RF-based Ranging for Mobile Robots: Using Time-of-Flight and RSSI for Channel Estimation

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***Abstract*—Mobile robotic units are ideal candidates for applications where the presence of humans is impossible or should be avoided. Furthermore, using multiple units cooperating as a team can maximise the utility of the whole system. For such cooperation one of the key factors is knowing the positions of the robots. A possible solution, which is considered in our work, is to derive relative positions from local communication. For that purpose, we propose an anchor-less online channel estimation method aimed to be used in small multi-robot teams. We combine Time-of-Flight (ToF) and RSSI ranging to perform an online estimation of the log-distance path loss model without using extra sensors, a priori knowledge, and supporting the high dynamics of RSSI with the improved precision of ToF.**

I. Introduction

Mobile robotic units are ideal candidates for applications where the presence of humans is impossible or should be avoided. Applications such as transportation of large volumes, surveillance and cleaning, to search and rescue [1], [2], [3], can benefit from the use of such units not only by ensuring the safety of the people they replace, but also by allowing performing tasks that would be impossible for a person. Furthermore, similarly to other animal behaviour, using multiple units cooperating as a team can maximise the utility of the whole system. For example by increasing the effectiveness of surveillance by performing cooperative sensing, improving the rate of coverage in search and rescue, and by performing motion coordination for the transport of large parts.

For such cooperation one of the key factors is knowing the positions of the robots. Occasional situations may allow to build an infrastructure thus making absolute positions available; however, building infrastructure is costly and it is probably unavailable in urgent scenarios. GPS may be a possible solution for outdoors; however, it may not available in locations such as in indoor spaces and street canyons. A possible solution, which is considered in our work, is to derive relative positions from local communication.

One of the technologies used for obtaining distances with RF communications is Time-of-Flight (ToF) measurements, where one unit measures the time a message needs to reach the destination and return, thus obtaining the distance that separates them. The problem of using solely ToF ranging with mobile units is that it is only possible to range one robot per ranging operation, thus making this method less responsive to fast robot dynamics. Despite that, the ranging operation produces a distance in meters that is accurate enough to be used for localisation. Another possibility is Received Signal Strength Indicator (RSSI) based ranging that, on the other hand, produces faster measurements since several units can measure the signal strength of one unit at the same time, i.e. if several units receive a message from another one, all of them can obtain the RSSI value from that message. The disadvantage is that the RSSI is a measurement of signal strength, thus dependent of the propagation medium, antenna, and obstacles. In open space, the relationship between signal strength and distance can be represented by the log-distance path loss model Eq. (1).

$$\rho_d = \rho_0 - 10\alpha \log\left(\frac{d}{d_0}\right) \Leftrightarrow d = d_0 \times 10^{(\rho_0-\rho_d)/(10\alpha)} \qquad (1)$$

Where ρ_d is the RSSI value at distance d, ρ_0 is the RSSI value at a reference distance d_0, and α is the path loss exponent.

II. Proposal

In this work, we propose an anchor-less online channel estimation method aimed to be used in small multi-robot teams. We combine both the Time-of-Flight (ToF) and RSSI ranging, provided by the nanoLoc devices [4], to perform an online estimation of the log-distance path loss model, which we assume to be valid for indoors as well. This will lead to less accuracy but it can be accurate enough for applications such as team coordination. The advantages to previous work are: 1) we do not use any extra sensors, since all the data is captured from the transceiver module; 2) do not use any a priori knowledge, the channel model is estimated online and we do not use well localised anchor nodes; 3) we support the high dynamics of RSSI with the improved precision of ToF.

III. Related work

A lot of effort has been put into localisation of robots using RF communications. Several methods rely on a priori channel measurements [5][6], however, those may be unavailable or unreliable, i.e. either there is no previous knowledge or there were severe changes to the environment. Other methods perform online channel estimation, however estimations are often performed based on measurements between anchor nodes [7],

[8], which are not compatible with unknown environments, or with external sensors [6] which require extra equipment.

Several works use anchor-less RF-only localisation methods without previous knowledge. Examples include [2], where RSSI-based localisation is performed. However, in that work, since location accuracy is not a concern, no propagation model is considered and all localisation is performed assuming RSSI is linear. Also, in [9] the authors show a method of ranging using ToF, however, as they show, this method is very slow and does not accommodate fast moving robots.

IV. Parameter estimation

In order to use the propagation model we need to estimate some of the equation parameters, namely the reference RSSI value (ρ_0) at the respective reference distance (d_0), and the path loss exponent (α). For that purpose, we define a vector of predefined n log-separated distances ($\mathbf{g}_{1\times n}$) and create the matrices $\mathbf{A}_{(n+1)\times 2}$ and $\mathbf{b}_{(n+1)\times 1}$ (considering $d_0 = 1$) Eq. (2). The first n lines represent the previously estimated model $\widehat{\mathbf{x}_{t-1}}$, and the $n+1$ point represents the new measurement. Then we run a Maximum-Likelihood Estimator (MLE) Eq. (3) to obtain the new channel model $\widehat{\mathbf{x}_t}$. This allows us to run MLE using a fixed number of samples ($n+1$), and at the same time to fuse the new knowledge into previous knowledge, with n defining the weight of the new measurement.

$$\mathbf{A}_t = \begin{bmatrix} 1 & -10\log(g(1)) \\ 1 & -10\log(g(2)) \\ \vdots & \vdots \\ 1 & -10\log(g(n)) \\ 1 & -10\log\left(\overline{d}_t\right) \end{bmatrix} \mathbf{b}_t = \begin{bmatrix} \rho_{0,t-1} - 10\alpha_{t-1}log(g(1)) \\ \rho_{0,t-1} - 10\alpha_{t-1}log(g(2)) \\ \vdots \\ \rho_{0,t-1} - 10\alpha_{t-1}log(g(n)) \\ \overline{\rho}_t \end{bmatrix} \quad (2)$$

$$\widehat{\mathbf{x}_t} = \begin{bmatrix} \widehat{\rho_{0,t}} \\ \widehat{\alpha_t} \end{bmatrix} = (\mathbf{A}_t^T \mathbf{A}_t)^{-1} \mathbf{A}_t^T \mathbf{b}_t \quad (3)$$

V. Preliminary results

We have collected distance-RSSI ($\overline{d}, \overline{\rho}$) measurement pairs every $1m$ from $1m$ to $10m$ in a corridor. For every point we have collected 100 measurements, and repeated the experiment four times. Thus having a dataset with 400 ($\overline{d}, \overline{\rho}$) measurements per distance (Figure 1).

Then, we created a simulation in MATLAB using our previously collected data. The simulation consists of two nodes, one is static at 0, and the other is moved to different positions (in the range of $1m - 10m$) according to a circular buffer. For each of the positions, a random measurement is selected from our dataset, and used to calculate an estimate of the model parameters. The simulation results are available as a video that can be found in http://youtu.be/b6pLZh5SWz8.

VI. Conclusion and future directions

In this work we proposed to perform an online estimation of the log-distance path loss model to be used for applications such as coordination of a robot team. The estimation needs to be accurate enough for in team cooperation, and reactive enough to cope with the movement of robots in unknown

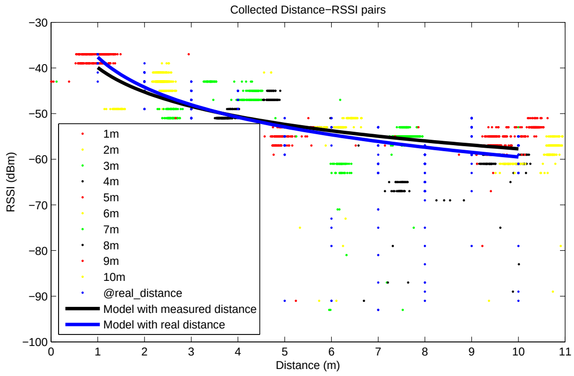

Fig. 1. Collected data: Different colours for each meter ($\overline{d}, \overline{\rho}$); Blue points represent real distance($d, \overline{\rho}$); lines represent models using MLE with all points

environments where the position of all robots is initially unknown.

This is the first part of a work that is expected to provide a method to track relative positions of a team of robotic units. For that purpose the next steps of this work-in-progress are: 1) Implement an Unscented Kalman Filter to track the distances (using RSSI only when a distance measurement is not available); 3)Evaluate the performance in real robots by comparing the obtained results with a ground-truth localisation system.

This work is expected to be a major contribution on the thesis entitled “Communications and Middleware for Cooperating Heterogeneous and Autonomous Mobile Robots”.

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