for the normal distribution turned out to be particularly effective when modeling the movement of elderly users.

For updating the heading parameter h we exploit the Voronoi graph. The heading h is computed by taking the angle between the edge in which the particle is currently located and the position of the corresponding origin and destination vertex.

After having updated their speed and heading every particle is moved to a new predicted position.

For the Importance Sampling step of the SISR algorithm, we compute measurements using the sensor network data. Every measurement m has this form: $m = \langle t, p_m \rangle$; where t is the timestamp in which we gathered the data and p_m is the position in which the movement happened.

For computing the p_m position we can either consider the position of the PIR sensor which detected a movement or the centroid of an area associated to a particular environmental sensor activated by a user. Using this approach, also contextual information about the environment can be included in the filter, as detailed in the following Section.

The likelihood for every particle is then computed using the following Equation 1

$$p(d_p) = \begin{cases} 1.0 & \text{if } 0.0 \le d_p < 1.5 \\ Q(d_p) & \text{if } 1.5 \le d_p \le 4.0 \\ 0.1 & \text{if } d_p > 4.0 \end{cases} \quad (1)$$

where $Q(d_p)$ is the Q-function with $\mu = 2.0$ and $\sigma = 1.0$ for the computed distance d_p between the particle and the movement position p_m.

III. Data Association. Exploiting The Context

As previously outlined, in our approach we want to address situations in which users do not want or cannot wear a transmitting device in order to be localized. Given this assumption, the data association problems arise when more than one user is moving in the environment. This is caused by the fact that it is impossible to identify with absolute certainty which user is causing the activation of a particular sensor.

By properly using the knowledge about the context in which the user is moving it is still possible to track, with some assumptions, more than one user at the same time.

Our approach consists of using multiple instances of the previously described PF exploiting the knowledge about the particular context in which the system is deployed.

The main assumption we made is to known a "starting" position for every user (e.g. the user bedroom). The position is used for resetting the PF associated to a particular user when having problems, given for example by noisy data, during the tracking process. This is particularly interesting in home environments where it is more common for a user to periodically return back to a reference room.

Assuming the knowledge of a starting position for each user enables to better associate the motion data gathered by the system with the movements of a particular user.

The association can be performed using the motion model included in the PF we implemented. If the filter determined that a user is moving with a certain speed and heading we can expect which are the possible infrastructural sensors that should trigger. On the contrary, if a certain sensor detected a movement, we can exclude users that have an incompatible position with the measurement.

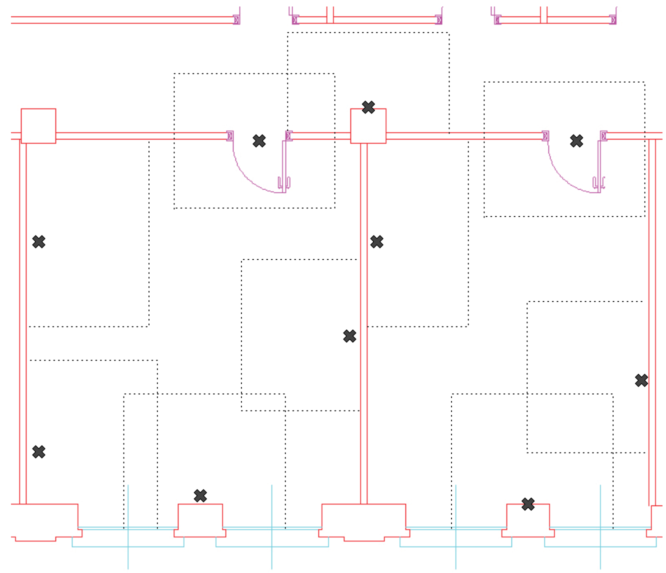

Fig. 2: Preliminary test environment, showing the position of data-gathering nodes and the movement sensors coverage areas.

Of course, these assumptions are not enough for giving precise tracking results when all the users are continuously moving at the same time, however turned out to be effective and sufficient for tracking users when the movements are somehow limited, for example during the night.

IV. Evaluation

For the preliminary evaluation of the VoroLoc system we deployed a network of ten data-gathering nodes in two zones (two rooms), as shown in Figure 2. As you can also see in the same Figure, every zone contains several areas and every node covers a certain area in the zone. The nodes gather environmental and movement information for the corresponding area.

Given this setting, two different evaluations of the VoroLoc system have been completed, the first one focused on measuring the accuracy of the approach and the second one focused on testing the usage of context information.

The first tests have been completed using the Ubisense system [9] as a benchmark.

Ubisense Ltd. produces an UWB-based localization system that exploits the time difference of arrival (TDoA) and angle of arrival (AoA) techniques, combining the measurements in order to estimate tag location. The tags are equipped with 802.11b transceivers for data communication and proprietary UWB transmitters for localization. In typical deployments of the Ubisense system, the location accuracy of 25 cm in 3D attained 95% of the time has been reported. We measured a slightly worse performance of 28 cm for 95% of the time.

In this first kind of tests, the person moved around the testing environment carrying a Ubisense tag. At the same time, the user movement data are collected using the VoroLoc data-gathering infrastructure and position estimated using PFs. The positions computed by Ubisense are used as ground truth for VoroLoc.

We performed several data acquisitions by asking a person to walk freely back and forth between the two zones. In addition to the verification of the system in general, the focus of the tests if to stress the behavior of the VoroLoc system in respect to boundary positions between different areas.

In order to measure the accuracy of the VoroLoc system, we then compared the estimated position with ground truth using a metric called Mean Absolute Error (MAE) [10].

The MAE metric is very similar to the common Root Mean Square (RMS) and it consists of computing the residual errors between the estimated and actual node positions for every node in the network, summing them and averaging the results, as shown in the following Equation 2,

$$MAE = \frac{\sum_{i=1}^{n} \sqrt{(x_i - \bar{x}_i)^2 + (y_i - \bar{y}_i)^2 + (z_i - \bar{z}_i)^2}}{n} \quad (2)$$

where $(\bar{x}_i, \bar{y}_i, \bar{z}_i)$ are the coordinates of the target estimated position and (x_i, y_i, z_i) the ground truth ones.

The result of this first kind of tests shows a MAE of 93 cm with an accuracy variance of 43 cm.

In the second kind of tests, we performed several data acquisitions by asking two users to follow predetermined paths, returning from time to time to their "starting" position (see Section III). The data gathered were used for simulating different time frames both for daily and nightly usage.

In this tests the VoroLoc system showed a good accuracy always tracking users at least at room level, giving more accurate results detecting the proper zone when simulating night situations.

After this preliminary evaluation, the VoroLoc system has been deployed and it is currently under test in an independent-living environment composed on four apartments with a total of 15 users. In this setting, we deployed more than one hundred data-gathering nodes and the system has shown interesting results especially during the night, tracking users' movement with a good accuracy and precision.

V. Conclusions

This paper described an approach to the indoor position estimation problem based on Particle Filters (PFs), Voronoi graphs and ambient sensor data gathered by an infrastructure of wirelessly-connected sensors.

The VoroLoc system, an implementation of this approach, has been described and evaluated and initial field data collected. The performance has been evaluated informally by the paramedical personnel and judged useful for the automation of the monitoring process.

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