Mobile geolocation techniques for indoor environment monitoring

Ridha Ouni[1*], Monji Zaidi[2], Maazen Alsabaan[1], Wadood Abdul[1], Amr Alasaad[3]
[1] Department of Computer Engineering, College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia.
rouni@ksu.edu.sa
[2] College of Engineering, Department of Electrical Engineering, KKU, KSA
amzaydi@kku.edu.sa
[3] National Center for Electronics and Photonics Technology, KACST, KSA
alasaad@kacst.edu.sa
*Corresponding author: Ridha Ouni

Received November 9, 2018; revised March 8, 2019; accepted March 25, 2019; published March 31, 2020

Abstract

Advances in localization-based technologies and the increase in ubiquitous computing have led to a growing interest in location-based applications and services. High accuracy of the position of a wireless device is still a crucial requirement to be satisfied. Firstly, the rapid development of wireless communication technologies has affected the location accuracy of radio monitoring systems employed locally and globally. Secondly, the location is determined using standard complex computing methods and needs a relatively long execution time. In this paper, two geolocalization techniques, based on trigonometric and CORDIC computing processes, are proposed and implemented for Bluetooth-based indoor monitoring applications. Theoretical analysis and simulation results are investigated in terms of accuracy, scalability, and responsiveness. They show that the proposed techniques can locate a target wireless device accurately and are well suited for timing estimation.

Keywords: Geolocation techniques, RSSI, CORDIC, localization accuracy.

1. Introduction

Recently, mobile location estimation has attracted significant attention for various types of applications. These applications have stimulated research on location-finding techniques [1,2,3,4]. Location-finding refers to the process of obtaining the location information of a mobile station (MS) with respect to a set of reference positions within a predefined space [5]. Global Positioning System (GPS) is the most popular technology used in mobile and wireless networks. It is reliable and accurate in free space and line-of-sight (LOS) environments, but its performance deteriorates greatly in non-line-of-sight (NLOS) indoor and urban areas. Other techniques have been developed to work in ubiquitous and pervasive mobile environments.

Network-based location-estimation techniques based on radio signals between mobile devices and access points (APs) have been widely adopted. Currently, given that many buildings are equipped with Wireless Local Area Network (WLAN) access points (shopping malls, museums, hospitals, airports, etc.), it may be practical to use these access points to determine user location in these indoor environments. However, indoor localization techniques are always associated with a set of challenges such as NLOS signals, obstacles, and the mobility of humans.

In the literature, a variety of wireless location techniques have been studied and investigated [2,6,7]. Location-estimation techniques can be divided into three general categories: proximity, triangulation, and scene analysis. Within the triangulation category, location estimation of an MS is based on the measured radio signals (or RS) from its neighborhood APs. The representative algorithms for network-based location estimation are time of arrival (ToA), time difference of arrival (TDoA), and angle of arrival (AoA). These algorithms use location parameters received from different sources, and are based on the intersections of circles, hyperbolas, and lines, respectively. The ToA scheme estimates the MS's location by measuring the arrival time of the radio signals coming from different wireless APs, while the TDoA method measures the time difference between the arriving radio signals. The AoA technique is utilized within the AP by observing the angles of the signals coming from the MS. The equations associated with network-based location-estimation schemes are inherently nonlinear.

Network synchronization is a crucial functionality in wireless applications where nodes are required to operate under a collaborative fashion [8]. Cooperative wireless networks play an important role in both data communication and nodes localization [9]. Cooperative location-aware networks employ two types of measurements: (a) measuring the range to estimate the distance between each pair of nodes, and (b) measuring the waveform to identify the range and channel state associated with each link [10].

Bluetooth is a wireless standard operating in the 2.4-GHz ISM (industrial, scientific, and medical) band and is used for wireless personal area networks (WPANs). For the purpose of exchanging information between wireless devices, Bluetooth technology provides high security, low cost, low power consumption, and small product size. A unique ID is assigned to each Bluetooth tag, allowing users to easily locate a static or mobile target. Several researchers have been developing Bluetooth-based localization systems [11,12]. However, the signaling process is the major drawback of Bluetooth technology.

This work considers designing new geolocation techniques for confined areas based on triangular and COordinate Rotation DIgital Computer (CORDIC) algorithms. The first contribution, named Triangular Convergence Location (TCL), is based on received signal strength (RSS) information and a trigonometric triangulation process applied in a wireless propagation environment consisting of three APs. The second contribution, called COrdic Localization (COL), is based on a rotation process applied on two vectors issued from two APs. These two algorithms have been proposed to determine the position of an MS under LOS and/or NLOS environments. The MS's position is obtained by confining the estimation based on the signal variations and the geometric layout between the MS and the APs in indoor environments.

The rest of this paper is organized as follows: Section 2 surveys various related works on wireless location estimation techniques. Section 3 provides the computational details of the proposed geolocation techniques, TCL and COL. The simulation results and performance evaluation of the proposed techniques are described in Section 4. Finally, section 5 concludes the paper and mentions future research objectives.

2. Literature review

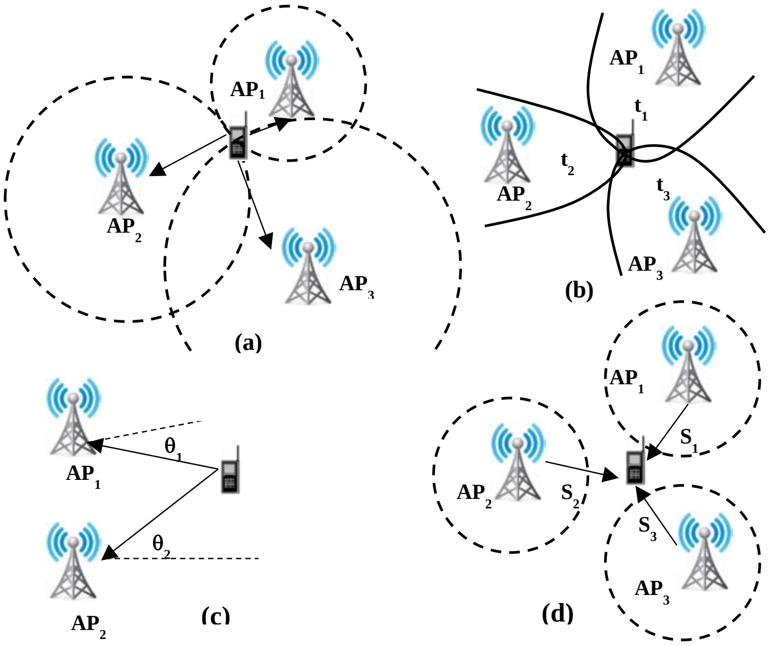
Accurately locating a wireless node or device is an active research topic. The literature provides different solutions, namely RSS, ToA, EToA, AoA, TDoA, and fingerprinting (**Fig. 1**). The main process involved in positioning is based on coordination and communication between wireless devices and existing infrastructure (**Table 1**).

ToA is one of the most basic triangulation methods used for 2D position measurement [13,14]. ToA enables locating a node by calculating the time of arrival of the signal from the node to three base stations (BSs). The propagation time can be directly translated into distance, based on the known signal propagation speed. Therefore, to determine the time difference between the transmitter and receiver, synchronizing the wireless device with the locating reference stations is required. The main advantage of ToA is its immunity to multipath effects.

EToA is an extended version of ToA designed by simplifying the recursive and intensive computing of the localization process [15]. In EToA, the computing process is only performed by the MS with a view to improving handover latency. EoTA is an efficient technique that calculates the coordinates of the mobile station based on basic vector functions (shift, addition, and rotation). EToA can directly authenticate and associate with the nearest base station without a scanning phase, which represents the major part of the handover latency. It replaces the scanning phase with a localization mechanism that is completed within a fixed number of iterations. The major advantages of EToA are low computational cost and simplicity of implementation.

In [16], the authors proposed a ToA-based iterative geolocation algorithm alternating between two steps: probability density function (PDF) estimation and parameter estimation (PE). The first step approximates the PDF of the exact measurement error via adaptive kernel density estimation. The second step resolves a position estimate from the approximate log-likelihood function via a quasi-Newton method. This algorithm performs similarly to maximum likelihood estimator (MLE), the geolocation accuracy of which is comparable to that of other studies found in the literature. However, this accuracy is achieved at a higher computational cost.

The study in [17] used ToA measurements based on cooperative and robust localization in mixed LOS and NLOS conditions. It proposed an iterative localization approach to reduce the impact of NLOS propagations. This approach mitigates the impacts of scattering, diffraction, and reflection caused by the presence of multiple obstacles between the transmitter and receiver nodes. It uses the least-median deviation to estimate the initial positions of the sensor nodes. Moreover, it improves the convergence likelihood and estimation accuracy of the covariance matrix of the measured noise.



(a) ToA (b) TDoA (c) AoA (d) RSSI

Fig. 1. Basic architecture of geo-localization techniques.

DOLPHIN (Distributed Object Locating System for Physical-space Internetworking) [18] is an ultrasonic peer-to-peer positioning system using both RF and ultrasonic signals. This system focuses on innovative positioning hardware and techniques to determine positions inside buildings or in the underground. DOLPHIN is easy to configure and provides a high degree of accuracy in three dimensions. It allows accuracy of 2 cm on a test bed of 3 m in size.

Cricket [19] is an indoor location system which utilizes RF and ultrasound based on static transmitters and mobile receivers. The system has been successfully implemented to obtain full 3D real-time coordinates of a mobile device based on a purpose tailored Matlab program. Cricket allows easy flexibility and programmability of devices as a beacon or as a listener. However, cricket suffers from multipath signals which requires high redundancy of range measurements as well as speed of ultrasound which is highly correlated to the temperature. A later version, called Cricket Compass [20], is designed to determine orientation as well as position of mobile devices.

The Active Bat [21] is an ultrasonic positioning system based on pulse transmission between roaming Active Bat tags and fixed ultrasonic receivers mounted on the ceiling. The active Bat computes the tag's coordinates and provides direction information by performing multilateration based on the time-of-flight of the ultrasonic pulse between them. This positioning system allows an accuracy of 9 cm within a range of 50 m. However, Active Bat employs centralized system architecture and requires a large number of precisely positioned ultrasonic receivers.

The RSS approach uses the strength of the received transmission to estimate the distance between nodes. This is performed by calculating the attenuation in the propagation path. The ratio of the transmitted to the received power is used to estimate the position of the node. Indoor location tracking using RSS [22,23] employs three or more nodes to perform fine-grained device tracking, similar to ToA [24]. Using the method of ranging, where the distance between two nodes is predefined, the coordinates of the device are computed using lateration or angulation approaches.

Table 1. Comparison of various indoor localization techniques.

Solution	**Measurement**	**Accuracy**	**Coverage**	**LOS / NLOS**	**Multipath effect**	**Cost**	**Notes**
ToA [13]	Time of arrival	High	Good / Multipath issues	LOS	Yes	High	(1) Predefining antenna location is necessary. (2) Time synchronization is required.
Extended ToA [15]	Time of arrival	High	Good	Both	Yes	Medium	(1) Geolocation replaces scanning phase for reduced handoff latency. (2) Hardware implementation is undertaken.
Iterative-based ToA [17]	Time of arrival	High	Good	LOS	Yes	High	(1) Iterative geolocation process based on two steps: PDF and PE. (2) Adaptive kernel density estimation and quasi-Newton method result in a higher computational cost.
RSS-based [22,23]	RSS	High	Good	Both	Yes	Medium	(1) RSS-based indoor localization with PDR tracking to compensate NLOS error. (2) Location based on least squares lateration algorithm.
TDoA [26]	Time difference of arrival	High	Good / Multipath issues	LOS	Yes	High	(1) Predefining antenna location is necessary (2) Time synchronization is required.
AoA [28]	Angle of arrival	Medium	Good / Multipath issues	LOS	Yes	High	(1) Accuracy depends on the antenna's angular properties. (2) Predefining antenna location is necessary.

Finger-printing [30, 31]	RSS	High	Good	Both	No	Medium	(1) Predefining antenna location is not necessary (2) Heavy calibration is required.
Proximity [35]	Signal type	Low to high	Good	Both	No	Low	(1) Accuracy is approximated to the cell boundaries. (2) Additional antennae improve accuracy but increase cost.
WSNs-based [36,37]	Signal type	Medium to High	Good / Multipath issues	Both	Yes	High	(1) Strongly depends on the technology used and the localization algorithm. (2) Energy efficiency is low.

Extensive researches for indoor positioning system (IPS) has focused on the machine learning approaches such as Extreme Learning Machine (ELM) [25]. In this context, [25] proposed the ELM in order to overcome the shortcomings faced by the traditional positioning methods and provide higher positioning accuracy and robustness. The major contribution of that work consists of a Gaussian filter combined with ELM. This positioning system has been tested in a real experimental environment and provided an accuracy of 70 cm within an area of 11 m x 6 m.

TDoA utilizes an estimation method involving the downlink positioning reference signal (PRS) of long term evolution (LTE) [26] technology. As conventional correlation approaches are unable to calculate the time difference when the sampling interval is shorter than a second, this phase is used to estimate the TDoA by constructing a one-to-one relationship table between the time delay and phase. Simulation-based results along with theoretical analysis support TDoA's ability to accurately estimate the time difference within one sampling interval. Additionally, TDoA satisfies LTE requirements for location-awareness services.

In [27], the authors proposed a TDOA-based indoor visible light positioning (VLP) system using cross correlation. It uses virtual local oscillator for cross correlation in order to reduce the hardware complexity. It applies cubic spline interpolation to reduce the sampling rate and enhance the time-resolution of cross correlation. As result, this system provides an average accuracy of 9.2 cm in an area of 1.2m x 1.2m.

The Angle of Arrival (AoA) technique is based on the bearing measurement or the direction of arrival measurement. This technique calculates the angle at which the signal arrives from the BS to the unknown wireless node [28]. In AoA measurement, at least two BSs are needed to calculate the position. AoA's accuracy depends on the directionality of the antenna and is sensitive to the presence of shadowing and multipath effects in the measurement environment. AoA does not provide high localization performance unless large antenna arrays are used [29].

For indoor positioning, the authors of [30,31] proposed localization approaches based on fingerprinting, in which fingerprint matching is employed to determine wireless device location. A fingerprint consists of the features of the scene at certain locations of interest that can be used to form a fingerprint database [32]. This enables determining the location of a particular object by fingerprint matching from the database. Fingerprint-based indoor localization approaches are carried out in software and do not require specialized hardware. In addition, such approaches do not require time synchronization. Recently, support vector classification (SVC) involving multiple classes and support vector regression (SVR) have been successfully utilized for location fingerprinting [33,34].

Proximity-based methods can only provide an approximate position of a device based on link or connection information [35]. The target location is approximated to the position of the access point directly connected with the user. When more than one antenna detects the same mobile target, the location is defined by the antenna receiving the strongest signal. This method is relatively simple to implement. It can identify which cell site the device is using at a given time [36]. This type of localization method is mostly used in GSM and has an accuracy range of 50–200 m. It has high variance, which sometimes might not satisfy the requirements of the positioning application.

Recently, wireless sensors have been used for a variety of new monitoring and control applications, especially target positioning and tracking [36]. Communication and measurement between multiple pairs of sensors is required to achieve localization for all sensors. Most sensor-network-based localization techniques use RSS measurements [37,38]. Four sensor-based localization configurations exist: (1) static sensor nodes and static anchor nodes [39], (2) mobile sensor nodes and static anchor nodes [40], (3) static sensor nodes and mobile anchor nodes [41], and (4) mobile sensor nodes and mobile anchor nodes [42]. The study in [43] surveys recent localization techniques considering wireless sensor networks and their fundamental limits, challenges, and applications.

Recently, cooperative techniques have been introduced for localization and navigation to improve the accuracy and reliability of position information. Information exchange and cooperation in the network is crucial for the design of location-aware networks. To perform these tasks, nodes are required to operate under a common clock without being affected by various imperfections caused by both internal and environmental issues. In this context, [9] explored cooperative network localization and navigation in terms of theoretical foundation, technologies and spatiotemporal cooperative algorithms. Later, [10] developed an experimentation methodology suited for localization in cooperative wireless networks. It established a database based on range and waveform measurements using cooperative wireless channels. Then, evaluation of network localization algorithms has been performed under various LOS and NLOS conditions. Recently, [8] analyzed the asymptotic synchronization performance of large-scale networks for both absolute and relative synchronization. [8] used Cramer-Rao bound, cooperative dilution intensity (CDI) and relative CDI concepts in order to characterize interaction between agents and evaluate the network synchronization in both dense and extended networks.

3. Proposed solutions

The proposed solutions locate a mobile device in an indoor environment, enabling the support of tracking applications. It is based on computing the distance between an AP and the mobile device and then employing a geometrical approach for localization. The position of the mobile device is determined using two RF positioning techniques. In the first technique, the device is located by the intersection point of three circles. Each circle has a radius equal to the distance between the mobile device and the AP under consideration, as illustrated in **Fig. 3**. In the second technique, the position of the mobile device is determined by the intersection of two vectors rotated using the CORDIC algorithm.

3.1 System model

The mobile geolocation system considered in this study is based on four major concepts:

- The indoor environment is equipped with multiple APs organized in a triangular structure/architecture, i.e., at any time, a mobile station can be located by two or three APs.
- Each AP is capable of detecting the mobile station's RSSI and measuring the corresponding/associated distance.
- A centralized geolocation system is designed to determine the relative position of the mobile device. A positioning algorithm is integrated to estimate the position of the mobile device by computing metrics from the APs.
- Additional iterations can easily be built into the positioning algorithm for more accuracy as well as to track the mobile device.

3.2 Signal transmission model

The path-loss model allows calculating the distance between a mobile device and an AP of known location. Various path-loss models exist. Generally, path-loss models use trilateration to determine the location of the mobile device [44,45]. However, measurements from indoor radio communication channels [46] have shown the presence of outliers that result in heavy-tailed measurement noise. Therefore, Bluetooth-based transmission in indoor environments can be affected by noise, multipath and signal attenuation. Therefore, NLOS factors should be considered by the proposed algorithms to provide accurate localization in realistic conditions.

3.3 Triangular Convergence Localization – TCL

In geometrical triangulation, researchers assume that the measured noise is additive and the NLOS error is a large positive bias where the measured ranges are greater than the acceptable values [2]. These techniques require three wireless links to be established simultaneously with three access points. Therefore, they assume that the MS is located in the overlapping region (ABC) of the transmission ranges of the three access points (**Fig. 2**). However, (a) the MS may be elsewhere in the triangle defined by three access points, and (b) in some cases, no overlapping area may exist [47,48]. In this section, we propose improvements, including a geometric localization process able to coordinate with the MS with low computational cost based on the locations of three access points.

The TCL technique is based on the network architecture given in **Fig. 3**, containing three access points and an MS. The MS is located inside the triangle defined by the three access points (AP_1, AP_2, AP_3) and coordinated by the distance d_j ($j = 1,2,3$) far from each access point AP_j. The MS position defines three triangles: AP_1MSAP_2, AP_2MSAP_3, and AP_3MSAP_1. TCL focuses on them successively in order to reduce the localization field of the MS. TCL is an iterative geometric process, which consists of reducing the localization field until it converges on the MS location.

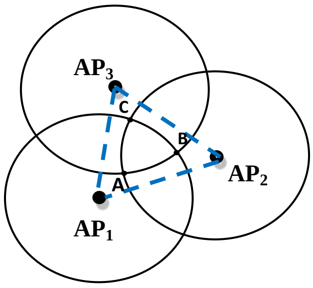


Fig. 2. Three neighboring APs and the associated overlapping area.

The main assumptions of TCL are as follows:

- AP coordinates are predefined
- D is the distance between two APs
- $d_1 + d_2 > D,\ \ d_2 + d_3 > D, \text{and}\ \ d_3 + d_1 > D$

where:

A_0, B_0, and C0 are the orthogonal projections of the MS on the sides (AP1, AP2), (AP2, AP3), and (AP3, AP1), respectively.

d1, d2, and d3 are the distances separating the MS from AP1, AP2, and AP3, respectively. The MS is able to measure the distance dj based on the power received from APj.

θ12 is the geometrical angle $(MS - \widehat{AP1, AP}1 - AP2)$. θ_{13}, θ_{21}, θ_{23}, θ_{31}, and θ_{32} are defined similarly.

TCL focuses primarily on the triangle AP_1MSAP_2. The same tests will be repeated for the triangles mentioned above (AP_2MSAP_3 and AP_3MSAP_1). Based on the above assumptions and **Fig. 3**, we can propose the following approach:

$$r_1 = d_1 \cos\theta_{12}$$

$$d_2{}^2 = (D - r_1)^2 + (d_1{}^2 - r_1{}^2) \Longrightarrow$$

$$d_2{}^2 = (D - d_1\cos\theta_{12})^2 + (d_1{}^2 - d_1\cos\theta_{12}{}^2) \Longrightarrow$$

$$d_2{}^2 = D^2 + d_1{}^2 - 2Dd_1\cos\theta_{12} = D^2 + d_1{}^2 - 2Dr_1 \Longrightarrow$$

$$r_1 = \frac{D^2 + d_1{}^2 - d_2{}^2}{2D} \tag{1}$$

We define here the first factor q_1 as follows:

$$q_1 = \frac{r_1}{D} = \frac{D^2 + d_1{}^2 - d_2{}^2}{2D^2} \tag{2}$$

The range of parameter q_1 can determine the shape of the triangle AP_1MSAP_2 (**Table 2**).

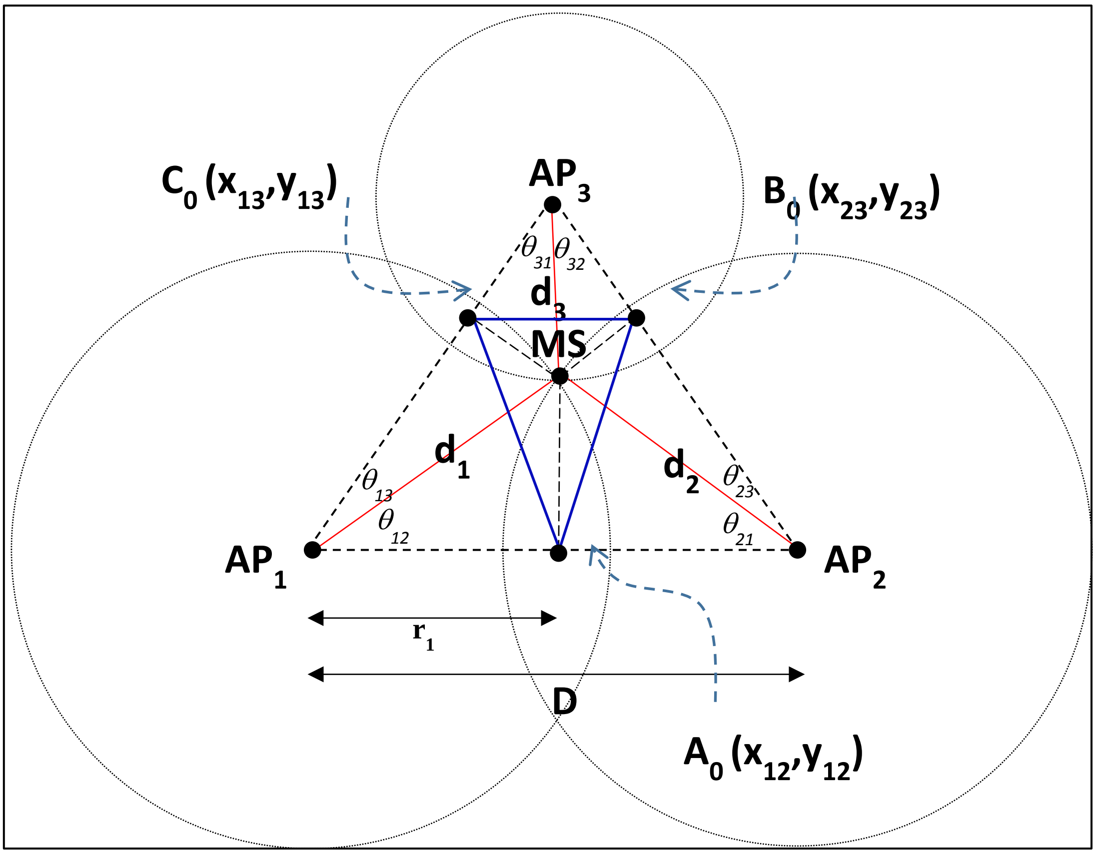
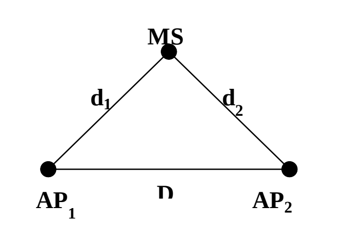
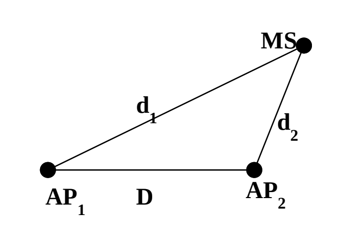
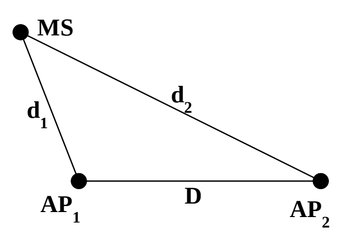


Fig. 3. Network architecture and geometric representation of triangles for MS positioning.

Table 2. Different forms of the triangle (AP1MSAP2).

$0 < q_1 < 1$	$q_1 > 1 \Leftrightarrow d_1 > d_2$	$q_1 < 0 \Leftrightarrow d_1 < d_2$
		

We propose to narrow the size of the triangle containing the MS location. In this context, we orthogonally project the MS location on the (AP_1, AP_2), (AP_2, AP_3), and (AP_3 AP_1) sides, which results in triangles A_0, B_0, and C_0 respectively. Consequently, the triangle (A_0, B_0, C_0) is smaller than (AP_1, AP_2, AP_3). In other terms, we have just created three new virtual APs, placed at A_0, B_0, and C_0. Based on [49], the coordinates (x_{12}, y_{12}) of the point A_0 are given as follows:

$$x_{12} = q_1 X_2 + (1 - q_1) X_1$$

$$y_{12} = q_1 Y_2 + (1 - q_1) Y_1$$

Where (X_1, Y_1) and (X_2, Y_2) are the coordinates of AP_1 and AP_2, respectively.

Let r_2 be the distance between AP2 and B0 and r3 be the distance between AP3 and C0. As described previously, we can obtain the coordinates of the points B_0 and C_0 as follows:

$$x_{23} = q_2X_3 + (1 - q_2)X_2$$

$$y_{23} = q_2Y_3 + (1 - q_2)Y_2$$

$$x_{31} = q_3X_1 + (1 - q_3)X_3$$

$$y_{31} = q_3Y_1 + (1 - q_3)Y_3$$

Where:

$$q_2 = \frac{r_2}{D} = \frac{D^2 + {d_2}^2 - {d_3}^2}{2D^2} \qquad q_3 = \frac{r_3}{D} = \frac{D^2 + {d_3}^2 - {d_1}^2}{2D^2}$$

Using the Pythagorean Theorem, we can calculate the distances between the MS and the new points A_0, B_0, and C_0:

$$d(MS, A_0) = \sqrt{{d_1}^2 - {r_1}^2} \quad d(MS, B_0) = \sqrt{{d_2}^2 - {r_2}^2} \quad d(MS, C_0) = \sqrt{{d_3}^2 - {r_3}^2} \tag{3}$$

Now, the MS exists inside a smaller triangle defined by three new virtual APs located at A_0, B_0, and C_0. As a result, we return to the first step of the computational process for a new iteration using the distances between the MS and each access point as well as the location of those APs. During the second iteration, the orthogonal projections of the MS on the (A_0B_0), (B_0C_0), and (C_0A_0) sides lead to three new points, A_1, B_1, and C_1 (i.e., their coordinates) as well as their distances from the MS. Moreover, the area of $A_1B_1C_1$ is smaller than that of $A_0B_0C_0$.

At the i^{th} iteration, the MS will be located in a triangle $A_iB_iC_i$ that is smaller than $A_{i-1}B_{i-1}C_{i-1}$. The triangle $A_iB_iC_i$ allows the designing of the next triangle $A_{i+1}B_{i+1}C_{i+1}$. After a few iterations, the coordinates of the three vertices of the triangle (A, B, and C) converge to the actual MS coordinates. At this stage, the triangle $A_{conv}B_{conv}C_{conv}$ with vertices A_{conv}, B_{conv}, and C_{conv} is considered a point. It is therefore possible to write the following:

$$x_{Aconv} \approx x_{Bconv} \approx x_{Cconv} \quad \text{and} \quad y_{Aconv} \approx y_{Bconv} \approx y_{Cconv}$$

We suppose that the MS coordinates can be obtained by the average, as given in Eq. 4. The division by 3 assumes that the MS exists at the center of gravity of the triangle $A_{conv}B_{conv}C_{conv}$.

$$x_{MS} = \frac{x_{Aconv} + x_{Bconv} + x_{Cconv}}{3}, \qquad y_{MS} = \frac{y_{Aconv} + y_{Bconv} + y_{Cconv}}{3} \tag{4}$$

3.4 CORDIC-based localization (COL)

Location-based services are the most significant characteristic of 3G/4G wireless communication systems, which enables support for several new types of applications. The ToA localization technique is most frequently used for MS position estimation. This technique uses standard methods based on complex computing processes that are generally implemented with software tools [1,50]. The main challenge of ToA resides in the power limitations of MSes, which requires optimization combined with the ability to be used in an indoor environment.

To overcome these limitations, we propose a CORDIC approach based on our previous contributions [47,48,16] considering two technical aspects. Firstly, the proposal is expected to simplify the intensive and recursive computation of the localization process by reducing the execution time, cost, and power consumption. Secondly, a suitable topological architecture including only two APs has been considered to adapt to indoor environment localization.

Fig. 4 represents the basic architecture of the network topology considered for the COL algorithm. We assume that the coordinates (X_j, Y_j) (j = 1, 2) of two APs are predefined. For signal propagation, we consider two path-loss models: free space and noisy. Using these models, d_j (j = 1, 2) values are calculated based on the measured received signal strength indicator (RSSI), as outlined in Eq. 5. These parameters are illustrated in a local coordinate system, as shown in **Fig. 4**.

$$Pr = Pt.Gt.Gr.\left[{}^{\lambda}/_{4\ \pi d}\right]^2 \tag{5}$$

Consider the following:

- $(X_1, Y_1) = (0, 0)$ and $(X_2, Y_2) = (D, 0)$
- $\boldsymbol{\theta} = (\widehat{AP1 - MS, AP1} - AP2)$
- $\boldsymbol{\beta} = (\widehat{AP2 - MS, AP2} - AP1)$
- **D** is the distance between AP_1 and AP_2.
- **d** is obtained in the convergence state (i.e., when MS location is identified).

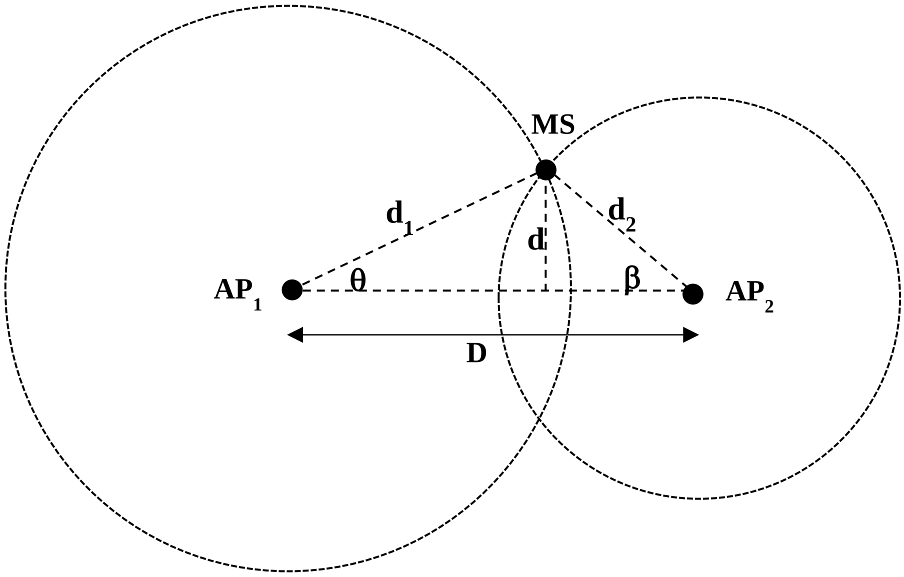


Fig. 4. Basic network architecture of COL deployment.

The question now is how do we calculate the coordinates of the MS from these two angles and the parameters mentioned above?

The proposed technique is based on using two vectors $\vec{V}_1$ and $\vec{V}_2$ whose origins are located at the positions of the APs and ends on the circle ζ_i (AP_i, d_i). The principle of this technique is rotating these two vectors $\vec{V}_1$ and $\vec{V}_2$ until they cross at a focal point, denoted by (x_c, y_c) (**Fig. 5**).

The initial positions (x_1,y_1) and (x_2,y_2) of the ends of the vectors $\vec{V}_1$ and $\vec{V}_2$ are (d_1,0) and (D - d_2,0), respectively. The initial and final positions of the first vector $\vec{V}_1$ are the following, respectively:

$$\vec{V}_1\begin{pmatrix} x_1 \\ y_1 \end{pmatrix} = \begin{pmatrix} d_1 \\ 0 \end{pmatrix} \text{ and } \begin{pmatrix} x_1^n \\ y_1^n \end{pmatrix} = \begin{pmatrix} xc \\ yc \end{pmatrix}.$$

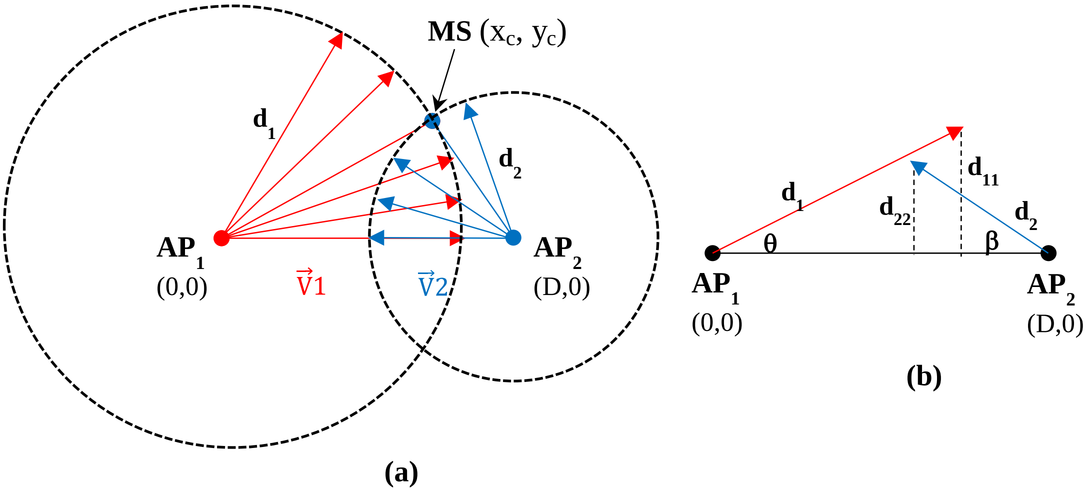


Fig. 5. Localization principle of COL.

This vector undergoes a global rotation with an angle θ, which we propose here to study its complete evolution. Elementary rotations with angles θ_i were performed on the vector $\vec{V_1}$ to reach the final position and therefore calculate the MS position with a given accuracy. To simplify the computing complexity, an iterative process has been developed by following these steps:

1. Applying CORDIC process to θ and β variations,
2. Checking/testing vector convergence condition,
3. Optimizing for more accuracy,
4. Computing MS coordinates.

Applying CORDIC process to θ and β variations

From **Fig. 5(b)**, the angles θ and β can be defined using Eq. 6:

$$\theta = \sin^{-1}\left({d_{11}}/{d_1}\right), \qquad \beta = \sin^{-1}\left({d_{22}}/{d_2}\right) \tag{6}$$

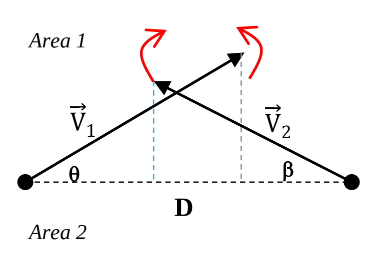
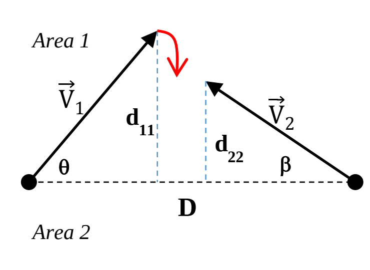
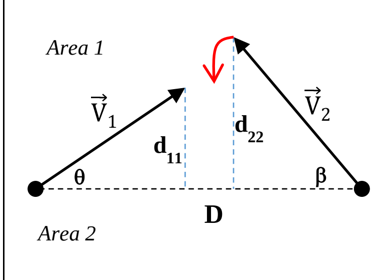
where θ and β are managed by the CORDIC process within the rotation interval $[-\pi/2,\pi/2]$. The convergence conditions on vectors $\vec{V}_1$ and $\vec{V}_2$ must be checked and verified constantly. Two conditions are required to satisfy vector convergence (Eqs. 7 and 8). Only one condition is useful but not sufficient for the convergence state.

$$d_{11} = d_{22} \rightarrow d_1 sin\theta = d_2 sin\beta \qquad (7)$$

$$d_1 cos\theta + d_2 cos\beta = D \qquad (8)$$

If the MS is located in area 1, defined by θ∈[0, π/2], θ and β are assigned the middle value (θ = β = π/4). Then, θ and β are adjusted according to three different cases of the vectors $\vec{V}_1$ and $\vec{V}_2$ (**Table 3**). In case (a), θ and β are increased by a certain fraction (ε) of their values. However, in cases (b) or (c), only one angle θ or β has to be adjusted by decreasing its value by a certain fraction (ε). This fraction decreases with the iteration number.

Table 3. Three cases for adjusting θ and β.

Case (a)	*Case (b)*	*Case (c)*
		
$D < d_1 cos\theta + d_2 cos\beta \rightarrow$ $\theta = \theta + \theta*\varepsilon$, $\beta = \beta + \beta*\varepsilon$ $\varepsilon = f(1/iteration)$	$D > d_1 cos\theta + d_2 cos\beta$ & $d_{11} > d_{22}$ $\rightarrow \theta = \theta - \theta*\varepsilon$	$D > d_1 cos\theta + d_2 cos\beta$ & $d_{22} > d_{11}$ $\rightarrow \beta = \beta - \beta*\varepsilon$

Checking/testing vector convergence condition

However, the equalities in Eqs. 7 and 8 represent a strict requirement/condition that may not be satisfied due to the estimation error when measuring d_1 and d_2 from signal strength. Therefore, these conditions should be satisfied within a certain range that reflects the accuracy level with which we are computing the convergence conditions. In other terms, the convergence conditions are now given by Eqs. 9 and 10, using a predefined accuracy level α.

$$\alpha \leq {d_1 sin\theta}/{d_2 sin\beta} \leq 1/\alpha \qquad (9)$$

Where α is the accuracy level.

$$\alpha \leq {(d_1 cos\theta + d_2 cos\beta)}/{D} \leq 1/\alpha \qquad (10)$$

Optimizing for more accuracy

Within the optimization phase, θ and β are adjusted in order to improve their localization accuracy. Once the convergence conditions are justified/verified, additional iterations are performed with finer variations to obtain coordinates close to the ideal case, as defined in Eqs. 7 and 8. The optimization process continues adjusting θ and β while the convergence conditions are limited within a narrow interval.

Computing MS coordinates

The optimization phase outlines the most suitable values of θ and β that represent the most accurate values of the convergence conditions of vectors $\vec{V}_1$ and $\vec{V}_2$. As a result, the mobile station coordinates are expressed by Eqs. 11 and 12, based on the representation in **Fig. 4**.

$$X_{MS} = d_1 cos\theta \approx d_2 cos\beta \tag{11}$$

$$Y_{MS} = d_1 sin\theta \approx d_2 sin\beta \tag{12}$$

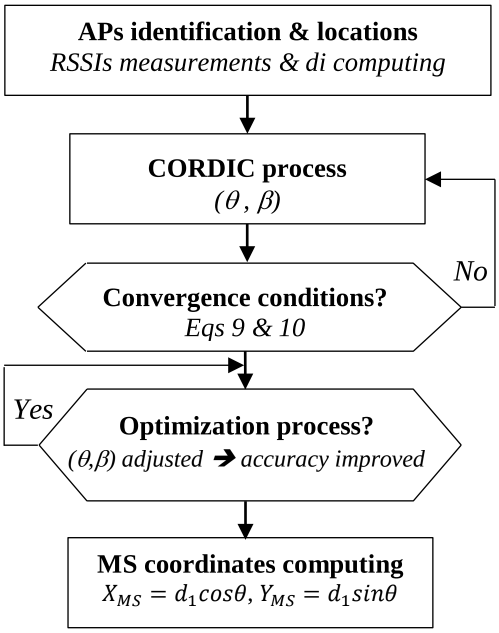


Fig. 6. COL flowchart.

Fig. 6 shows the COL localization flowchart, primarily consisting of processes and conditions responsible for computing MS coordinates. COL constitutes an efficient geolocation method able to estimate MS coordinates based on fundamental vector rotation functions in a 2D space.

4. Simulation results and performance evaluation

In an effort to design two new localization techniques, this framework was thoroughly focused on the utilization and employment of Matlab-based platform coding, for a sophisticated simulation of an MS and two or three APs. Matlab was selected as the most suitable tool for the design of the TCL and COL algorithms, since they are mainly based on computational algorithms ranging from elementary functions to more sophisticated ones. Matlab is a high-level matrix/array language with control flow statements, functions, data structures, input/output, and object-oriented programming features and is fit for our purpose.

4.1 Performance metrics

The performance criteria associated with localization systems can be classified into the following areas:

Accuracy or *location estimation error (LEE)*. This measures the Euclidean distance between the real and estimated positions of the MS (13).

$$\mathrm{LEE} = \sqrt{(Xr - Xe)^2 + (Yr - Ye)^2} \quad r\text{: real , } e\text{: estimated} \tag{13}$$

Responsiveness. Responsiveness is how fast the geolocation technique/system is able to determine the location of a certain target (or to update the location of a moving target). In our results, responsiveness corresponds to the number of iterations useful for localization. It reflects the amount of time in which the location is determined.

Scalability. Scalability measures the performance of the location system/technique when it operates with a larger number of location requests and coverage. In this regard, several simulations have been performed with various coverage areas.

Adaptiveness. Adaptiveness is the ability of the localization system to cope with environmental changes. Better adaptiveness reduces the need for repeated calibration.

Cost and complexity. Cost may include extra infrastructure, additional bandwidth, lifetime, weight, energy, and nature of deployed technology. Complexity is related to the signal processing and algorithms used to estimate the location.

In this study, performance is measured in terms of accuracy, responsiveness, and scalability.

4.2 Simulation parameters

In this section, we illustrate the validity of the proposed methods for wireless device localization in indoor environment using Bluetooth technology. The simulation parameters employed to evaluate the performance of our algorithms are shown in **Table 4**.

Table 4. Parameters of the simulation system.

Mac / phy	Bluetooth
Channel	Wireless channel
Propagation model	Free space and noisy models
Area (m^2)	4, 8, 16, 20, 30, 36, 42, 49, 64.
Number of nodes	2 / 3 APs and 1 MS

4.3 Comparative study

A comparative study is conducted in this section between different localization approaches found in the literature. The major metrics featuring localization techniques reside on: complexity (cost), accuracy and responsiveness. These metrics allow evaluating the localization performances and outlining the targeted applications.

Complexity of a system can be attributed to hardware, software or computational processes. The key idea of “mathematical programming” based approaches is to formulate the position estimation problem as a constraint optimization problem, which can be solved by iterative (e.g. [16-21, 32, 36, 42]) or direct methods (e.g., [23, 25, 28, 31]). Direct methods are generally based on factorization of the matrix where this operation is absent in iterative methods. Such operations can accomplish/perform execution efficiency on advanced computer architectures, but are the major factor for high computational complexity (**Table 5**). However, iterative methods are usually simpler to implement than direct methods since no full factorization has to be stored.

Furthermore, the basic operations in our proposed iterative method relies on an effective combination between (a) simplifying the trigonometric operators and (b) optimizing the iterative process. This combination implies low computational complexity and reduces the total solution time for the positioning system. The recent iterative localization techniques [16-21, 32, 36, 42] are based on very complex computational aspect in terms of operators, matrices, long iterative processes and components (broadband ultrasound, filters, correlators etc…) which impact their implementation cost (**Table 5**).

Table 5. Comparison of indoor localization techniques.

Wireless positioning system	**Localization technique**	**Range (m) Area (m^2)**	**Accuracy (cm)**		**Computational / Hardware Complexity**
			Existing	**TCL** **COL**	
Dolphin [18]	ToA, trilateration	3 m	2	0.18 10^{-12} 4.5	Medium
Cricket [19][20]	ToA, trilateration	10 m	2	0.76 10^{-12} 9.4	Medium
TDoA-based VLP [27]	TDoA, hyperbolic trilateration	1.44 m^2	9.2	0.03 10^{-12} 1.7	Medium
ELM-Gauss filtering [25]	RSSI - Extreme Learning Machine	66 m^2	70	0.52 10^{-12} 6.7	High
PSO-Gauss filtering [25]	RSSI - Extreme Learning Machine	66 m^2	80.2	0.52 10^{-12} 6.7	High
Geometric [47]	RSS, triangulation	66 m^2	6.14	0.52 10^{-12} 6.7	Low
TCL – proposed	RSS, triangulation	variable	--	--	Low
COL – proposed	RSS, bilateration	variable	--	--	Low

Accuracy is the key factor to describe how close the estimation from a positioning technique is to match the actual position of devices for indoor areas. It is usually determined by the location estimation error (13). **Table 5** shows the results of comparison between the state of the art and the proposed approaches TCL and COL. **Table 4** compares Dolphin [18], Cricket [19,20], TDoA-based VLP [27], ELM-Gauss filtering [25], PSO-Gauss filtering [25] and Geometric localization [47] approaches with the proposed approaches. To do that, we used unified conditions under which the simulations have been performed for both existing and proposed algorithms. In other terms, the accuracy of our proposed algorithms are extracted/collected within the same condition under which each existing algorithm has been applied.

It is very clear from this table that our approaches TCL and COL performs well not only in terms of accuracy but as well in terms of computational complexity. It also reflects that the accuracy requirements depend on the scale of the transmission; hence, it will impact the type of application supported by the corresponding localization technique. Furthermore, TCL and COL perform localization process within a reduced delay which allows to support real-time tracking applications (section 4.4 - responsiveness).

4.4 Performance evaluation and analysis

Two different localization scenarios are created and analyzed for the proposed localization techniques COL and TCL. In the first scenario, a grid of stationary APs in an indoor environment is maintained and an MS is randomly placed in an area with variable size. In the second scenario, measurements are generated by adding white Gaussian noise introducing a certain deviation in the range domain from the true values. For TCL, simulation is performed with three stationary APs. However, only two APs are sufficient for simulating COL. The performance evaluation compares these algorithms in terms of accuracy, scalability, and responsiveness.

Accuracy

The LEE represents the Euclidian distance between the estimated and real target locations. The MS locations have been selected randomly in an area defined by the APs' positions. This area forms a triangle ABC for TCL and a square for COL. **Figs. 7** and **8** illustrate the performance of the TCL and COL algorithms in terms of localization accuracy for different channel models.

In a free channel model, TCL provides a very high accuracy level of around 10^{-14} m. TCL is also capable of determining the position of any MS located outside the triangle ABC. However, the accuracy level increases significantly when moving away from the triangle ABC, as shown in **Fig. 9**. On the other hand, COL provides an acceptable accuracy level, averaging at 10^{-2} m based on several scenarios. This result is very interesting since in a Bluetooth environment with a range 10 m, the positioning error is around 10 cm, which is considered a reasonable error for various types of Bluetooth-based applications.

In the noisy channel model, the TCL and COL algorithms provide similar performances with LEE slightly lower than 10 cm (**Fig. 8**).

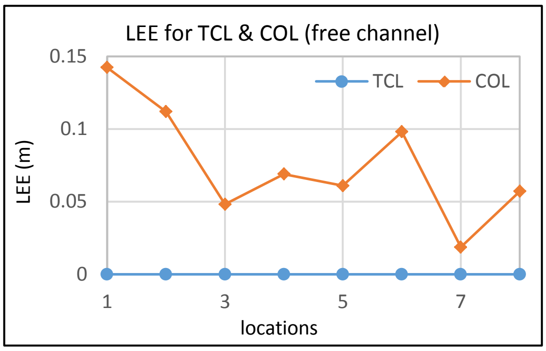


Fig. 7. Localization accuracy: LEE for free space channel.

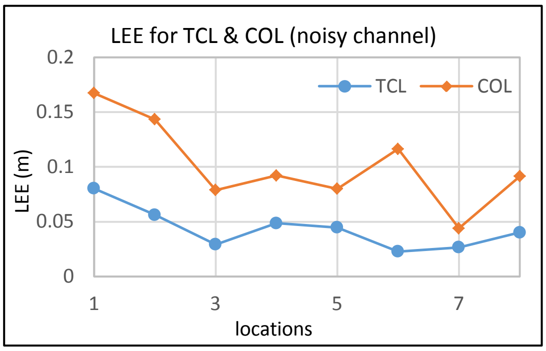


Fig. 8. Localization accuracy: LEE for noisy channel.

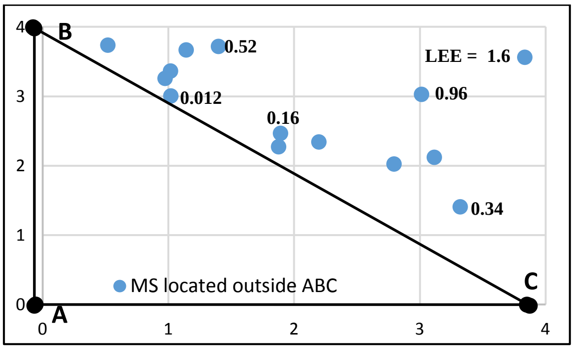


Fig. 9. LEE for MS located outside the triangle ABC (LEE in meter for TCL).

These types of results have been averaged over N random MS positions (N=30), and then re-extracted for various coverage area sizes in order to provide more credibility to both algorithms. These results provide, in the following section, the scalability effectiveness of TCL and COL.

Scalability

In order to measure the scalability performance of the proposed localization techniques, several simulations have been performed with various coverage areas. The coverage area is determined by the APs locations in a rectangular form. For the first scenario, where the path-loss model is deployed in free space, **Fig. 10(a)** shows that TCL is capable of identifying the location of the MS with a negligible LEE of around 10^{-15} m. As expected, LEE increases slightly with coverage area. For the second scenario, the LEE is around 10^{-2} m and increases almost linearly with the coverage area (**Fig. 10(b)**).

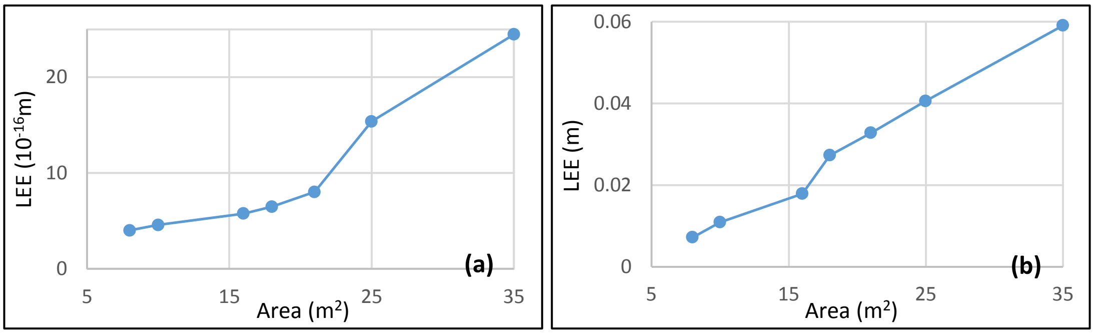


Fig. 10. TCL: location estimation error vs. coverage in (a) noiseless and (b) noisy environments.

Similar simulations have been performed with COL, where **Figs. 11(a)** and **11(b)** show the LEE obtained for several coverage areas. In **Fig. 11(a)**, the COL technique has an LEE of around 10^{-2} m in the free space path-loss model. COL maintains almost the same accuracy level in the noisy channel model (**Fig. 11(b)**) compared to the free space. This result proves that COL is less sensitive to noise and multipath compared to TCL. Moreover, similar variations in LEE for the same area is a common feature of TCL and COL (**Figs. 10** and **11**).

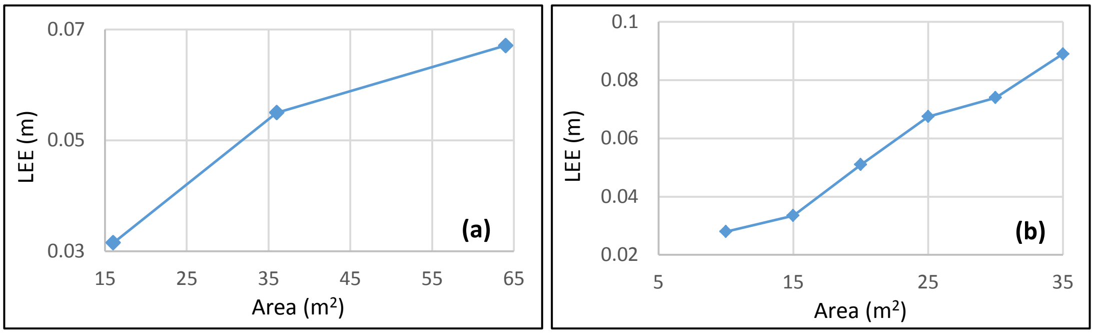


Fig. 11. COL: location estimation error vs. coverage for (a) noiseless and (b) noisy environments.

Responsiveness

Fig. 12 shows how coordinates (X,Y) of the triangle vertices (A,B,C) converge on the MS coordinates. It shows the number of iterations required to determine the MS position. By running TCL and based on several simulations performed for random positions of the MS, around 10 iterations are required to determine the coordinates of the MS. This result reflects a high responsiveness level of the TCL algorithm, especially when operating on fast hardware. It is an indication of the usefulness of TCL for tracking applications, where the localization process must recompute and update the MS position within a restricted period. In a noisy channel, the responsiveness is almost similar, and the number of iterations is around 11 (**Fig. 13**).

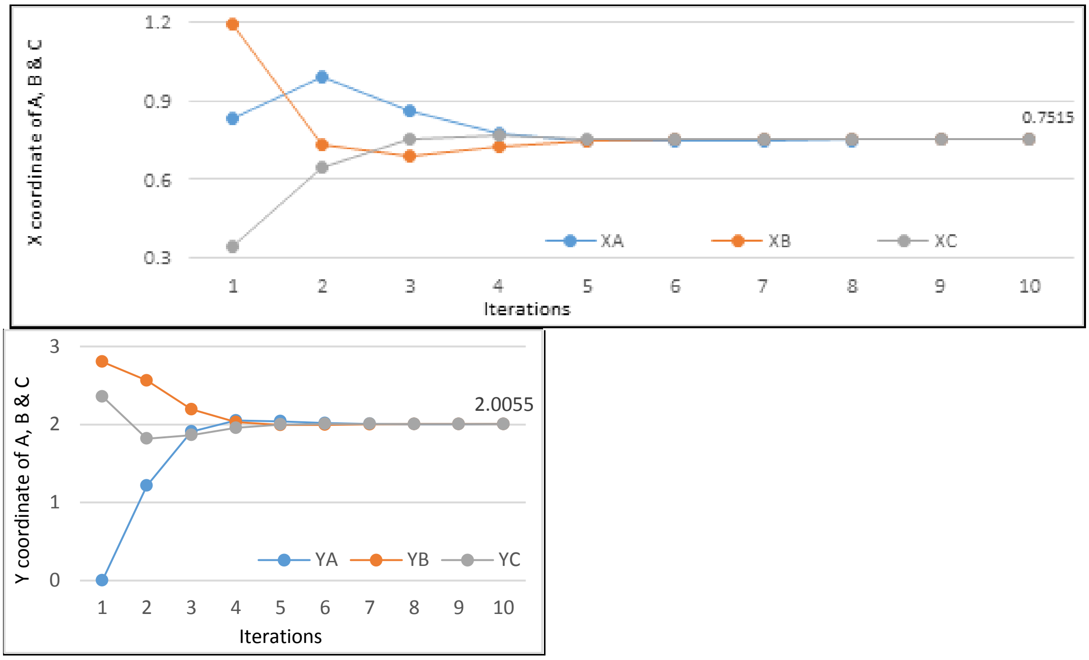


Fig. 12. Number of iterations useful for locating the MS (TCL noiseless).

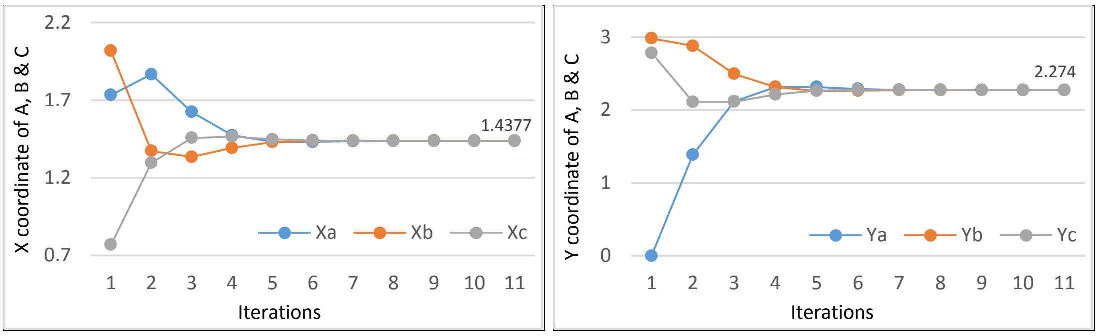


Fig. 13. Number of iterations useful for locating the MS (TCL noisy).

Fig. 14 shows the number of iterations useful to determine MS position based on COL technique. The number of iterations is mainly affected by (a) the predefined accuracy level and (b) the elementary angle value used for rotating vectors $\vec{V}_1$ and $\vec{V}_2$ during the optimization phase. The responsiveness is slightly lower with COL compared to TCL, which requires 7 iterations for MS positioning. This result has been averaged based on 30 different scenarios. **Fig. 14** outlines the number of iterations and the real and estimated (x,y) coordinates of the MS for an accuracy level of $\alpha = 0.99$. COL was also tested in a noisy channel, and the average number of iterations increased by 1.

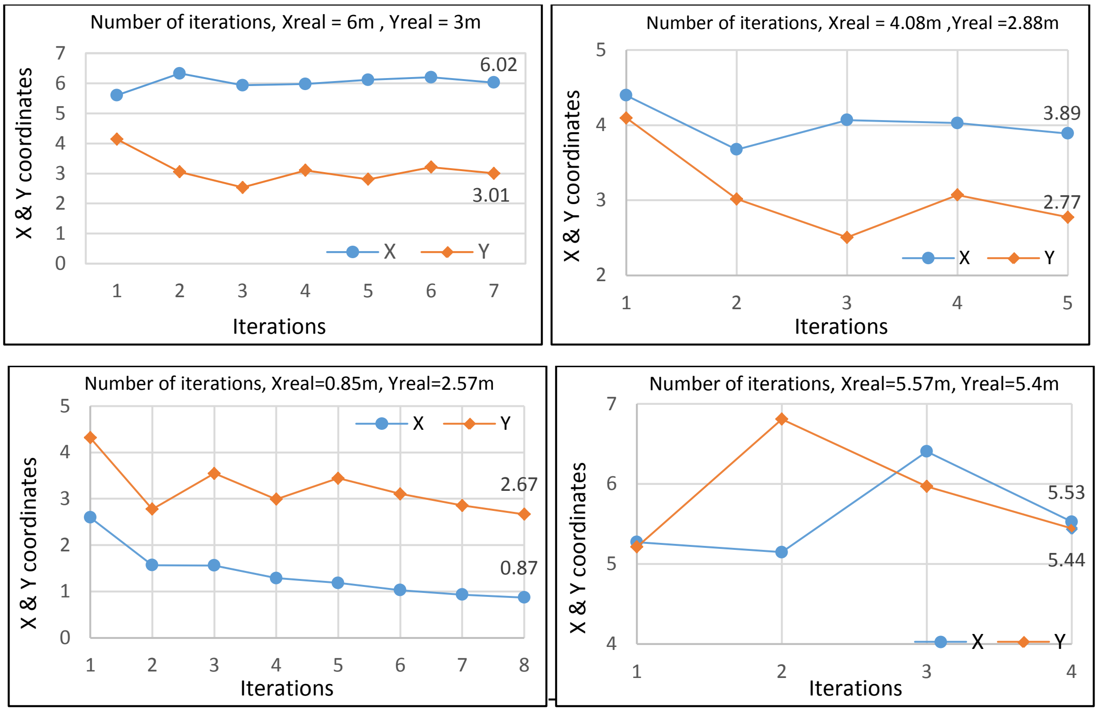


Fig. 14. Number of iterations useful for locating the MS (COL noiseless).

5. Conclusion

This paper covers different technological solutions for wireless indoor positioning and outlines several trade-offs amongst them. It proposed COL and TCL, which are recent advances in wireless indoor localization. COL and TCL are based on 2D geometric approaches consisting of trigonometric computing models. The performance of both techniques was evaluated. Accuracy, responsiveness, and scalability were considered for comparison. TCL displayed better performance particularly in terms of accuracy and responsiveness. In addition, the implementation simplicity and low computational overhead are major advantages.

In future work, two alternatives will be investigated. (1) Propagation channel modeling already realized in [51] will be considered in order to improve localization for line of sight (LOS) and non-line of sight (NLOS) positions of the MS. (2) A hardware implementation of these techniques can be designed in order to reduce the cost, an area in which most positioning systems suffer. Localization speed is also a very interesting factor in evaluating an explicit hardware implementation and proving the efficiency of these techniques for tracking.

References

[1]. A. P. Zamora, J. Vidal, D. H. Brooks, "Closed-form solution for positioning based on angle of arrival measurements," in *Proc. of 13th Sym. on Personal, Indoor and Mobile Radio Communications*, vol. 4, pp. 1522–1526, September 2002. Article (CrossRef Link)

[2]. Y. Zhao, "Standardization of mobile phone positioning for 3G systems," *IEEE Communications Magazine*, 40 (7), 108–116, 2002. Article (CrossRef Link)

[3]. C.K. Hwang, K.F. Cheng, “Wi-Fi Indoor Location Based on RSS Hyper-Planes Method,” *Chung Hua Journal of Science and Engineering*, Vol.5, No.4, pp.37-43, 2007. Article (CrossRef link)
[4]. Y. Chen and H. Kobayashi, “Signal strength based indoor geolocation,” in *Proc. of The IEEE International Conference on Communications (ICC’02), NY, USA*, vol. 1, pp. 436–439, April-May 2002. Article (CrossRef Link)
[5]. Z. Farid, R. Nordin, M. Ismail, “Recent advances in wireless indoor localization techniques and system,” *Journal of Computer Networks and Communications*, Vol. 2013, Article ID 185138, 12 pages, 2013. Article (CrossRef Link)
[6]. H. Koshima and J. Hoshen, “Personal Locator Services Emerge,” *IEEE Spectrum*, vol. 37, pp. 41-48, Feb. 2000. Article (CrossRef Link)
[7]. Sakpere, W., Adeyeye-Oshin, M. and Mlitwa, N.B.W., “A state-of-the-art survey of indoor positioning and navigation systems and technologies,” *South African Computer Journal*, 29(3), pp 145–197, 2017. Article (CrossRef Link)
[8]. Y. Xiong, N. Wu, Y. Shen, and M. Z. Win, “Cooperative network synchronization: asymptotic analysis,” *IEEE Transaction on signal processing*, Vol. 66, No. 3, pp. 757-772, Feb 2018. Article (CrossRef Link)
[9]. M. Z. Win et al., “Network localization and navigation via cooperation,” *IEEE Commun. Mag*., vol. 49, no. 5, pp. 56–62, May 2011. Article (CrossRef Link)
[10]. A. Conti, M. Guerra, D. Dardari, N. Decarli, andM. Z.Win, “Network experimentation for cooperative localization,” *IEEE J. Sel. Areas Commun*., vol. 30, no. 2, pp. 467–475, Feb. 2012. Article (CrossRef Link)
[11]. F. Subhan, H. Hasbullah, A. Rozyyev, S.T. Bakhsh, “Indoor positioning in Bluetooth networks using fingerprinting and lateration approach,” in *Proc. of the International Conference on Information Science and Applications (ICISA ’11)*, pp. 1-9, April 2011. Article (CrossRef Link)
[12]. H. J. Perez Iglesias, V. Barral, and C. J. Escudero, “Indoor person localization system through RSSI Bluetooth fingerprinting,” in *Proc. of the 19th International Conference on Systems, Signals and Image Processing (IWSSIP’12)*, pp. 40–43, April 2012. Article (CrossRef Link)
[13]. M. Vossiek, L. Wiebking, P. Gulden, J. Wiehardt, C. Hoffmann, and P. Heide, “Wireless Local Positioning,” *IEEE Microwave Mag*., vol. 4, Issue 4, pp. 77-86, December 2003. Article (CrossRef Link)
[14]. J. Hightower and G. Borriello, “Location sensing techniques,” *Technical Report UW CSE 2001-07-30, Dept. of Computer Science and Engineering, University of Washington*, 2001. Article (CrossRef Link)
[15]. R. Ouni, M. Zaidi, “EToA: New 2D geolocation-based handover decision technique” *ICT Express*, Vol.2, No.1, pp.28–32, 2016. Article (CrossRef Link)
[16]. F Yin, C Fritsche, F Gustafsson and A. M. Zoubir, “TOA-based robust wireless geolocation and Cramér-Rao lower bound analysis in harsh LOS/NLOS environments,” *IEEE transactions on signal processing*, 61(9), pp.2243-2255, 2013. Article (CrossRef Link)
[17]. B. Y Shikur and T. Weber, “Robust cooperative localization in mixed LOS and NLOS environments using TOA,” in *Proc. of 11th Workshop on Positioning, Navigation and Communication (WPNC)*, pp. 1-6, 2014. Article (CrossRef Link)
[18]. Fukuju, Y.; Minami, M.; Morikawa, H. & Aoyama, T., “Dolphin: An Autonomous Indoor Positioning System in Ubiquitous Computing Environment,” in *Proc. of IEEE Workshop on Software Technologies for Future Embedded Systems (WSTFES2003), Hakodate, Hokkaido, Japan*, pp. 53–56, May 2003. Article (CrossRef Link)
[19]. Priyantha, N.; Chakraborty, A. & Balakrishnan, H., “The Cricket Location-Support System,” in *Proc. of the 6th Annual International Conference on Mobile Computing and Networking, Boston, MA, USA*, pp. 32–43, August 6-11, 2000. Article (CrossRef Link)
[20]. Priyantha, N., Miu, A., Balakrishnan, H. & Teller, S., “The Cricket Compass for Context-aware Mobile Applications,” in *Proc. of the 7th Annual International Conference on Mobile Computing and Networking, Rome, Italy*, pp. 1–14, July 16-21, 2001. Article (CrossRef Link)

[21]. M. Hazas and A. Hopper, "Broadband ultrasonic location systems for improved indoor positioning," *IEEE Trans. Mobile Comput.*, vol. 5, no. 5, pp. 536–547, May 2006. Article (CrossRef Link)

[22]. H. Cho, Y. Kwon, "RSS-based indoor localization with PDR location tracking for wireless sensor networks," *AEU – International Journal of Electronics and Communications*, Vol. 70, Issue 3, pp. 250-256, March 2016. Article (CrossRef Link)

[23]. T. Dag, T. Arsan, "Received signal strength based least squares lateration algorithm for indoor localization," *Computers and Electrical Engineering*, Vol. 66, pp. 114–126, 2018. Article (CrossRef Link)

[24]. Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Communications Surveys & Tutorials*, Vol.11, No.1, pp.13-32, 2009. Article (CrossRef Link)

[25]. Changzhi Wang, Zhicai Shi and FeiWu, "Intelligent RFID Indoor Localization System Using a Gaussian Filtering Based Extreme Learning Machine," *Symmetry journal*, Vol. 9, No.30, 2017. Article (CrossRef Link)

[26]. Y. Jiang, A. Hu and W Jin, "A TDOA Estimation Method of PRS in LTE Systems," *Journal of Information & Computational Science*, 11(2), pp.509-517, 2014.

[27]. P. Du, S. Zhang, C. Chen, A. Alphones, W. Zhong, "Demonstration of a Low-Complexity Indoor Visible Light Positioning System Using an Enhanced TDOA Scheme," *IEEE Photonics Journal*, Vol. 10, No. 4, August 2018. Article (CrossRef Link)

[28]. D. Niculescu and B. Nath, "Ad Hoc Positioning System (APS) using AoA," in *Proc. of IEEE INFOCOM, San Francisco, CA*, vol. 3, pp. 1734–1743, Apr. 2003. Article (CrossRef Link)

[29]. A. Yassin, Y. Nasser, M. Awad, A. Al-Dubai, R. Liu, C. Yuen, R. Raulefs, E. Aboutanios, "Recent Advances in Indoor Localization: A Survey on Theoretical Approaches and Applications," *IEEE Communication Surveys & Tutorials*, Vol. 19, no. 2, pp. 1327–1346, 2017. Article (CrossRef Link)

[30]. D. Zhang, F. Xia, Z. Yang, L. Yao, and W. Zhao, "Localization technologies for indoor human tracking," in *Proc. of the 5th International Conference on Future Information Technology (FutureTech '10)*, pp. 1-6, May 2010. Article (CrossRef Link)

[31]. M. A. Youssef, A. Agrawala, and A. U. Shankar, "WLAN location determination via clustering and probability distributions," in *Proc. of the 1st IEEE International Conference on Pervasive Computing and Communications*, pp.143–150, March 2003. Article (CrossRef Link)

[32]. N. V. T. Ngo, J. G. Kim, "Sequential learning for fingerprint based indoor localization," *AEU - International Journal of Electronics and Communications*, Vol. 71, pp.105-109, January 2017. Article (CrossRef Link)

[33]. M. Brunato and R. Battiti, "Statistical learning theory for location fingerprinting in wireless LANs," *Computer Networks*, vol.47, no. 6, pp.825–845, 2005. Article (CrossRef Link)

[34]. C. L. Wu, L. C. Fu, and F. L. Lian, "WLAN location determination in ehome via support vector classification," *IEEE Int. Conf. Netw., Sens. Control*, vol.2, pp.1026–1031, 2004. Article (CrossRef Link)

[35]. N. Sundaram, P. Ramanathan, "Connectivity based location estimation scheme for wireless ad hoc networks," in *Proc. of IEEE Globecom* 2002, vol. 1, pp. 143–147, 2002. Article (CrossRef Link)

[36]. P. Singh, A. Khosla, A. Kumar, M. Khosla, "Optimized Localization of Target Nodes using Single Mobile Anchor Node in Wireless Sensor Network," *AEU - International Journal of Electronics and Communications*, vol. 91, pp. 55-65, 2018. Article (CrossRef Link)

[37]. J.J. Robles, "Indoor localization based on wireless sensor networks," *International Journal of Electronics and Communications (AEÜ)*, Vol. 68, no. 7. pp 578–580, 2014. Article (CrossRef Link)

[38]. N. Patwari, A. O. Hero, M. Perkins, N. S. Correal, and R. J. O'Dea, "Relative location estimation in wireless sensor networks," *IEEE Trans. Signal Process.*, vol.51, No.8, pp.2137–2148, Aug. 2003. Article (CrossRef Link)

[39]. Han, S.; Lee, S.; Lee, S.; Park, J.; Park, S. "Node distribution-based localization for large-scale wireless sensor networks," *Wireless Networks*, Vol. 16, pp. 1389–1406, 2010. Article (CrossRef Link)

[40]. Chen, H.; Shi, Q.; Tan, R.; Poor, H.V.; Sezaki, K. "Mobile element assisted cooperative localization for wireless sensor networks with obstacles," *IEEE Trans.Wirel. Commun*., Vol. 9, pp. 956–963, 2010. Article (CrossRef Link)

[41]. M. Singh, P.M. Khilar, "An Analytical Geometric Range Free Localization Scheme Based on Mobile Beacon Points in Wireless Sensor Network," *Wireless Networks*, Vol. 22, No. 8, pp. 2537–2550, 2016. Article (CrossRef Link)

[42]. Mei, J., Chen, D., Gao, J., Gao, Y., Yang, L., "Range-free Monte Carlo localization for mobile wireless sensor networks," in *Proc. of International Conference on Computer Science and Service System, Nanjing, China*, pp. 1066–1069, 11–13 August 2012. Article (CrossRef Link)

[43]. A. K. Paul, T. Sato, "Localization in wireless sensor networks: A Survey on algorithms, measurement techniques, applications and challenges," *Journal of sensor and actuator networks*, Vol. 6, No. 24, pages 23, 2017. Article (CrossRef Link)

[44]. Zhao, X., Rautiainen, T., Kalliola, K., and Vainikainen, P., "Path-Loss Models for Urban Microcells at 5.3 GHz," *Antennas and Wireless Propagation Letters*, Vol. 5, Issue 1, pp.152 – 154, December 2006. Article (CrossRef Link)

[45]. V.S. Abhayawardhana, I.J. Wassell, D. Crosby, M.P. Sellars, M.G. Brown, "Comparison of Empirical Propagation Path Loss Models for Fixed Wireless Access Systems," in *Proc. of IEEE 61st Vehicular Technology Conference – VTC, Stockholm, Sweden*, pp 73-77, December 2005. Article (CrossRef Link)

[46]. T.K. Blankenship, D.M. Kriztman, and T.S. Rappaport, "Measurements and simulation of radio frequency impulsive noise in hospitals and clinics," in *Proc. of IEEE Vehicular Technology Conference (VTC'97)*, vol. 3, pp.1942–1946, 1997. Article (CrossRef Link)

[47]. M. Zaidi, R. Ouni, J. Bhar, R. Tourki, "A novel positioning technique with low complexity in wireless LAN: hardware implementation," *The World Congress on Engineering*, Vol. II, July 6 - 8, 2011. Article (CrossRef Link)

[48]. M. Zaidi, J. Bhar, R. Ouni and R. Tourki, "Reducing Wi-Fi handover delay using a new positioning process," in *Proc. of* The *International Conference on Communications, Computing and Control Applications (CCCA'11)*, 2011. Article (CrossRef Link)

[49]. K. Seada and A. Helmy, "Efficient Geocasting with Perfect Delivery in Wireless Networks," in *Proc. of IEEE International Conference on Wireless Communications and Networking, Atlanta*, 2004. Article (CrossRef Link)

[50]. H. A. Karimi and P. Krishnamurthy, "Real-Time Routing in Mobile Networks Using GPS and GIS Techniques," in *Proc. of The 34th Hawaii International Conference on System Sciences (HICSS'01), Maui, Hawaii*, January 2001. Article (CrossRef Link)

[51]. M. Zaidi, R. Ouni, R. Tourki, "Wireless propagation channel modeling for optimized handoff algorithms in wireless LANs," *Computers and Electrical Engineering*, Vol. 37, pp. 941-957, 2011. Article (CrossRef Link)

Ridha OUNI. is Associate professor in the department of computer engineering, college of Computer and Information Sciences, King Saud University, since Feb 2009. He received his HDr in wireless networking field in 2015 from the University of Monastir, Tunisia. His research interests include wireless sensor networks, mobility & QoS management, networks interoperability and Internet of Things.

Previously, he received his Ph.D from the University of Monastir in cooperation with the "Institut Polytechnique de Grenoble", France in 2002. He was Assistant Professor in the 'Institut Préparatoire aux Études d'Ingénieurs de Monastir (IPEIM)', Tunisia, from 1999 to 2009.

Monji ZAIDI. is Assistant professor in the college of engineering of King Khaled University, KSA, since Sep 2014. He was Assistant Professor in the 'Institut Superieur d'Informatique de Monastir (ISIM)', Tunisia, since 2013. His research interests include Management of WLAN technologies, mobility and hardware implementation.

Previously, he received his B.s degree in electrical engineering for automation and processes control in 2005 from the National engineer's school of Sfax (Tunisia) and his Master degree in Nanostructures, devices and micro-electronics systems and his Ph.D degree in electronic and communication from the University of Monastir in 2007 and 2011, respectively.

Wadood Abdul received his Ph.D. in signal and image processing from the University of Poitiers, France, in 2011. Currently, he is working as an Associate Professor in the Department of Computer Engineering, CCIS, King Saud University. His research interests are focused on color image watermarking, multimedia security, steganography, fingerprinting, and biometric template protection.

Maazen Alsabaan received the B.S. degree in the electrical engineering, from King Saud University, Saudi Arabia, in 2004, the M.A.Sc. and Ph.D. degrees in Electrical and Computer Engineering from University of Waterloo, Canada, in 2007 and 2013, respectively. He is currently an Assistant Professor in the Department of Computer Engineering, King Saud University (KSU), Saudi Arabia. He was the Chairman of the department from 2015 to 2018. Dr. Alsabaan serves as a consultant in deferent agencies and awarded many grants from KSU and King Abdulaziz City for Science and Technology (KACST). Dr. Alsabaan has a publication record with 8 journal papers, most of them are published in the IEEE prestigious journals. He is an associated editor of Circuits, Systems and Computers Journal. His current research interests include surveillance systems, vehicular networks, green communications, intelligent transportation systems, and cybersecurity.

Dr. Amr is an Associate Professor of Electrical and Computer Engineering, and the Director of the National Center for Telecommunication Systems and Command and Control Technology at King Abdulaziz City for Science and Technology in Riyadh, Saudi Arabia. Previously, Dr. Amr was the Co-director of the Joint Center of Excellence for Future Telecommunication with The University of California at San Diego (UCSD), and the Director of the Joint Center of Excellence in Wireless Communication and Mobile Computing with Huawei. He was a visiting researcher at UCSD in 2015 working in Qualcomm institute. His research areas focus on design and performance evaluations of communication and computer network protocols, architectures and management strategies of telecommunications and computer networks, with applications in wireless communities, mesh networks, mobile, sensor, cloud computing, smart grid, and broadband networks. In 2013, Dr. Amr obtained his PhD in electrical and computer engineering from the University of British Columbia, Vancouver - Canada. In 2005, he got his Master of Science in electrical and computer engineering from the University of Southern California, Los Angeles - USA; and got his Bachelor of Engineering in the field of Electrical Engineering from King Saud University, Saudi Arabia in 2000. During his Ph.D. research, he worked on the problem of content sharing and distribution in a wireless mesh community network (WMCN). His dissertation studied the technical challenges involved while deploying P2P applications over WMCNs and proposed innovative schemes to enhance the performance while reduce energy and bandwidth consumption in the network. Currently, he is working on software defined networking; cloud computing, and internet of things and its applications in health and industry. Dr. Amr authored over 50 research papers in premium international conferences and prestigious international journals including IEEE Transactions, IET, ACS applied materials & interface, ACM Wireless networks, IEEE Globecom, IEEE ICC, IEEE Pimrc, IEEE WNCC, and other. He also co-authored a book chapter in Cloud computing, architecture and applications published by INTECH. He also has 7 patents granted by The United States Patent and Trademark Office. He is also the principal investigator of a number of national research projects including Software Defined Networking, and Internet of Things.