Fusing Time-of-Flight and Received Signal Strength for Adaptive Radio-Frequency Ranging

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***Abstract*—Teams of mobile cooperative robots are ideal candidates for applications where the presence of humans is impossible or should be avoided. Knowing the positions of the robots in crucial in such scenarios. A possible solution is to derive relative positions from local communication. In this work, we propose an anchor-free online channel estimation method aimed at small multi-robot teams. By combining both the Time-of-Flight (ToF) and Received Signal Strength Indicator (RSSI) ranging, provided by the nanoLoc devices, we perform an online estimation of the indoor log-distance path loss model. This model will then be used together with an Extended Kalman Filter to track distance between every pair of units. The advantages compared to previous work are: 1) we do not use any extra sensors, since all the data is captured from the transceiver module; 2) we do not use any a priori knowledge, the channel model is estimated online, without the need of fixed anchor nodes; 3) we support the high dynamics of RSSI with the improved accuracy of ToF.**

I. Introduction

Mobile robotic units are ideal candidates for applications such as transportation of large volumes, surveillance, search and rescue, and cleaning [1], [2], [3]. They can either ensure the safety of the people they replace, or perform tasks that would be impossible for humans. Furthermore, using multiple units cooperating as a team can maximise the utility of the whole system, e.g., 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 emergency scenarios. GPS may be a possible solution for outdoors; however, it may not be 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 using algorithms such as the MultiDimensional Scaling (MDS) [4], [5], which minimises the dissimilarities of a connectivity matrix up to a rigid formation. However, in order to implement such solution the robots must first collect inter-robot distance information. The problem of collecting such distance measurements is the focus of this work.

In a common situation, every robot wants to communicate with the other team members, therefore every robot transmits messages regularly. Every such message can be received by all robots in range, that in turn can extract Received Signal Strength Indicator (RSSI) information from it. As it will be explained further on, RSSI can be used to extract distance information. Consequently, any messages exchanged between the robots can potentially be used for inferring localisation. In this work we use the nanotron's nanoLoc kit [6], which allows to perform Time-of-Flight (ToF) ranging, to provide a ToF/RSSI hybrid ranging method aimed at small multi-robot teams. For that purpose, we propose an anchor-free online channel estimation method that uses the ToF and RSSI to perform an estimation of the log-distance path loss model. Using this model it is possible to dynamically improve the accuracy of RSSI-based distance measurements. Then, we present a distance tracker based on an Extended Kalman Filter (EKF), providing both a distance estimate and the confidence on that estimate. Finally, we present some experimental results using real robots that confirm the superior accuracy of our system with respect to a simple RSSI-based approach, while keeping its reactivity. The advantages to previous work are:

- we do not use any extra sensors, since all the data is captured from the transceiver module
- we do not use any a priori knowledge, the channel model is estimated online
- there are no pre-installed anchor nodes
- we support the high dynamics of RSSI with the improved accuracy of ToF

II. Related work

Localising nodes in a network of mobile robots is essential in order to put into practice a diversity of coordination algorithms, such as team formation and path planning. For example, in [7] the idea of using feedback laws to control multiple robots together in a formation is explored. However, in this work it was assumed that each robot had the ability to measure the relative position with respect to its closest neighbours. Also, in [8], the robots path is computed to ensure that the network partition never occurs during the robots motion, but the knowledge of global location (e.g. GPS) is assumed available at each robot. The work in [9] explores the sensor relocation in order to deal with sensor failure or respond to new events. Methods of finding redundant sensors

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and moving sensors to specific areas are proposed, assuming that sensors are placed into grids and global information is shared to support relocation planning. These works essentially consider that distances among robots are known, as opposed to the situations we are aiming at.

Measuring distance between wireless nodes is a topic that has been widely explored by many authors. Some focus on time-based techniques, some focus on signal strength techniques, and others on hybrid approaches.

The most common time based techniques rely on one-way Time-of-Arrival (ToA) measurements [10], [11], [12], Time Difference of Arrival (TDoA) [13], [14], [15], and Round-Trip Time-of-Flight (RT ToF) measurements [16], [17]. However, ToA and TDoA require global time synchronisation, since the measurement is unilateral. On the other hand, RT ToF eliminates the need for global clock synchronisation. For simplicity, we will refer to the RT ToF, simply as ToF. In order to do that, instead of measuring the time of one-way trip, it measures the time that a message needs to go to the receiver and return to the transmitter. Despite that, since some local processing needs to be done on the receiver before sending the reply, the processing time has to be very well known, thus it is usually done in hardware. Adding to that, since the ranging operation is between two units, it needs a long time to range several units, thus it may not accommodate fast moving robots. Angle of Arrival (AoA) based approaches that require antenna arrays have also been proposed [18], [19].

The signal strength based techniques, as the name implies, obtain range estimations from the strength of the received RF signal [20]. In open space and without interference there is a predictable relation between RSSI and distance, however, in the presence of interference, reflection, and refraction, this relationship is no longer accurate. Despite that, most of the current wireless transceivers possess the capability of measuring the RSSI intrinsically. Therefore, if the application only requires a coarse localisation, either for navigation or topology estimation purposes, the RSSI can still be very useful. In order to obtain ranging data from RSSI, some researchers use anchor-free RF-only localisation methods without previous knowledge, such as in [2], [21], where RSSI-based localisation is performed. In [2], [21], the authors do not consider a propagation model and all localisation is performed considering the "distance in the RSSI space", i.e., not an estimate of relative physical distance. Other researchers rely on channel models to estimate real distance based on RSSI, some using a priori channel measurements [22], [23], and others performing online channel estimation, either based on anchor nodes [24], [25] or based on external sensors [23]. However, a priori data may be unavailable or unreliable, i.e. either there is no previous knowledge or there were severe changes to the environment; estimations based on measurements between anchor nodes are not compatible with unknown environments; and estimations performed with external sensors require extra equipment.

As the work on [26] shows, hybrid techniques greatly improve results, namely the authors simulated positioning using combinations of ToA, TDoA, and RSSI, showing that RSSI has limited usefulness where time-based techniques are available. Despite that, ToF ranging requires a long time to range one robot [27], and RSSI allows several receivers to "range" one transmitter simultaneously, thus making RSSI appealing for applications with mobile robots where the dynamics of the movements are not negligible. In this paper we explore using the higher accuracy of ToF measurements to improve the accuracy of a faster RSSI-based distance estimator by recurrent online recalibration. In [28], a hybrid approach fusing RSSI and round-trip time-of flight measurements is used. Unlike the work in [28], which assumes the channel parameters to be estimated in advance, our approach assumes no prior knowledge and estimates the channel parameters in real time.

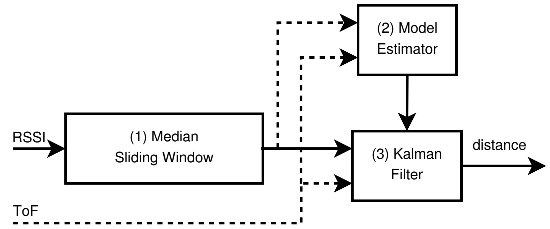

Fig. 1. RF-based ranging: Dotted lines apply only when ToF data is available

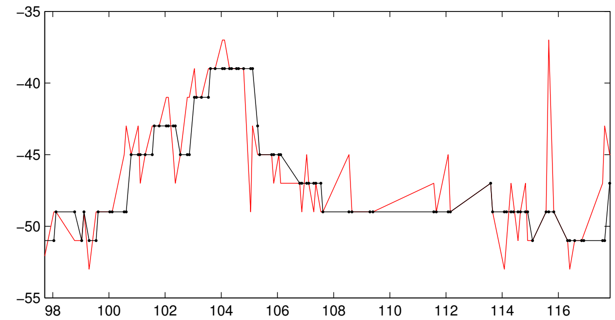

Fig. 2. Sliding window median filter (k = 5): The median filter (black) filters out the outliers in the raw measurements (red)

III. RF-based Ranging using ToF and RSSI

In this section, we describe our proposal to collect distance information between cooperating robots using both ToF and RSSI information. For that purpose, we propose to use three distinct blocks (Fig. 1):

(1) A median sliding window to filter raw RSSI data
(2) A log-distance path loss model estimator
(3) An extended Kalman filter to estimate distance between robots

A. Filtering the RSSI readings

In indoors, the RSSI readings experience large fluctuations, even when the robots are static, due to complex propagation phenomena. For a group of mobile nodes, this instability becomes even harder to handle. Therefore, in order to filter those fluctuations, we use a sliding window median filter. Whenever an RSSI reading is received, the measured value goes through the filter that returns the median of the last k measurements (Fig. 2). This may affect response time to true variations on the RSSI of moving robots, therefore a small value of k should be used.

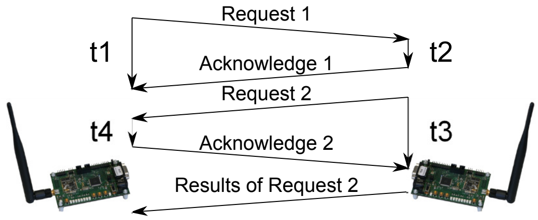

Fig. 3. Time-of-Flight ranging procedure: Node on the left requests a ranging to node on the right.

B. Online Channel Estimation

1) Time-of-Flight Ranging: As shown before, one of the methods that can be used for obtaining distances with RF communications is ToF measurements. It works by measuring the time a message needs to reach the destination and return. The ranging is done in two phases (Fig. 3). The first phase measures $r_1 = V \times (t_1 - t_2)/2$ and the second one measures $r_2 = V \times (t_3 - t_4)/2$, where V is the propagation speed of the RF signal. Finally, r_2 is sent back and the values are averaged, thus the whole ranging procedure returns $\overline{d} = (r_1 + r_2)/2$. 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. Moreover, each complete ranging, as measured by [27], takes around 20ms. Consequently, in a five robot team, the time required for one robot to range all the others is 80ms, and the time needed for all robots is 400ms (plus overheads). In spite of that, the ranging operation produces a physical distance estimate that is accurate enough to be used for localisation.

2) Using RSSI as a distance measurement: RF power decays as the electro-magnetic waves travel through air. By measuring the RSSI of a message, and using a propagation model, it is possible to infer the distance to the transmitter. However, in order to be able to calculate the distance based on RSSI, we need to know several parameters: transmission power, antenna gains, frequency of the carrier, and medium characteristics. In open space, the relationship between signal strength and distance can be represented by the log-distance path loss model. The model is given in Eq. (1), where ρ_d is the RSSI value at distance d; ρ_0 is the RSSI value at a reference distance d_0 (we consider $d_0 = 1$), and includes the aggregated effects of transmission power, antenna gains, and frequency attenuation; and α) is the path loss exponent that represents the propagation medium properties.

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

Note that unlike ToF, RSSI 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.

3) Using ToF and RSSI to estimate the propagation model: We combine both the Time-of-Flight (ToF) and RSSI ranging, provided by the nanoLoc devices [6], to perform an online estimation of the log-distance path loss model. With this model we are able to provide RSSI-based distance measurements accurate enough for localisation, while simultaneously coping with high movement dynamics. 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 equally spaced log-distances ($\mathbf{g}_{1\times n}$) and create the matrix $\mathbf{A}_{(n+1)\times 2}$ and vector $\mathbf{b}_{(n+1)\times 1}$ (see Eq. (2)). The first n lines represent the previously estimated model $\widehat{\mathbf{m}_{t-1}}$, and the $(n+1)$th point represents the new measurement. Then we minimise the square error Eq. (3) to obtain the new channel model $\widehat{\mathbf{m}_t}$. This allows us to use 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.

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

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

C. Extended Kalman Filter for Range Tracking

In order to track the distance between robots, we implemented an extended Kalman filter [29]. The state equation is given in (4), where X is the state vector, d is the estimated distance, and $\dot{d}$ is the discrete-time approximation of the derivative of distance. The prediction equation is Eq. (5), where Δt is the time between consecutive state predictions and ω is Gaussian noise. When we measure both ToF and RSSI, we use measurement Eq. (6), and when we measure RSSI only we use measurement Eq. (7). In these equations, $\bar{\rho}_k$ is the measured RSSI at time k, $\overline{d}_k$ is the measured distance using ToF, ρ_0 and α are the propagation model parameters, $\mathtt{bias}_d$ = is the bias of the ToF measurements, $\omega(k)$ is the state noise, and $\nu(k)$ is the measurement noise.

$$X = \begin{bmatrix} d & \dot{d} \end{bmatrix}' \tag{4}$$

$$X_k = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} X_{k-1} + \begin{bmatrix} \frac{\Delta t^2}{2} & 0 \\ 0 & \Delta t \end{bmatrix} \omega(k) \tag{5}$$

$$\begin{bmatrix} \overline{d} \\ \overline{\rho} \end{bmatrix}_k = \begin{bmatrix} d_k - \mathtt{bias}_d \\ \rho_0 - 10\alpha \log_{10}(d_k) \end{bmatrix} + \nu(k) \tag{6}$$

$$\left[\overline{\rho}\right]_k = \left[\rho_0 - 10\alpha \log_{10}(d_k)\right] + \nu(k) \tag{7}$$

IV. Experimental Results

A. Setup

We programmed the nanoLoc devices with the software developed for [27], which synchronises the communications with an adaptive TDMA scheme. In our setup, we used three such units with a communication period of 250ms (Fig. 4). Consequently, in the absence of communication failures, each node ranges one different node every 250ms, and receives one

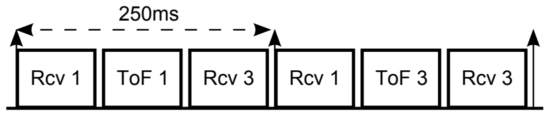

Fig. 4. Communication period as seen by node 2: Receives broadcast from node 1, ranges node 1, receives broadcast from node 3, receives broadcast from node 1, ranges node 3, receives broadcast from node 3, and repeats.

communication from each node between ranges. Those three nodes were then placed on top of three robots [30] in an indoor laboratory (approx. 20m×6m) , with a small (9.90m×5.75m) soccer field. There, the robots are able to localise themselves using an omnidirectional camera, which we consider as our ground-truth distance.

We want to show that our system correctly adapts to a new communication environment. For that purpose, we estimated the communication channel parameters in a corridor, Eq.(8), very different from the model estimated in the field for either robot, Eq. (9). The bias of the ToF measurements $\mathtt{bias}_d = -0.3399$ was experimentally determined using the data set collected in the corridor. The state noise $\omega \sim \mathcal{N}(0, 100)$. The covariance of the measurement was set according to whether a TOF measurement is available or not. When the TOF was available, the covariance was a 2-by-2 diagonal matrix with the diagonal elements $x_{11} = 0,3646$ and $y_{22} = 19.6444$, otherwise, only y_{22} was considered.

$$\begin{bmatrix} \rho_0 \\ \alpha \end{bmatrix} = \begin{bmatrix} -37.6455 \\ 2.1849 \end{bmatrix} \tag{8}$$

$$\begin{bmatrix} \rho_0 \\ \alpha \end{bmatrix}_{\mathtt{robot\ 1}} = \begin{bmatrix} -38.1485 \\ 1.6505 \end{bmatrix} \quad \begin{bmatrix} \rho_0 \\ \alpha \end{bmatrix}_{\mathtt{robot\ 3}} = \begin{bmatrix} -39.6955 \\ 1.1558 \end{bmatrix} \tag{9}$$

Robot 1 and Robot 3, were stopped in each side of the mid-field and robot 2 was moved manually (remote control) to preform the trajectory, see Fig. 5. We logged the data from three experiments containing ground truth, ToF distances, and RSSI measurements. Then, we post-processed them using five different approaches:

1. Using the corridor model without ToF
2. Using the lab model without ToF
3. Using the online estimator whenever data is available
4. Using the online estimator every second
5. Using the online estimator every ten seconds

In the first approach we set both models to the parameters corresponding to the corridor environment (Eq. (8)). In the second approach, the models were set to the parameters corresponding to the lab environment (Eq. (9)). Finally, in the last three approaches, we aim to test the adaptability of the model estimation algorithm to a different environment. Therefore, in spite of the robots being located in the lab environment, the initial channel parameter values were set in purpose to the values in Eq. (8) corresponding to the corridor environment.

Note that the behaviour in all three experiments was similar, favouring their confidence level. Therefore, only plots from the first experiment are presented.

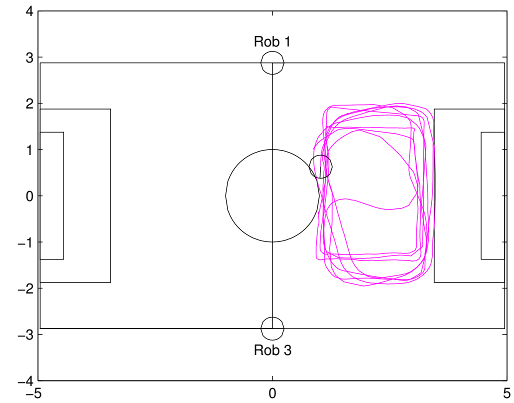

Fig. 5. Soccer field where experiments were made: Robot 1 on the top mid-field, Robot 3 on the bottom mid-field, Robot 2 moving along the magenta trajectory

B. Results

We use an online channel model estimator to improve the accuracy of RSSI-based distance measurements. However, in order to estimate the true channel parameters, we would need to take measurements at several distances. In our case, the robots will only have access to a small observation window in a certain time frame Δt. Therefore, the estimated channel will not be the true channel, but rather a local approximation about a given distance. Despite that, if we can obtain parameters that approach the true channel locally, then we can estimate correct distances from the RSSI measurements. In order to prove the capabilities of our channel estimation algorithm to adapt to the time-varying channel conditions. we have plotted in Fig. 6 the 15-sample average of $10^{(\rho_0 - \mathtt{median\ rssi})/(10\alpha)} - d_{\mathtt{ground\ truth}}$. This data represents the error imposed by the communication channel model on the accuracy of RSSI-based distance measurements. When the corridor model is used (blue line with no markers), the distance is always underestimated, i.e. is biased, and since this bias will vary with the environment it cannot be filtered Consequently if we change the environment, the wrong model will degrade our estimate. When the lab model is used (grey 'o'), the results are substantially improved, the estimation bias tends to oscillate around the zero error instead of being negative. The third and fourth approaches (black '+', and magenta 'X' respectively) produce a result very similar to the lab model, which implies that the model is locally correct. The fifth approach (red '.') initially is very similar to the corridor model. This was expected, since it only estimates the model every ten seconds. Despite that, in the end it behaves very similarly to the lab model, which means that it converged to a locally correct model.

The effect of these different approaches on the estimated distance can be seen in Table I that summarises the results of the three experiments. Figures 7, and 8 present the distribution of the errors on experiment 1 using the five different approaches. As expected from the previous results, when the robots are using the corridor model, the Kalman filter produces an error with a large bias. Moreover, when we compare our online estimator with the lab model, we can still improve on those results. That can be justified by the usage of the highly

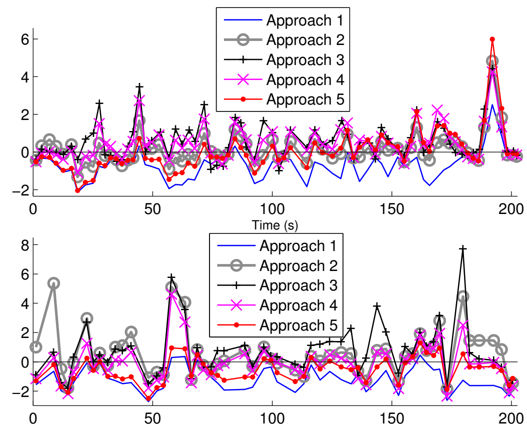

Fig. 6. Error imposed by the communication channel model on the accuracy of RSSI-based distance measurements $(10^{(\rho_0 - \mathtt{median\ rssi})/(10\alpha)} - d_{\mathtt{ground\ truth}})$:(top) Robot 1; (bottom) Robot 3

accurate ToF ranging on the data fusion. Finally, by comparing the three approaches of the online estimation, we can see that by increasing the number of ToF ranges we can improve the results of the estimation. This was expected because of the high accuracy of ToF when compared with RSSI ranging. However, we also show that if the medium is constant enough that allows for a small number of channel estimates, we can still have a good accuracy with RSSI only. Consequently, depending on the conditions the robots are expected to operate in, we can trade-off accuracy for bandwidth. If we have a high number of ToF rangings, we have more accuracy, if we have less ToF rangings we have less accuracy. Note that each ranging uses 20ms, in which the robots cannot communicate.

V. Conclusion and future work

In this work, we have successfully combined the ToF and RSSI ranging to perform an online estimation of the indoor log-distance path loss model, which together with an EKF was used to track distance between three robots. Results show that by using our online estimator, we can approach the performance of a pre-calibrated channel model, with the advantage of supporting dynamic changes on the communication environment. Moreover, we show that it is possible to dramatically reduce the number of ToF ranges, with negligible accuracy loss. This reduction is only possible if the communication channel is stable for large periods of time, however, it translates in bandwidth gain. Some issues still remain open, specifically, the optimization of the time interval between ranges.

VI. Acknowledgements

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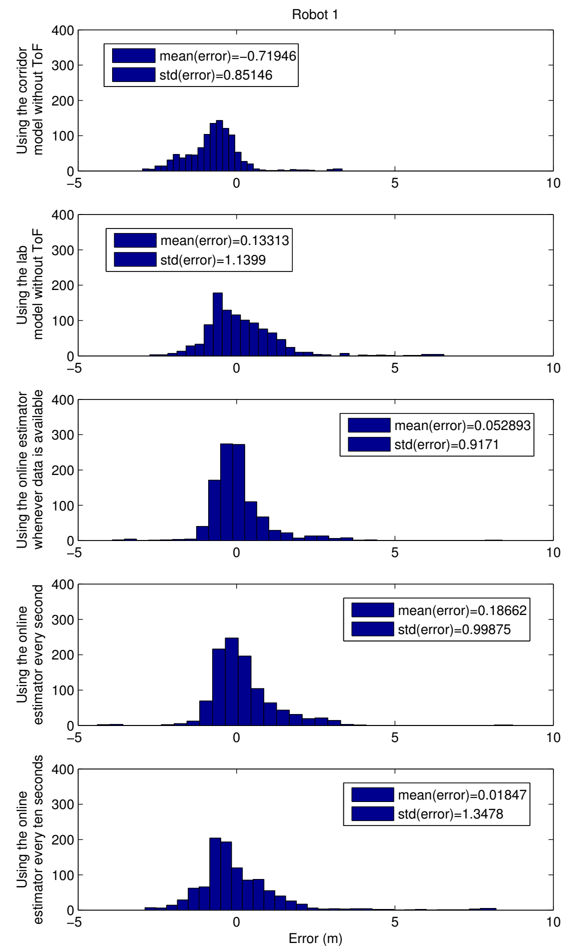

Fig. 7. Error of distance between robot 1 and robot 2

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TABLE I. Error of the estimate from all three experiments

		Appr. 1	Appr. 2	Appr. 3	Appr. 4	Appr. 5
Exp 1	mean	-0.7195	0.1331	0.0529	0.1866	0.0185
	std	0.8515	1.1399	0.9171	0.9988	1.3478
Exp 2	mean	-0.8199	0.1033	0.0457	0.1024	0.0431
	std	0.7640	0.9319	0.8025	0.8613	0.9024
Exp 3	mean	-0.8086	0.0778	0.0394	0.1417	0.0452
	std	0.6918	0.8676	0.8075	0.8637	0.8233

(a) Robot 1

		Appr. 1	Appr. 2	Appr. 3	Appr. 4	Appr. 5
Exp 1	mean	-1.1927	0.4849	-0.1341	-0.3496	-0.5593
	std	1.0129	2.3984	1.4321	1.4109	1.1715
Exp 2	mean	-1.2319	0.3017	-0.1866	-0.3893	-0.5199
	std	0.9976	2.7022	1.3593	1.9220	1.2927
Exp 3	mean	-1.2279	0.1954	0.0151	-0.1349	-0.6710
	std	0.9923	2.3229	1.9418	1.8334	1.3242

(b) Robot 3

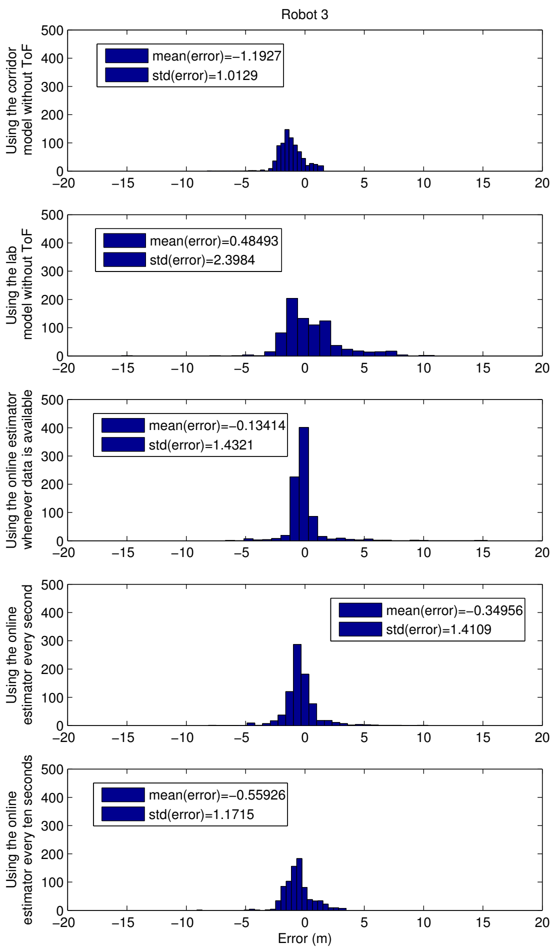

Fig. 8. Error of distance between robot 3 and robot 2

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