Comparison of Algorithms for UWB Indoor Location and Tracking Systems

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Abstract

With the popularity of navigation applications and the integration of GPS in user devices, location-awareness is becoming an essential feature demanded by users. Nevertheless, location-awareness in indoor environments is still limited by the inability of GPS to operate indoors. With a centimeter-level ranging resolution, Ultra-Wideband (UWB) is one of the most promising technologies to provide indoor location. Several location & tracking algorithms have been proposed in the literature to compute user's position according to the estimated distances to some reference nodes, each one providing the best performance in certain conditions. Nevertheless, most of these proposals are evaluated under too specific or simplistic conditions that do not account realistically for the specific implications of the UWB-based distance estimation and the indoor environment. This paper aims to evaluate the performance of different location and tracking algorithms on a realistic indoor scenario and with a specific UWB indoor ranging model, analyzing their advantages and drawbacks in relation to different conditions and system design parameters.

Keywords: indoor; location; ranging; tracking; UWB.

1 Introduction

Location-awareness is rapidly becoming an essential feature of many commercial, public service, and military wireless networks. Whereas in outdoor environments GPS is widely extended in applications such as vehicle navigation, fleet management or emergency calls localization, the potential of location-awareness in indoor environments is not being exploited as GPS is unable to operate indoors.

In general, location determination comprises two phases, distance estimation, which is commonly referred to as ranging, and position calculation. Distance estimation can be based on different parameters such as Received Signal Strength Indication (RSSI), Angle of Arrival (AOA) and Time of Arrival (TOA) of reference signals exchanged between the element to be located and some reference nodes. On the other hand, several location & tracking (LT) algorithms can be used to compute the position according to the estimated angles or distances.

Multiple studies can be found in the literature concerning both ranging (Dardari et al., 2009) (Dashti et al., 2008) and location & tracking algorithms (Seco et al., 2009). Algorithms can be classified into four main categories: geometry-based, cost function minimization, fingerprint and Bayesian techniques. Geometry-based techniques compute the position based on estimated angles or distances using simple algebraic relationships, and range from simple techniques such as triangulation or trilateration to more advance approaches such as least square minimization (Cheung et al., 2004) and multidimensional scaling (Wei et al., 2008). Cost function minimization assumes the knowledge of the measurement statistical model to minimize a certain cost function (Caffery and Stuber, 1998). Fingerprinting methods are based in the comparison of the measurements with a previous survey of the location area in a calibration stage (Kaemarungsi and Krishnamurthy, 2004). Finally, Bayesian techniques, such as Kalman and particle filters, infer position from past and present measurements and require knowledge of both motion and measurement statistical models (Fox et al., 2003).

Positioning accuracy is highly dependent on the signal parameters and especially on the wireless technology used, since it determines the quality of the estimation of those parameters. Coarse location information can be obtained from cellular networks but, especially in indoor environments, their accuracy is unsuitable for most of applications. Several proposals can be found in the literature for indoor LT systems based on different radio technologies such as WiFi, Bluetooth, ZigBee or Ultra-wideband (UWB) with different levels of accuracy, range and complexity (Liu et al., 2007) (Gu, Lo and Niemegeers, 2009). In general LT systems based on RSSI estimation are not very suitable for indoor location, as RSSI is very sensitive to multipath and non-line-of-sight (NLOS) situations and their accuracy is usually within a few meters (Bahl and Padmanabhan, 2000).

UWB is one of the most promising technologies for indoor location, combining remarkable features concerning size and power consumption, providing high accuracy on distance estimation and allowing simultaneous location and data transmission (Yang and Giannakis, 2004). IR (Impulse Radio) UWB communication systems are based on the transmission of very short duration pulses, which originates very high bandwidth signals. The short duration of the pulses allows a high level of accuracy in TOA estimation with centimeter-level ranging resolution and unmatched performance on multipath environments (Gezici et al., 2005). Low complexity and power consumption is essential in order to design battery-powered sensors. In contrast, short range and limited data rate are the main drawbacks of IR UWB systems.

Although most of the proposals of tracking algorithms that can be found in the literature include the evaluation of these proposals against other existing algorithms, many times these studies are too simplistic and do not account realistically for the implications of the indoors environment and the distance estimation technology (Choi et al., 2007) (Shen, Zetik and Thomä, 2008). Therefore, the main objective and contribution of this paper is the evaluation of different kind of algorithms, both parametric and non-parametric, for IR UWB indoor tracking systems. With this purpose, a realistic indoor scenario, defined by a layout of walls and corridors, and a specific UWB indoor ranging model, which was identified through a measurement campaign in an office environment with real UWB equipment, are used.

2 Location System Proposal

The proposed indoor LT system is composed of multiple UWB picocells, although for simplicity a single picocell is considered. The picocell is composed of mobile nodes to be tracked (targets) and fixed nodes with known positions (anchors). Distances between the target and the anchor nodes are estimated through a ranging frame exchange. Distances are sent to a location controller (LC) that executes the tracking algorithm to obtain the estimated position of the targets.

2.1 Distance Estimation. Ranging model

In order to track the position of the target nodes, the distances between the target and the anchor nodes must be estimated. This is done through the ranging procedure. The procedure initiator (target or anchor) transmits a ranging request to another node, which estimates the time of arrival and sends a ranging response after a predefined time. The initiator measures the time of arrival of the response and can estimate the transmission delay and the distance between the nodes (Two Way Ranging). In order to improve the accuracy of distance estimation, two ranging responses can be sent in order to compensate for the clock drift (Three Way Ranging).

A ranging model is used to characterize the ranging error distribution and to generate the distance estimation samples. Range measurements based on round-trip TOA estimation through n-Way Ranging transactions can be modeled as:

$$\tilde{d}_{ij} = d_{ij} + \varepsilon_{ij} + n_{ij} = d'_{ij} + n_{ij}$$

where d_{ij} is the actual distance between nodes i and j, d'_{ij} is the biased distance (with bias ε_{ij}) and n_{ij} is a residual noise term. As proposed in (Denis, Pierrot and Abou-Rjeily, 2006), the biased distance d' is modeled as a weighted sum of Gaussian and Exponential components conditioned upon the actual distance d and channel configuration C that takes its value among {LOS, NLOS, NLOS2}. The model is enhanced by taking into account the probability $W_C(d)$ to have a particular channel configuration at a distance d. As a result of the indoor measurement campaign in (Denis, Pierrot and Abou-Rjeily, 2006), these weights were described as Gaussian-like functions. The residual noise is modeled as additive and centered, with a variance σ_n^2 that depends on detection noise terms affecting unitary TOA estimates (i.e. receiver sampling rate) and involved protocol durations, and is independent of the distance. This ranging model was proposed and validated through a measurement campaign with real UWB equipment in an office environment in (Denis, Pierrot and Abou-Rjeily, 2006), where the values for the different parameters of the model were also identified.

2.2 Tracking Algorithms

With respect to the tracking technique itself, parametric and non-parametric approaches can be distinguished. Parametric approaches compute the location based on the a priori knowledge of a model, while non-parametric approaches process straightforward the data with the usage, in some cases, of some statistic parameters. Specifically, the following algorithms are considered in this study: Trilateration, Weighted Least Square with Multidimensional Scaling (WLS-MDS), Least Square with Distance Contraction (LS-DC), Extended Kalman Filter (EKF) and Particle Filter (PF). More information on the mathematical background of each algorithm can be found in the references.

Trilateration is a non-parametric algorithm that computes the position based on the distance estimated between the target and three anchor nodes using a geometrical method for determining the intersection of three sphere surfaces (Sahinoglu, Gezici and Güvenc, 2008). Consequently, regardless of the number of anchors selected, only the three with smallest estimated distance to the target are used for position computation.

The algorithm WLS-MDS is a completely non-parametric approach combining Multidimensional Scaling (MDS) with Weighted Least Squares minimization (WLS) (Macagnano and de Abreu, 2006). MDS is a multivariate data analysis technique used to map “proximities” into a space. These “proximities” can be dissimilarities (distance-like quantities). Given *n* points and corresponding dissimilarity, MDS finds a set of points in a space such that a one-to-one mapping between the original configuration and the reconstructed one exists. MDS is used to obtain a previous estimation of the solution. Then the Procrustes transformation is used to map back the solution to the absolute reference system. Finally, an iterative low-complexity minimization algorithm known as SMACOF is applied to optimize the solution. Weights based on the dispersion of the estimated distances are used in the optimization phase in order to diminish the importance of less reliable estimations.

Distance Contraction (DC) aims to correct the distance measurements by subtracting a certain value in order to minimize the impact of biased measurements on the Least Square (LS) objective function (Destino and Abreu, 2010). First the existence of a feasibility region, defined as the area formed by the intersection of the circles with centre at the anchors and radio equal to the estimated distance, is checked and an initial solution is computed inside the feasibility area. The contracted distances are computed as the shortest distance from each anchor to the feasibility region. Once the contracted distances are computed, then the LS-objective function is generally convex, and any optimization method (i.e. global distance continuation, steepest descent) can be used to find the global minimum, thus reducing complexity. Specifically, we have used SMACOF as optimization method.

The Extended Kalman Filter (EKF) is a Bayesian technique known for its low-complexity, performance and stability as a tracking algorithm (Daum, 2005). The Kalman-based tracking algorithm has two major stages, namely, the update and the correction stages, which are iterated k times for every observation occurring at a given time. A state vector x is defined that contains the variables of the process, namely target’s position and speed. A measure vector z is defined containing the process observations, namely the estimated distances between the target and the anchors. A function f that describes the evolution of the state vector through time, and a function h that describes the relation between the state vector and the measure vector, are identified. Process noise (acceleration) and measurement noise (ranging error) are Gaussian with a certain variance that was optimized through simulations.

Finally, Particle Filters (PF) are recursive implementations of Monte Carlo based statistical signal processing. The use of particle filters for positioning in wireless networks was proposed in (Gustafsson, 2002). The particle filter is based on a high number of samples of the state vector (particles), which are weighted according to their importance (likelihood) in order to provide an estimation of the state vector. As for EKF, a state vector x, a measure vector z and functions *f* and *h* are defined. On each step, the particles are moved according to the process model and the weights are updated according to the likelihood of the observations (estimated distances) according to the distribution of the measurement error. The advantage of the particle filters over other parametric solutions is that non-linear models and non-Gaussian noise can be defined. Specifically, two different measurement error models have been defined as a weighted sum of two and three Gaussian components for the different channel configurations (LOS/NLOS and LOS/NLOS/NLOS2). Consequently, the filter is defined by the variance of process noise (acceleration) and the parameters of the measurement error model that were optimized through simulations. As a drawback, its computational complexity is higher, so it is suitable in applications where computational power is rather cheap and the sampling rate slow.

2.3 Design Parameters

Tracking may be performed with all the anchors in coverage of a given target or with a subset of them. The number of anchors used for position calculation is an important design parameter, as a higher number of anchors provides higher reliability, although distant anchors provide less accurate distance estimations, which degrades accuracy. Another important parameter is the distance between anchors. A shorter distance between anchors entails more accurate estimations, but a higher number of anchors are needed to cover the scenario, increasing the cost and complexity of the tracking system. Finally, position update rate defines how often the positions of the mobile nodes are updated. Frequent updates allow more precise tracking of mobile targets, but require a higher amount of resources. Position update rate is closely related to target mobility.

3 Performance Evaluation

3.1 Simulation Scenario and System Evaluation Parameters

In order to evaluate the impact of the different system design alternatives and parameters, we have developed a specific simulation application using C++. The simulation scenario is the representation of a relatively wide indoors area of size 50 m x 50 m. A UWB network, composed of N_a anchors, regularly distributed, and N_m mobile targets, is deployed. Two scenarios with 10 m and 12.5 m between anchors are considered, which result in 36 and 25 anchors respectively (Fig. 1). A wall layout is defined as well as the area where the targets may be located. Targets move along the corridors according to previously defined probabilities of going forward or backwards, and a random speed that remains constant along a corridor.

The system performance has been evaluated in terms of the average absolute positioning error. The number of targets to be tracked has been set to 10. Concerning the dynamics of the mobile nodes, minimum and maximum speeds have been set to 0.1 and 3 m/s respectively. Position update rate has been set to 1 update per second and UWB nodes range to 15 m. Ideal anchor selection has been considered so the closest anchors are always selected.

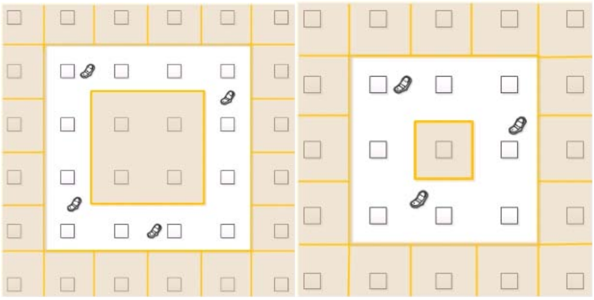

Figure 1: Simulation scenarios with 10 m and 12.5 m between anchors

3.2 Algorithm Comparison

The performance of each algorithm has been evaluated depending on the number of anchors used for positioning for the different scenarios, i.e. distance between anchors.

Fig. 2 shows the average positioning error for the scenario with 10 m between anchors and ranging residual noise $\sigma_n = 0.7$ m. As it can be observed, the best performance is achieved with the 3-component particle filter (PF-3C). Nevertheless, the performance of PF-3C is far better than it can be expected in a real situation. The reason is that the 3-component measurement error model behaves almost exactly as the ranging model used to generate the distance estimation samples. Consequently, the 3-component particle filter can deal even with highly biased measurements and the error decreases as the number of anchors used for location increases. In a real system, the precise characterization of the specific ranging model of the scenario would require costly measurement and calibration phases, and the use of a generic model would not provide so good results. In fact, results for the 2-component particle filter (PF-2C) are worse as it does not take into account NLOS2 situations.

LS-DC, WLS-MDS and EKF have a similar evolution with an optimum number of anchors for location of 5. As more anchors are used, the added anchors are likely to be in NLOS or NLOS2, so the positioning error increases for EKF and LS-DC. Nevertheless, the error does not increase for WLS-MDS due to link weighting, as anchors in NLOS/NLOS2 situations will have a lower weight and will not be detrimental to position optimization. Finally, trilateration shows the worst performance, which is independent on the number of anchors used to compute the position, as only the three closest anchors will be used. For every algorithm, there is an increase of the error when only 3 anchors are used.

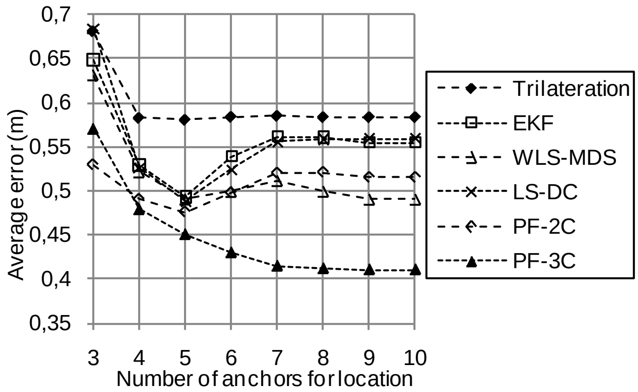

Figure 2: Positioning error. Distance between anchors = 10 m. σ_n=0.7 m

The performance for the scenario with 12.5 m between anchors is shown in Fig. 3. Consequently, some of the anchors used for positioning will be relatively far from the target and accuracy is degraded for all the algorithms. In this situation, PF-3C outperforms the other algorithms, as it takes advance of its precise measurement error model, which can deal with highly biased estimations from distant anchors. PF-2C does not provide so good results, as its simple LOS/NLOS model cannot deal with the NLOS2 situations. Concerning the rest of algorithms, LS-DC and WLS-MDS show a performance comparable to PF-2C, as distance contraction and dispersion-based weighting are able to deal with the high bias of the distant anchors. Finally, EKF and trilateration show the worst performance. It must be noted that the error is constant for 6 or more anchors, as for this configuration the target is not likely to be in coverage of more than 5 anchors.

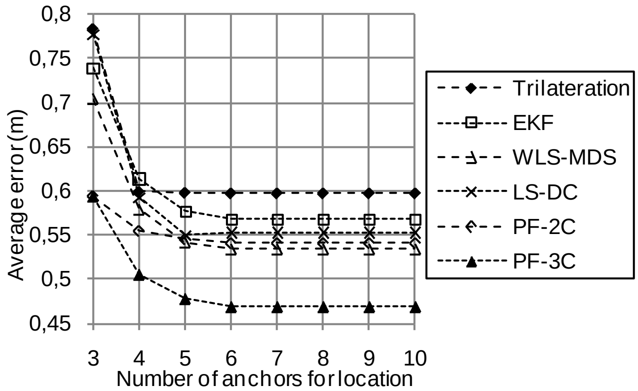

Figure 3: Positioning error. Distance between anchors = 12.5 m. σ_n=0.7 m

Following the performance of the tracking algorithms is evaluated considering that TOA detection is improved, for example increasing the sampling frequency, so the residual ranging noise is reduced. Fig. 4 shows the average error for the scenario with 10 m. between anchors and a residual ranging noise σ_n = 0.3 m. As expected, performance is improved for all the algorithms compared to the same configuration with ranging residual noise σ_n = 0.7 m and the minimum error for all the algorithms is between 15 and 25 cm. The improvement for trilateration is especially remarkable, with only PF-3C getting better results. This means that trilateration requires accurate TOA estimation in order to provide good results, as it always uses three measurements for position computation and cannot take advance of diversity of measurements. As ranging residual noise is reduced, the impact of ranging bias is more important and anchors in LOS provide much more accurate estimations than anchors NLOS/NLOS2. Consequently, the optimum number of anchors is reduced to 4 for EKF and LS-DC and 5 for WLS-MDS, and performance severely degrades as the number of anchors increases.

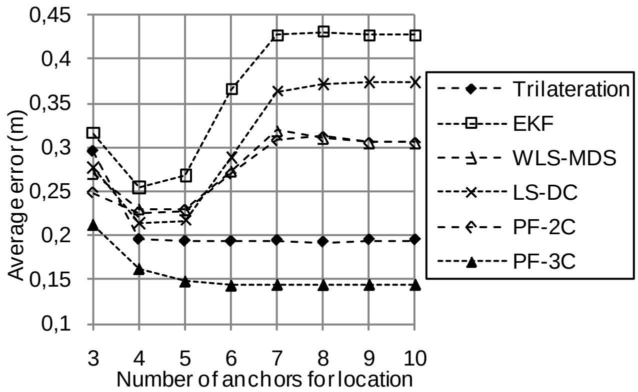

Figure 4: Positioning error. Distance between anchors = 10 m. σ_n=0.3 m

3.3 Effect of Target Mobility

In this section the effect of target mobility and position update rate is discussed. 10 m. between anchors and 4 anchors used for location have been considered. Fig. 5 shows the average error depending on target speed. As it could be expected, non-parametric methods such as trilateration and LS-DC show no dependence on target speed, as position computation is independent on previous position estimations. Nevertheless, WLS-MDS shows a slight dependency on target speed due to link weighting, as weights are based on the dispersion of distance estimations computed using the last 5 samples, so it degrades as target speed increases. On the other hand, EKF shows good results when target speed is below 1.5 m/s but severely degrades for higher speeds, as position is computed using previous position and target's dynamic model. Finally, although the particle filter uses the target's dynamic model to move the particles, it is almost independent on target speed, as particles are weighted on each step according to the likelihood of their position in relation to the measurements, so the new position is almost independent of the previous one.

Fig. 6 shows the positioning error depending on position update rate, or inversely the time between position updates. As expected, trilateration and LS-DC are independent of time between updates, whereas WLS-MDS shows a slight dependency due to dispersion-based weighting. EKF shows good results for update intervals shorter than 800 ms and severely degrades as the time between updates increases. As the new position is computed based on previous position, the interval between two successive updates must be as short as possible in order to accurately track the target. Finally, positioning accuracy for the particle filter shows a slight dependence on time between updates, increasing from 45 cm. for 400 ms between updates to 55 cm. for 2 s between updates.

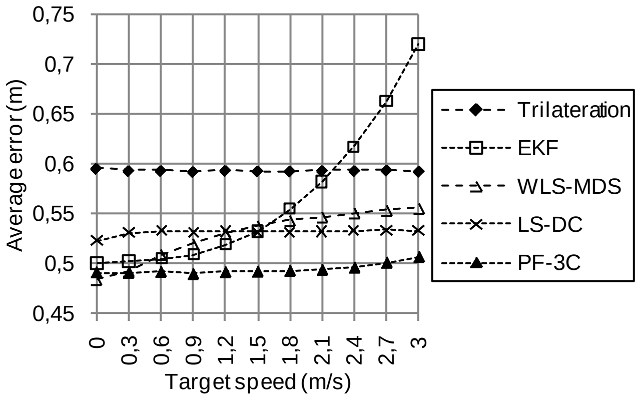

Figure 5: Positioning error depending on target speed

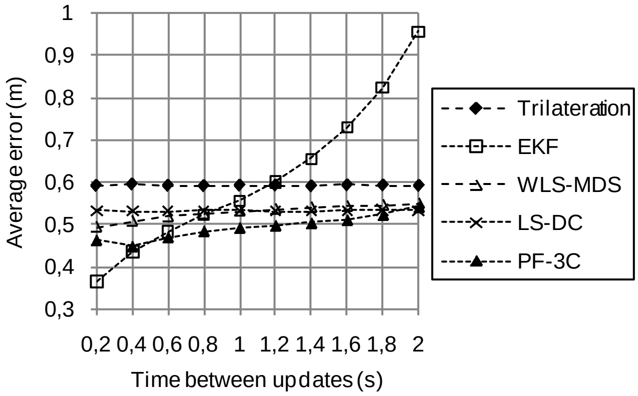

Figure 6: Positioning error depending on time between updates

4 Conclusion

According to the analysis presented here, the particle filter shows the best performance. Nevertheless, this algorithm assumes that the ranging error model is known, which would entail an exhaustive calibration campaign in order to identify the specific model of the location where the tracking system is going to be deployed. Alternatively a generic ranging model may be used, but the filter performance would be degraded. WLS-MDS and LS-DC provide high accuracy in most of the configurations simulated. Furthermore, no characterization of the target dynamics or the measurement model is required. EKF has a good performance on static and slow moving targets (less than 1 m/s), but severely degrades as speed increases. Trilateration only performs well when TOA estimations are very accurate.

With the developed simulator as a test-bed for algorithm evaluation, the focus is now on the enhancement of existing algorithms with the addition of techniques such as measurement pre-filtering and NLOS identification. A particular enhancement envisioned is the improvement of positioning accuracy taking advance of the available geographical information, such as the knowledge of user routes and walls location.

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