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SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

Executive Summary of the Thesis

Analysis of the performance of an ultra-wide band localization system using Bayesian tracking filters

Laurea Magistrale in Telecommunication Engineering - Ingegneria delle telecomunicazioni

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1. Introduction

The usage of Ultra Wide-Band (UWB) technologies for localization applications outside of military purposes started to increase twenty years ago. The higher frequency range was optimal to be utilized in many indoor scenarios due to the resistance to phenomena like multi-path fading and the reach of higher precision positioning trough the use of short pulses signals. Since then, the number of fields in which this technology could spread have become numerous: from medical, security, road and driving management, automotive and even sportive applications have been deployed [4].

More than any other scenarios, indoor positioning is very challenging, more so if the tracking of a moving target is involved. Many positioning methods that can be extracted from the radio signal have been tested: RSS based techniques, ranging techniques using TOA (Time of arrival) or TDoA (Time difference of arrival) needs to be combined with adaptive algorithms in order to localize a moving target with high accuracy, exploiting also statistical approaches. Defining the driving process of movement of the target is fundamental and matching its statistical representation with the actual information obtainable from the devices, such as velocity or acceleration data from inertial sensors, can increase the probability of actually performing an accurate positioning [1].

2. Objectives and contributions

The objective of this project is to test the performances of UWB devices, provided by Tracking 4 Fun (T4F), and improve the functioning in different scenarios with the use of tracking filters to increase the localization's precision. The main focus is the indoor application, where several experiments were made in an environment resembling an office-like or industrial scenario, in order to test the system in in a highly disturbed and cluttered situation.

In addition to the testing phase, the research required the implementation of a tracking filter (Extended Kalman filter) to improve the performance of the devices and with respect to different methods, such as an LS algorithm and the raw data extrapolated from the T4F application. Comparing different motion models and testing the reliability of the anchor's auto-localization algorithm was also part of the re-

Figure 1: T4F system: the red boxes indicate tag, anchor and master anchor.

quirements, providing a complete overview of the system's behaviour and the possible applicable improvements.

3. System overview

The system shown in Figure1, is the one provided by T4F for the localization experiments campaign.
The provided devices are a set of UWB anchors and tags. The first represents a set of antennas designed to transmit radio signals as well as listening to packets coming from other anchors, based on the time stamps they can elaborate the information about the other anchor's positions and the very target the system is aiming to localize. The tag is an UWB device equipped with an antenna that can use data sent by the anchor's packets to sand back information about its position, successively calculated by the anchors. The idea is to create a system that is not fixed in one place and can be easily configured according to the user's need.
The anchors are a set of UWB antennas composed by the Decawave DWM1000 module, which supports ranging measurements using both Time of Flight (ToF) measurements based on Two-Way Ranging (TWR), and Time Difference of Arrival (TDOA) measurements. The devices are able to achieve a ranging accuracy of ± 10 cm in Line of Sight (LOS) conditions, supporting up to 6 channels ranging from 3.5 GHz to 6 GHz. The system is able to achieve an overall maximum coverage of approximately 60 m by using the channel 4 of frequency range and setting a bit rate of 850 Kb/s.

Figure 2: MADE building, Politecnico di Milano, campus Bovisa, office.

Figure 3: MADE building, Politecnico di Milano, campus Bovisa, AGV area.

The set of tags are equipped with the Decawave DWM1001 module and supports only channel 5 providing a bit rate of 6.8 Mb/s. The location rate depends on the number of active tags. The devices uses TDMA (Time Division Multiple access) to coordinate between each others the radio channel used making the location rate dependent on the active tags, from 0.01667 to 10 Hz, corresponding to a number of active tags of 9000 and 15 respectively. The maximum coverage of the tag is approximately 60m.

4. Experimental set-up

The experimental campaign has been carried out in the MADE structure at Politecnico di Milano, campus Bovisa. The building is a 2.500 mq indoor space used for co-working, teaching and meetings providing a large number of environments fitting for the desired scenarios, involving

Figure 4: MADE building map, Politecnico di Milano, campus Bovisa. Highlighted the areas where the office and AGV experiments were performed.

many obstacles, as well as metal machines and busy areas, perfect for testing a cluttered situation. As it is possible to see in Figure3, the presence of challenging materials and busy areas make the structure optimal for the experiments. As shown in Figure4 the two main areas where the experiments took place are an office room (Figure2) inside the MADE structure, to test the system in a small closeted environment involving a walking human target, and an open space area in the building, tracking the movement of an AGV (Automated Guided Vehicle) (Figure3) to simulate the performance in a a factory-like environment.

5. Tracking filter and motion models

To track the position evolution of a moving target the most known tools are Bayesian tracking filters. This family of filters represent the state at time t by random variables x_t, at each point in time. The aim is to sequentially estimate a belief (or guess) over the state space conditioned on all information gathered up to the current time.
Kalman Filters (KF) are the most widely used variant of Bayes filters. This type of filter is optimal for linear-Gaussian systems. While a much more fitting case is the Extended Kalman Filter (EKF) which expands the solution for non-linear systems (TDoA) [2]. Going step by step in the EKF equations, it is possible to start with the definition of both the prior and the posterior pdf as Gaussian:

$$p(\mathbf{u}_t|\mathbf{y}_{1:t-1}) = \mathcal{N}(\hat{\mathbf{u}}_{t|t-1}, \mathbf{P}_{t|t-1}) \tag{1}$$

$$p(\mathbf{u}_t|\mathbf{y}_{1:t}) = \mathcal{N}(\hat{\mathbf{u}}_{t|t}, \mathbf{P}_{t|t}) \tag{2}$$

In case of TDoA measurement model, the linearization is applied only around the mean value computed in the prediction step $\hat{\mathbf{u}}_{t|t-1}$:

$$\mathbf{h}_t(\mathbf{u}_t) \approx \mathbf{h}_t(\hat{\mathbf{u}}_{t|t-1}) + \frac{\partial \mathbf{h}_t(\mathbf{u})}{\partial \mathbf{u}}|_{\mathbf{u}=\hat{\mathbf{u}}_{t|t-1}} \Delta\mathbf{u}_t \tag{3}$$

$$\mathbf{h}_t(\mathbf{u}_t) \approx \mathbf{h}_t(\hat{\mathbf{u}}_{t|t-1}) + H_t(\hat{\mathbf{u}}_{t|t-1})\Delta\mathbf{u}_t \tag{4}$$

where $\Delta\mathbf{u}_t = \mathbf{u}_t - \hat{\mathbf{u}}_{t|t-1}$. At each interval t, the prediction step and update step are then executed. Once the update step is completed, the position of the target is estimated using the MMSE estimator (equal to the MAP estimator in this case) [2]. The prediction step is described by the following equations:

$$\hat{\mathbf{u}}_{t|t-1} = \mathbf{A}\hat{\mathbf{u}}_{t-1} \tag{5}$$

$$\mathbf{P}_{t|t-1} = \mathbf{A}^T\mathbf{P}_{t-1|t-1}\mathbf{A} + \mathbf{Q} \tag{6}$$

The update step is then described as follows:

$$\mathbf{G}_t = \mathbf{P}_{t|t-1}\mathbf{H}_t^T(\mathbf{H}_t\mathbf{P}_{t|t-1}\mathbf{H}^T + \mathbf{R}_t)^{-1} \tag{7}$$

$$\hat{\mathbf{u}}_{t|t} = \hat{\mathbf{u}}_{t|t-1} + \mathbf{G}_t(\mathbf{y}_t - \mathbf{h}_t(\hat{\mathbf{u}}_{t|t-1})) \tag{8}$$

$$\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \mathbf{G}_t\mathbf{H}_t(\hat{\mathbf{u}}_{t|t-1})\mathbf{P}_{t|t-1} \tag{9}$$

The position is then estimated as:

$$\hat{\mathbf{u}}_t = \mathbf{u}_{\text{MMSE}} = \hat{\mathbf{u}}_{t|t} \tag{10}$$

To fulfil the goal of achieving a better localization accuracy we can use a-priori information about the target's character of motion on the filter. In the experiments three different motion models are used[3]:
Random walk (RW) model: Considering the complexity of the human walking process, it is possible to adopt the simplest solution, using then a Random Walk model, which is characterized in the following way:

$$\mathbf{x}_t = \mathbf{u}_t = \begin{bmatrix} u_{x,t} \\ u_{y,t} \end{bmatrix} \tag{11}$$

$$\begin{cases} u_{x,t} = u_{x,t-1} + Tw_{vx,t-1} & \text{(12a)} \\ u_{y,t} = u_{y,t-1} + Tw_{vy,t-1} & \text{(12b)} \end{cases}$$

where $w_{v,t-1} = \frac{u_t - u_{t-1}}{T}$ is the driving process.
Random force (RF) model: In this case the zero-mean driving noise is the position variation given the velocity measured. The equations (12a) and (12b) become:

$$\begin{cases} u_{x,t} = u_{x,t-1} + T(v_{x,t-1} + w_{vx,t-1}) & (13a) \\ u_{y,t} = u_{y,t-1} + T(v_{y,t-1} + w_{vy,t-1}) & (13b) \end{cases}$$

with:

$$\mathbf{v}_t = \begin{bmatrix} v_{x,t} \\ v_{y,t} \end{bmatrix} \tag{14}$$

Random jerk (RJ) model:this model can be described using the acceleration as a white noise process $w(t) = \dot{a}(t)$. The corresponding state-space representation is:

$$\dot{x}(t) = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} w(t) \tag{15}$$

which we can write as discrete-time equivalent as:

$$x_{k+1} = F_3 x_k + w_k \tag{16}$$

with:

$$F_3 = \begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix} \tag{17}$$

in the state equation, we can then find the state vector expressed as:

$$\begin{bmatrix} x & \dot{x} & \ddot{x} & \dddot{x} \end{bmatrix}^T \tag{18}$$

where $x, \dot{x}, \ddot{x}, \dddot{x}$ are respectively the position, velocity, acceleration and jerk of the target.

6. Experimental results

The results were processed in the following way:

- Acquiring the TOA data using the T4F anchors and tags and converting it to TDoA.
- Analyze the data and remove possible outliers and missing measurements.
- Compute the measurement error, building the covariance matrix.
- Generate a ground truth track to reconstruct the real path of the related target. The path was reconstructed trough the use of video tapes acquired during the experimental campaign and temporal time stamps measurements trough motion sensors to detect the passing of the target in a specific position.

	RW Velocity	RF Acceleration	RJ Turn
Uffici	0.83 m/s	$1m/s^2$	1 m/s^3
AGV	1 $m/$	1 m/s^2	1 m/s^3

Table 1: Table of the driving process variances for all the used models.

- Calibrate the EKF, deriving the driving process variance trough the comparison of the position error, derived using the filter's output and the ground truth's difference. The Table1 show the obtained results, reporting the values of the driving process variances for each used motion model. Respectively the Random velocity process variance for the Random Walk model, the Random acceleration process variance for the Random Force model and the Random turn process variance for the Random Jerk model.

6.1. Office experiment results

As shown in Figure5, the positions extracted from the use of the EKF random walk model are reported, as well as the ones calculated from an LS (Least square) Gauss-Newton algorithm and the Raw data extracted from the T4F application, provided directly from the devices.
The motion models visualization in Figure6 provides an actual confirmation of how the random walk model is actually the one that best follows the ground truth path, presenting a smoother path and better following of the curved portions of the trajectory. The model is in fact the most suited for walking targets, thus is the one chosen for the other confrontations. Figure5 provide a visual representation of how the EKF algorithm is improving the tracking of the target. In particular it is possible to observe how the path is much smoother and more precise than the one obtained by the LS and T4F.
The same experiment was also performed to compare the different motion models introduced in section 5.
The result is also evident by looking at the CEP95 derived from the CDF (cumulative density function) of the position error. The circular error probable measures the accuracy of a posi-

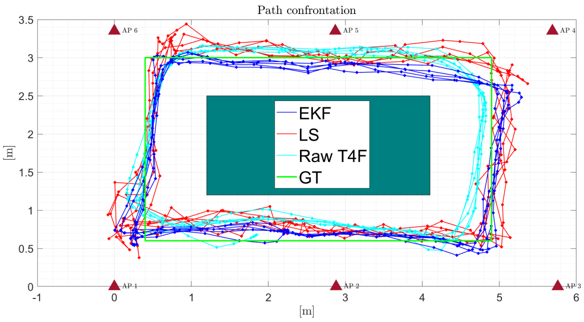

Figure 5: Path difference of the office acquisition for tag 1. With: EKF random walk model, LS algorithm, T4F positioning data and estimated ground truth path.

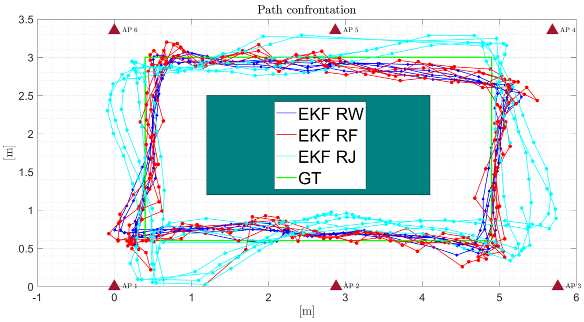

Figure 6: Plot of the different motion models path used for the tag 1 of the office acquisitions.

	EKF	LS	Raw T4F
Tag 1	0.41 m	1.02 m	1.23 m
Tag 2	0.48 m	1.02 m	2.03 m

Table 2: Table of the CEP95 values for the office experiments

	RW	RF	RJ
Tag 1	0.41 m	0.77 m	1.03 m
Tag 2	0.48 m	1.13 m	1.14 m

Table 3: Table of the CEP95 values for the office experiments

tion in a localization system, giving in response the measure of the radius of a circle containing the position estimate with a probability of 95%. In Table3 the CEP95 values are repeated for both of the tags. While the following one is reporting the values for the motion models used for the same experiment: The EKF with Ran-

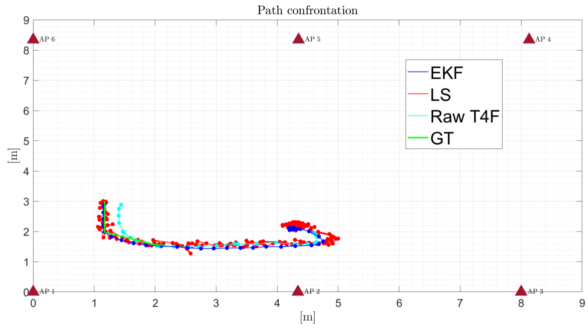

Figure 7: Paths of the AGV acquisition for tag 1. Highlighted EKF with a random walk, LS algorithm, T4F result and estimated ground truth path.

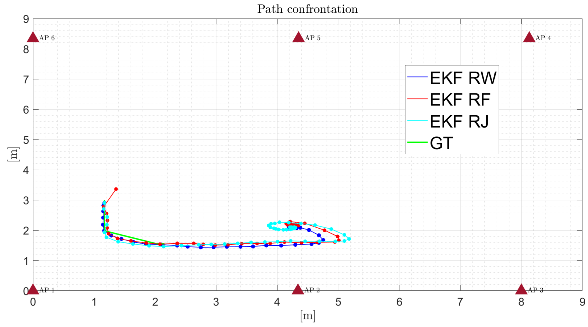

Figure 8: Plot of the different motion models path used for the tag 1 of the AGV first acquisition.

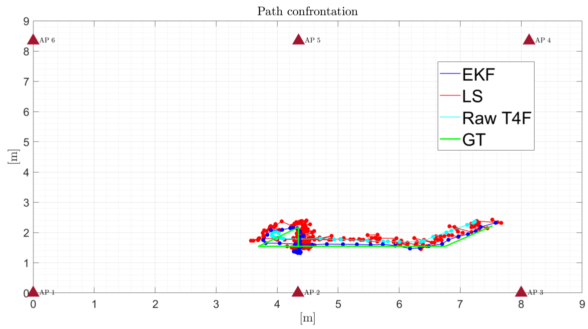

Figure 9: Paths of the AGV second acquisition for tag 1. Highlighted EKF with a random walk, LS algorithm, T4F result and estimated ground truth path.

dom walk model is performing the best in all cases.

6.2. AGV experiment

As for what concerns the AGV experiments the same results are shown in Figure7, 8,9 and 10 for two acquisitions path of the vehicle.
The observations are the same resulting from the

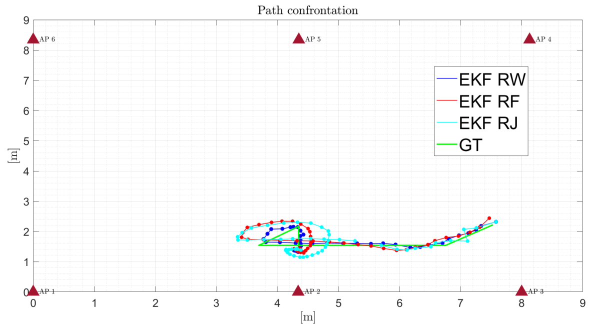

Figure 10: Plot of the different motion models path used for the tag 1 of the AGV's second acquisition.

	EKF	LS	Raw T4F
Acq 1 Tag 1	0.41 m	0.77 m	1.03 m
Acq 1 Tag 2	0.44 m	0.76 m	0.61 m
Acq 2 Tag 1	0.35 m	0.37 m	0.46 m
Acq 2 Tag 2	0.34 m	0.45 m	0.60 m

Table 4: Table of the CEP95 values for the office experiments

	RW	RF	RJ
Acq 1 Tag 1	0.13 m	0.25 m	0.33 m
Acq 1 Tag 2	0.44 m	0.6 m	0.58 m
Acq 1 Tag 1	0.44 m	0.6 m	0.59 m
Acq 1 Tag 2	0.34 m	0.34 m	0.28 m

Table 5: Table of the CEP95 values for the office experiments

office experiments, and the EKF random walk is still providing a better tracking solution. The CDF results are also obtained with the respective CEP95 error values reported in Table4 and for the motion models comparison in Table5.
Also this time the results are compatible with what was expected. The EKF Random walk scenario experience a superior performance with respect to the others.

7. Conclusions

This thesis developed a Bayesian tracking filter (EKF) improving the T4F system's performances for possible busyness applications for the localization of a moving target in an indoor cluttered environment. The exploited solution is in fact improving the performance of the system. The UWB technology already allow the overall performance to reach good enough results, but following the movement of a target with precision can only be reached by using an actual tracking method and a fitting motion model. The devices can improve the performance with the utilization of more efficient inertial systems unit (IMU). The presence of an accelerometer can be used to provide more information to the filtering process and improve the localization error. The acceleration measurement can be used to detect possible outliers and predict position fast changes and predict the target's fast changes of direction. For tracking human walking targets, a more useful tool can consist in the use of a gyroscope, to keep track of the person's heading, or even consider the use of a sensor based step length measuring system, adding information to the overall walking features of the target which might change based on the current monitored activity.

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