A Hybrid Lateration Time-Fingerprint Position Estimation Technique for Indoor UWB Systems

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Abstract—This paper presents a hybrid position estimation technique that is based on the integration of Fingerprinting (FP), Time-of-flight (ToF), and Trilateration approach. When empirical channel models are used with Ultra Wideband (UWB) systems, there are plenty of challenges that must be taken into consideration due to their dependence on frequency. Thus, when the position of a Blind Node (BLN) is estimated using the aforementioned techniques and the values deriving from these models, positioning error occurs. In order to minimize the positioning error, the proposed hybrid technique, called Lateration Time-FingerPrint (LTFP), is developed. The efficiency of the proposed positioning scheme is demonstrated through simulation results in terms of error probability and comparisons with other state-of-the-art positioning schemes.

I. INTRODUCTION

Services and applications related to position estimation are based on emerging technologies and they are of great importance in our everyday life. The position information plays an important role in various applications that are related to industries, health systems, security and emergency services. In [1] a survey of indoor positioning systems in wireless personal networks is presented giving a comprehensive perspective of numerous Indoor Positioning Systems (IPSs), which include both commercial products and research-oriented solutions. Many integrated positioning systems have been developed in this research field, while different technologies, positioning techniques and propagation channels are used.

UWB signals offer various advantages for communication and radar systems. Many studies that involve position detection use UWB signals’ capabilities, mainly focusing on locating the position of a target node that is referred as BLN in the network. The location estimation of the BLN, is conducted using various algorithms.

In [2] UWB radios are used in order to locate a node in a wireless system, by applying different positioning techniques. In this work, different empirical path loss models, Multiband Orthogonal Frequency Division Multiplexing (MB-OFDM) UWB and Positioning techniques are combined in order to specify the positioning error. A hybrid position estimation technique that combines Trilateration, ToF and FP techniques is proposed aiming to improve the estimation’s accuracy i.e. to minimize the localization error. Moreover, the type of UWB system, the positioning schemes and the path loss models that are used in the simulations are given in detail.

This paper is organized as follows. In Section II, the state-of-the-art on UWB positioning is presented. Section III describes in detail, the proposed hybrid Lateration Time-FingerPrint (LTFP) based positioning scheme. In Section IV, the system model is described, while Section V includes the numerical results in the area of probabilistic localization error. Finally, conclusions and future directions are given in Section VI.

II. STATE-OF-THE-ART & SIMILAR WORKS

Many studies in the literature propose localization schemes that are based on time, Received Signal Strength (RSS) and Angle of Arrival (AoA) of the received signals. RSS-based positioning techniques, such as FP, are used in [3], where an analytical model of a positioning system is presented. The main contribution is the probabilistic algorithm that returns the correct fingerprint for localization. In [4], an improved FP technique based on the UWB channel measurement is proposed, which makes use of updated versions of the FP databases. Results show that the accuracy is improved, thus minimizing the effect of the environment.

Also in [5], the Trilateration technique is examined in relation with RSS and Time-of-Arrival (ToA) techniques. The results indicate that ToA outperforms RSS-based techniques in terms of positioning accuracy. The same conclusion is given in [2]. Moreover, a survey of the current indoor positioning techniques is presented in [6]. In this study, performance measurement criteria are discussed and several trade-offs among them are observed. Many works develop hybrid position estimation techniques aiming to enhance the performance of the criteria, as also described in [6].

In addition, time-based techniques are used in [7], where a modified Round Trip Time (RTT) ToA is used for measuring the distance between two UWB nodes. Results proved that localization accuracy is enhanced for all the considered deployments. Similar to this work, hybrid combinations of Channel Impulse Response (CIR)-based FP positioning and an iterative ToA real-time positioning method using UWB signaling is presented in [8] and [9]. It is shown that the proposed Levenberg-Marquardt-based iterative algorithm effectively reduces the Non-Line-of-Sight (NLOS) errors, in both cases.

Also, recently, many studies have been conducted in order to develop energy-efficient schemes for bandwidth allocation [10], or energy aware routing of traffic in cognitive radio networks [11]. It must be noted that such localization schemes
provide an overall improved performance by considering the energy efficiency of the localization system.

III. THE PROPOSED HYBRID LATERATION TIME-FP POSITION ESTIMATION TECHNIQUE

In this section, the features of different positioning techniques that are based on time and RSS data are combined, aiming to enhance the position estimation accuracy. The proposed LTFP position estimation technique calculates the Blind Node’s (BLN) position utilizing an extension of the FP position estimation technique of [6], by using time information instead of RSS measurements.

During the first phase of the proposed localization technique, which is called the off-line phase, a grid is placed upon the measurement area. In order to obtain more accurate estimations, knowing that UWB pulses have fine time resolution [2], a time-map of the measurement area is created, using the propagation time $t_k$ of each pulse to reach every point $(i,j)$ of the grid, instead of using RSS measurements, as proposed in [3]. The signal’s propagation time values is collected from the fixed positions of the system’s Beacon Nodes (BNs). Moreover, the space grid that is used in indoor conditions is usually equal to $1m$ [3].

The $t_k$ (in nanoseconds) is computed using the ToF technique, where the emission time $t_{em(i,j)}$ of signals from the BNs, is subtracted from the ToA $t_{rc(i,j)}$ of these signals to each point $(i,j)$ of the grid. This is expressed as follows:

$$t_k = (t_{rc(i,j)} - t_{em(i,j)}) \quad (1)$$

for $1 \leq k \leq N$. Since all the time-data from the $N$ BNs have been collected for each point $(i,j)$, a Fingerprint vector (FPv) is created for every point $(i,j)$, and is expressed by:

$$FPv_{i,j} = [\tau_1, \tau_2, \tau_3 \ldots \tau_N] \quad (2)$$

Each one of these vectors is stored in a data base, which represents the time-map of the measurement area.

Since the time-map of the measurement area has been created, the proposed technique moves on to the on-line phase where the position estimation process is conducted. During the on-line phase, the BLN tries to find its actual position or its estimation. So, as shown in Fig. 1, when the BLN is located somewhere in the measurement area, it receives signals from every $k$ BN of the system. By using the ToF technique of eq. 1, the BLN calculates the signals’ propagation time $t_k$ from each $k$ BN, to this specific unknown location. From these time data collected by the BLN, a new FPv of the BLN $FPv_{BLN}$ is created, and is defined as:

$$FPv_{BLN} = [t_1, t_2, t_3 \ldots t_N] \quad (3)$$

where, $t_k$ is signal’s propagation time from the $k$ BN to the BLN as $k \in [1,N]$.

In order to evaluate the position of the BLN, the $FPv_{BLN}$ is compared with each stored vector of the time mapping $(FPv_{i,j})$ from the previous phase. For this procedure, Euclidean Distance is used and expressed as follows:

$$d_{FPv(i,j),FPv(BLN)} = \left[ \sum_{i=1}^{N} (\tau_k - t_k)^2 \right]^{\frac{1}{2}}, \quad (4)$$

where, $\tau_k$ and $t_k$ are the elements of the vectors that have been calculated in eq. 2 and 3.

The smallest value that derives from the Euclidean Distance function, corresponds to the point of the grid which is nearest to the BLN. Thus, as shown in Fig. 1, the four smallest distances that are returned by eq. 4, correspond to the points that define a smaller region of the grid, where the BLN could be located. This region is always a cell of the grid. So, these values represent the time distances between BLN and the Nearest Points (NPs) of the grid. By multiplying them with the speed of light $3 \times 10^8 m/sec$ [2], an estimation of the actual distances (in meters) between the BLN and the NPs is computed, expressed as:

$$d_l = d_{NP_l} \cdot c \quad (5)$$

where, $d_{NP_l}$ is the time distance returned by eq. 4 between the BLN and three of the NPs, as $(1 \leq l \leq 3)$. The distance in meters $d_l$ is shown in Fig. 2. The last step of BLN’s position estimation, includes the Trilateration position technique as shown in Fig. 2. The BLN is assumed to be located on a sphere, centered in each $NP_l$. The spheres’ radii are equal to $d_l$ from eq. 5. By knowing the coordinates of three of the NPs and the distance in meters between them and the BLN, the equation of the sphere is used in order to calculate the values of the 3D coordinates $(x, y, z)$. This is expressed as follows:

$$d_l = \sqrt{(x-x_{NP_l})^2 + (y-y_{NP_l})^2 + (z-z_{NP_l})^2}, \quad (6)$$

where, $(x, y, z)$ is the BLN’s unknown 3D position, and the $(x_{NP_l}, y_{NP_l}, z_{NP_l})$ represent the 3D coordinates of the $l$ NP. So, by replacing the corresponding values from all the components, a linear equation system is obtained in matrix form and is expressed as follows:

$$A \cdot \vec{x} = \vec{b}, \quad (7)$$

Spheres are considered in order to find the position in three axes. Also, in order to minimize the distance error, which
occurs due to the variations of the environmental parameters that affect time delay, the Minimum Mean Square Error technique (MMSE) is used [12].

It is noted that this procedure can be used in order to locate an object in two-dimensional system, as long as using narrow-band systems.

IV. System Model

In this section, the system model is described. The system was simulated using Matlab®/Simulink® environment. Also, N = 3 BNs are used to estimate the position of a BLN, which tries to find out information about its position. The three BNs (Fig. 1) simultaneously, transmit UWB signals from their fixed positions. Then, when a BLN is found in the area, it receives the signals from the three BNs. By collecting time and RSS information of the transmitted signals, the LTFP technique calculates the BLN’s position. All the procedures are performed at the BLN and thus, the proposed technique is centralized.

The communication is based on the MB-OFDM UWB of [13]. The system operates on the mandatory frequency mode 1, where the first three sub-bands are used with central frequencies 3.43GHz, 3.96GHz and 4.48GHz. In each sub-band, OFDM is chosen to modulate the information. The signals are transmitted simultaneously and, in this way, high bit rate is achieved. A detailed list of the MB-OFDM UWB system can be found in [13]. The signal model is expressed as:

\[ s(t) = \sum_k Re[x_k(t - kT_{SYM})exp(2j\pi f_k t)] \]  

where \( f_k \) denotes the carrier frequency that specifies the sub-band in which the signal is transmitted during the \( kth \) OFDM symbol duration. \( T_{SYM} \) denotes the duration of a symbol that depends on 1) the cyclic prefix used for the multiple interference mitigation and 2) the length of the guard interval that is added in the end of the OFDM block [13].

Also, information, such as RSS or transmission time data, is collected using several empirical path-loss models (PM) and one statistical fading channel that are applied on the BLN. These models introduce their own time delay profiles and characteristics about the environment losses. More specifically, the Free-Space Loss (FSL) model, ITU environment for indoor attenuation (ITU), Log-Normal Shadowing path-loss model (Log), Motley-Keenan (MK) [14] and Rician fading channel model (eq. 13) [15], are used to simulate the indoor environment. The reception time is calculated according to the time-delay profile introduced by each model. The equations that describe the aforementioned propagation models are expressed as follows:

\[
PL_{FSL} = \left( \frac{G_1 G_2 \lambda}{4\pi d} \right)^n, \quad (9)
\]

\[
PL_{ITU} (dB) = 20\log(f) + n\log(d) + P_f(k) - 28, \quad (10)
\]

\[
PL_{Log} (dB) = PL_0 + 10n\log_10 \left( \frac{d}{d_0} \right) + X_g, \quad (11)
\]

\[
PL_{MK} = PL_0 + 10n\log(d) + \sum_{i=1}^{l} k_i L_{W_i} + \sum_{j=1}^{J} k_j L_{f_j}, \quad (12)
\]

\[
p(r_0) = \frac{r_0}{\sigma^2} \exp \left[ - \frac{r_0^2 + A^2}{2\sigma^2} \right] I_0 \left( \frac{r_0 A}{\sigma^2} \right), \quad (13)
\]

Different losses stemming from the materials of obstacles and walls, shadowing phenomena and other loss factors, are calculated and added to the transmitted signal depending on the individual model. Propagation phenomena, such as interference and noise, are not included in the measurements. However, shadowing and fading effects are considered in the propagation models. According to the topology of the system, localization error data are gathered at one hundred different positions in order to compare the performance of the proposed position detection schemes, within indoor environments with additional losses.

V. Numerical Results

At this point, statistical results of the localization error are presented in order to compare LTFP with the other positioning techniques. The empirical data of the localization error were collected from one hundred different position estimations, from each localization technique, for each propagation model. The proposed LTFP technique is compared to 1) Trilateration, 2) ToF and 3) FP, in terms of localization error performance and, additionally, with other state-of-the-art schemes.

The basic statistics of the localization accuracy are summarized in Table I. By comparing the positioning data between the propagation models, it is concluded that the proposed positioning technique performs better than the others for the same propagation models. The average error does not differ significantly between the propagation models, ranging from 0.12m to 0.17m. On one hand, in the case of FSL, the
average error is greater than Trilateration and ToF schemes, but not to a significant degree. On the other hand, in the statistical fading channel, LTFP’s localization accuracy offers a significant improvement over the other schemes. Especially for the ITU and MK models, the proposed technique seems to perform much better despite the additional losses.

The empirical CDFs (eCDF) of LTFP’s localization error in meters (m), is shown in Fig. 3 for each propagation model. From these plots one can see that in the proposed scheme the error rises up faster to the upper percentiles, than the FP and ToF positioning techniques. In LTFP, the localization error for the upper percentile corresponds to approximately 0.45m. Similar results with the eCDF are observed for the other positioning schemes, except for the FP technique, where the upper percentile of error eCDF reaches the 1m in the worst-case scenario of Rician fading channel model, MK and ITU pathloss models. These upper percentiles values are taken in positions where the error is larger, as mentioned before.

Results in comparison to other positioning schemes and [5], are depicted in Fig. 4, where the eCDF of FP, ToF, and the proposed hybrid LTFP is presented for the Rician fading channel model. In this case, LTFP exhibits superior performance and the upper percentiles reach an error value of 0.5m approximately. For the other localization techniques, the error of the upper percentiles is greater than LTFP, and the worst performance is provided by FP, where a localization error of approximately 1.2m is obtained in the same model. From this discussion, it is observed that shadowing losses and multipath fading directly affect the position estimation of time-based and FP-based techniques, respectively. However, hybrid LTFP combines the advantages of these two techniques and Trilateration, thus offering better accuracy than the stand-alone schemes. Similar results are observed for the other propagation models that were considered in the simulation procedure.

Also, as indicated by the error data collected from different positions, errors in x- and y- axes contribute almost equally to the measured error in FP and ToF cases. This observation does not stand in the case of the proposed technique LTFP, where y-axes contribute most to the error calculation. In z-axes, no error occurs in any case of positioning. In addition, for this implementation scenario, errors measured mainly at positions nearest to BN’s antennas and outside of the triangle that is formed by the three BNs. This fact stands for each case of positioning scheme, and the proposed one, for every different propagation environment.

According to [16], where a probabilistic error modeling technique is suggested, whiskers analysis provides a better way to compare different deployments, than relying only on the basic statistics, such as the mean value and standard deviation. Boxplot was introduced as a one-dimensional plot of the quartiles of an eCDF. Whiskers are shown in the boxplot diagram of Fig. 5 for the proposed hybrid technique. Outliers are observed in all the cases of propagation models. The upper whisker of the Log model is greater than the upper whisker of the MK and ITU models. Also, the upper whiskers of the empirical localization data from FSL and Rician are lower than the other models.

Additionally, empirical data were collected from the other positioning schemes. In the case of FP, the upper and lower whiskers are equal for all the considered models. The observed outliers were found to be lesser than the outliers of the LTFP.
as depicted in Fig. 5. Also, the value that corresponds to the upper bound of the interval of the empirical data in each model, is greater than the overall maximum upper whisker that is shown in Fig. 5, as it approximately reaches 1.2m. The other two positioning schemes exhibit the same behavior, except for several cases of Trilateration, where the upper whisker is equal to or lower to the upper whiskers of LTFP.

This analysis leads to the conclusion that the range defined from the whisker boundaries and expresses the normal operation of the system [16], is lower for LTFP than that of the other techniques. However, more outliers are observed in the case of the proposed technique than the other positioning schemes, especially for the FSL and Rician models. However, the interval of localization error of the proposed technique is lower than that of the other positioning schemes, and thus, localization performance is improved.

Moreover, the proposed LTFP technique presents superior improvement compared with other state-of-the-art described in Section II. The localization accuracy of the proposed LTFP is better, according to [4], where the updated databases of location FPs aim to minimize the localization error and to minimize the environmental effects. The localization performance is improved in a percentage of 9.41%, as the error of the proposed LTFP is measured in 0.51m for the worst case measurement. Also, the same improvements are provided, by comparing the proposed LTFP to the [7], [8], [9] and [12]. The comparison framework is based on mean localization error, Root Mean Square Error (RMSE), and on the values of the upper percentiles of the cCDF of localization error that are included by the proposed LTFP and each State-of-the-Art. Improvement accuracy results are shown in Table II, where the localization improvement percentage between State-of-the-Art algorithms and the proposed Hybrid LTFP is presented.

### VI. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, a hybrid Time-FP positioning technique combined with the Trilateration method, called LTFP, was presented in order to minimize the localization error that derives from FP, ToF, and Trilateration approaches. Also, various empirical path loss models and one statistical channel model have been used to simulate the indoor environment. Results show that the application of the proposed LTFP technique provides improved localization accuracy than other state-of-the-art localization schemes for the considered propagation models. It is derived that the proposed hybrid LTFP technique can effectively respond to path loss changes in the UWB environment, and can efficiently improve positioning estimation.

Future directions include the extension of LTFP by placing an additional BN in the system’s topology. Also, the combination of LTFP with AoA features seems a promising solution that can offer superior estimation performance. Finally, scenarios with a mobile BLN, should be studied as accurate mobile localization is of utmost importance in the fifth-generation of wireless communications.

### REFERENCES


### TABLE II

**Performance Evaluation - Accuracy Improvement in Relation to the State-of-the-Art (%)**

<table>
<thead>
<tr>
<th>State-of-the-Art Schemes</th>
<th>LTFP</th>
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<tbody>
<tr>
<td>Updated FP [4]</td>
<td>9.41</td>
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<tr>
<td>RTT ToA [7]</td>
<td>6.05</td>
</tr>
<tr>
<td>Hybrid ToA-FP [8]</td>
<td>10.52</td>
</tr>
<tr>
<td>Geo-Location Hybrid [9]</td>
<td>11.76</td>
</tr>
<tr>
<td>Kalman-based Hybrid [12]</td>
<td>8.69</td>
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