A New Time-Based Algorithm for Positioning Mobile Terminals in Wireless Networks

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This paper presents a positioning algorithm, named time of arrival to time difference of arrival (TOAD), which computes time-difference-of-arrival (TDOA) measurements from the messages that time-of-arrival (TOA) stations in sight exchange while their positioning processes are running. This study addresses the accuracy of the TOAD algorithm in two different environments: line-of-sight (LOS) and non-line-of-sight (NLOS). Simulation is used to set up a wireless network. The Gauss-Newton nonlinear least squares algorithm is used to compute the positions in both TOA and TOAD stations. Results indicate that the TOAD algorithm increases the root mean square error (RMSE) of the positioning error in LOS scenarios by 10 to 20% compared with the RMSE achieved by TOA. This drop in accuracy contrasts with the results for the NLOS scenarios. The RMSE of TOAD in such scenarios is at least 10% lower than that achieved by TOA. This result is specially important since this latter scenario is the most common. Consequently, this novel technique therefore improves the scalability and integrity of TOA techniques based on RTT, making it possible for the stations to position themselves without injecting traffic and with QoS figures close and most times better than that achieved by TOA.

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1. INTRODUCTION

In recent years, customer location has become particularly relevant in the case of wireless networks. Official regulators see location as a way of improving public safety by reducing emergency call response times. For instance, the Federal Communications Commission (FCC) made a proposal to include location in the 911 emergency service number, which resulted in the E911 ruling [1]. Currently, all the legacy handsets used in public cellular networks in the USA must provide the location of the customer whenever this number is dialed. The European Commission (EC) adopted a similar regulation to include location in emergency services on 112 [2].

In this scenario, network operators see location as a great opportunity for deploying new value-added services based on location [3, 4]. This set of new services would have a twofold impact, namely, it would increase the current revenue per user and outperform competitors. Location services would also allow smarter management approaches to be used [5]. To date, only a few location-based services (LBSs) have been implemented for the mass market, as factors such as low-bandwidth channels, and the lack of definition of location system architectures and protocol stacks are delaying their introduction. The recent deployment of the last generation of 3G networks has removed some of these factors, but other issues, such as the mismatch between QoS offer and demand and reduced availability in some scenarios, remain.

Several location techniques are ready for deployment: cell identification, terrestrial signal triangulation, satellite navigation, angle of arrival, and so forth [6–10]. Smart combinations of techniques are also proposed [11–13]. All of them provide a certain degree of quality of service (QoS), which is usually measured in terms of accuracy, response time, availability, and consistency [14]. The QoS provided by these techniques is usually enough for most of the location-based services provided on public cellular networks. However, there are specific scenarios and services that require QoS figures that cannot be achieved by means of the standard
location techniques deployed on these networks. For instance, the particularities of indoor scenarios, in which there is a drastic reduction in signal penetration and severe multipath, mean that most of the location techniques fail to provide a sufficiently accurate position. Therefore, location techniques specifically for indoor positioning have been developed [15–18]. All these indoor techniques are intended for wireless networks that are likely to be deployed in indoor environments, such as 802.11 networks, ZigBee networks, and so forth.

There are many solutions for indoor positioning, which can be grouped into two categories: solutions requiring custom hardware and solutions requiring software modifications only. Custom hardware usually provides the best performance in terms of accuracy. For instance, ultra-wide band (UWB) solutions based on time of arrival (TOA) [19, 20] provide accuracy in the order of centimeters. The drawback is that these techniques usually need specific signal transmitters, which do not work with legacy terminals. New terminals must therefore be developed and delivered to customers. Furthermore, some techniques do work with legacy terminals only if the software is updated. They use the resources of the wireless network to compute the position, which precludes the need for additional hardware. Cell-ID was the first technique that was proposed for use with legacy terminals, but poor accuracy figures meant that it was useless in indoor environments. Fingerprinting is another well-known example of indoor techniques [21]. It computes the position that best matches the received signal strength from several transmitters with the data stored in a previously built offload database. A great deal of research has been carried out on positioning customers by means of fingerprints on 802.11 networks [21–23]. Most of these solutions provide good accuracy and availability results. The drawback is that any change in the environment involves a database update, which makes the maintenance of this technique costly.

The use of TOA indoors shows promising according to the latest research published on the topic [13, 15, 19, 24]. The advantage of TOA-based techniques over fingerprinting is that they achieve a similar degree of accuracy but do not need further database maintenance. However, the techniques based on TOA reduce the goodput of the network and usually suffer from multipath in non-line-of-sight conditions. This drawback seriously compromises the scalability of the technique and its application to certain services, most of which are related to intensive traffic, such as tracking, tracing, and safety.

This paper introduces a novel positioning algorithm that aims to extend the capabilities of the two-way TOA techniques (i.e., those based on round-trip-time or RTT). It consists in turning the time-of-arrival measurements taken by a TOA station into TDOA measurements, which are used in a station that is not using TOA. This algorithm aims to provide accurate figures that are similar to those provided by TOA and, at the same time, to improve the scalability and integrity of such techniques, which are usually constrained. The rest of the paper is structured as follows. Section 2 presents the proposed positioning algorithm, provides its analytical formulation and few comments about the accuracy expected from the technique. Section 3 presents positioning errors resulting from this new algorithm, evaluated on the basis of TOA performance. Finally, Section 4 provides the main conclusions.

2. TOAD POSITIONING ALGORITHM

2.1. Introduction

Recent advances in indoor positioning have led to proposals that TOA techniques for locating users are preferable to other techniques such as fingerprinting. TOA achieves accuracy figures that are similar to those obtained by other techniques but it does not require additional assistance for setup and maintenance. However, TOA techniques need to calculate a client’s range from at least three receivers at known positions in order to obtain a 2D position. In addition, all the signal transmitters involved in the TOA positioning system must be synchronized. Two-way TOA techniques cope with this issue [15, 25] by computing the range from the client to the base station (or bearer) using an RTT procedure. Since only the client’s clock is used to calculate the range, synchronization between base stations (or bearers) is no longer necessary. The drawback is that more traffic is generated on the network, thus reducing its goodput.

The technique presented in this paper extends the capabilities of TOA location techniques, allowing stations in a network to position themselves without injecting traffic into the network. Thus, TOAD stations benefit from the TOA positioning processes that are taking place around them. The only requirement is that TOA positioning must be based on the RTT in a diffusion network.

2.2. Proposed algorithm

The performance of the positioning algorithm is described in Figure 1. The IEEE 802.11 notation is only used for the purposes of explanation. Figure 1 shows a network with three access points (APs) and two stations: MS1 and MS2. At a given
time, $MS_1$ begins a TOA positioning process to locate itself. Thus, $MS_1$ sends message (1) to $AP_1$ at $t_1$, which replies with message (2), which reaches $MS_1$ at $t_2$. The corresponding RTT is hence calculated as $t_2 - t_1$. Note, however, that other stations in the network also listen to all these messages, since it is a diffusion network. Thus, $MS_2$ hears message (1) at $t_3$ and the reply to that message, (2), is at $t_4$. Therefore, a TDOA measurement is generated as $t_4 - t_1$. The same process is followed by $MS_2$ to range with $AP_2$ and $AP_3$. Based on the assumption that $MS_2$ is only covered at $AP_1$ and $AP_3$, $MS_2$ is able to calculate two TDOAs: $t_4 - t_3$ and $t_7 - t_6$. These two measurements are enough to position $MS_2$ using a TDOA technique. Note that the TDOA position calculated at $MS_2$ involves hearing just two access points, which makes it possible for positioning to take place where TOA techniques would be ineffective. The only data needed by $MS_2$ in addition to the TDOA measurements is the position of $MS_1$. Therefore, once the TOA positioning is over, $MS_1$ must broadcast its position. This is not mandatory, however, since the positions of $MS_1$ and $MS_2$ can both be estimated at $MS_2$ if a sufficient number of TDOA measurements are available. Group services may find this approach extremely useful, as several people are known to be under the same reception conditions, that is, close enough. However, this is beyond the scope of this paper. Nevertheless, the authors assume that the positions of TOA-located stations are known by the rest of the stations nearby, because these positions have been broadcast once they have been estimated for example.

### 2.3. Applications of the TOAD algorithm

The TOAD algorithm has multiple applications in the field of location. The first has been discussed above, and consists in allowing a mobile station to be positioned without injecting traffic into the network. Figure 1 shows how TOAD is able to position a customer who only has two access points in sight. Under the same conditions, the TOA technique is not able to provide a location since this technique requires three transmitters to perform a 2D trilateration.

The TOAD algorithm would be able to go further in positioning under constrained scenarios. In fact, this technique would be able to compute the position of a station with just one access point in sight, by coupling the TOA measurements with the TOAD measurements. This makes the TOAD algorithm a very interesting solution for positioning under extreme conditions, such as in scenarios in which there is interference.

Additionally, TOAD improves the integrity of TOA techniques. The improvement is twofold: TOAD positioning can be performed in scenarios in which standalone TOA techniques are not able to compute a customer’s position; it is also able to mitigate the impact of some access points being down (e.g., due to maintenance, fire damage, etc.). Since TOAD can work with a fewer number of APs, it helps the system to continue to offer location-based services in those circumstances which TOA is not able to provide some positions.

All these applications of the TOAD algorithm give rise to dramatic improvements in the scalability of the system, since more customers can be located while only a few TOA positioning processes are running. Note, however, that all the applications of the TOAD algorithm depend on the accuracy expected from them, since a large error in the positions computed by TOAD will make these positions useless and, therefore, system scalability will not increase at all. This work analyzes the accuracy expected from TOAD under several conditions and compares it with the positioning error achieved by the TOA algorithm.

### 3. POSITION COMPUTATION BY MEANS OF TOAD

The TOAD algorithm may involve TDOA measurements from a single station, as shown in Figure 1, or from several stations. For the sake of simplicity, this paper focuses on the first case and leaves TDOA measurements taken from multiple stations as a subject for further research.

As shown in the diagram in Figure 1, TOAD stations need to store several pieces of data to carry out the technique. First of all, two matrices are stored in the TOAD station:

$$P = \begin{bmatrix}
AP_1(x) & AP_1(y) & AP_1(z) \\
\vdots & \vdots & \vdots \\
AP_n(x) & AP_n(y) & AP_n(z)
\end{bmatrix},$$

$$Q(t) = \begin{bmatrix}
MS_1(x,t) & MS_1(y,t) & MS_1(z,t) \\
\vdots & \vdots & \vdots \\
MS_m(x,t) & MS_m(y,t) & MS_m(z,t)
\end{bmatrix}.$$  \(1\)

$P$ and $Q$ gather the positions of the access points and mobile stations, respectively. The data stored in $P$ are static, that is, once the position of an access point is known, it is assumed that it does not change. However, data gathered by $Q$ are likely to change, since the TOAD station and the mobile stations surrounding it are moving continuously. However, in order to simplify the analysis, the $Q$ matrix is also considered to be static while the algorithm is running. Note that this assumption does not undermine the generality of the algorithm.

Access point positions are assumed to be available on the network (e.g., preloaded in terminals, broadcast across the network, etc.) and hence terminals build the $P$ matrices easily. The $Q$ matrix gathers the positions of the neighbors. In this paper, it is assumed that TOA stations broadcast their positions once they have been calculated. However, other approaches can be followed, such as computing the positions of TOA stations in the TOAD station, provided a sufficient number of TDOA measurements that are available. The impact of spreading the computed TOA positions is beyond the scope of this paper and will be addressed in future research.

Using $P$ and $Q$, the TOAD algorithm builds two new matrices. The first one is the ranging matrix:

$$R = \begin{bmatrix}
A & B & \cdots & C \\
\vdots & \vdots & \ddots & \vdots \\
D & E & \cdots & F
\end{bmatrix},$$  \(2\)
where $A$ denotes Ranging($MS_1, AP_1$), $B$ denotes Ranging($MS_1, AP_2$), $C$ denotes Ranging($MS_1, AP_n$), $D$ denotes Ranging($MS_m, AP_1$), $E$ denotes Ranging($MS_m, AP_2$), and $F$ denotes Ranging($MS_m, AP_n$). From (5), we obtain

\[ MS_i TDOA(MS_m, AP_t) = \sum_{j=1}^{n} \left( T(i, j) - R(i, j) \right)^2 \]  

Subsequently, by subtracting $W(i, k)^2$ from the left- and right-hand sides of (7) we obtain

\[ T(i, j)^2 + 2T(i, j)\left[ W(i, k) - R(i, j) \right] + R(i, j)^2 - 2R(i, j)W(i, k) = X_i^2 + Y_i^2 + Z_i^2 - 2X_iX_k - 2Y_iY_k - 2Z_iZ_k \]

\[ + X_k^2 + Y_k^2 + Z_k^2 - W(i, k)^2 \]

\[ = (X_i^2 + Y_i^2 + Z_i^2) - (X_k^2 + Y_k^2 + Z_k^2) - (2X_iX_k + 2Y_iY_k + 2Z_iZ_k) \]

\[ + (2X_iX_k + 2Y_iY_k + 2Z_iZ_k). \]

By moving the unknowns to the left, we obtain

\[ X_iX_k + Y_iY_k + Z_iZ_k + [T(i, j) - R(i, j)] \cdot W(i, k) = \frac{1}{2} \left[ (X_i^2 + Y_i^2 + Z_i^2) - (X_k^2 + Y_k^2 + Z_k^2) - T(i, j)^2 \right] \]

\[ - R(i, j)^2 + T(i, j)R(i, j), \]

where $X_i, Y_i, Z_i$ and $X_j, Y_j, Z_j$ are $X_i - X_j, Y_i - Y_j, Z_i - Z_j$, respectively. According to (9), the equation system can be rewritten as

\[ \begin{bmatrix} X_{ij} & Y_{ij} & Z_{ij} \end{bmatrix} \begin{bmatrix} T(i, j) - R(i, j) \end{bmatrix} = \begin{bmatrix} X_k & Y_k & Z_k \end{bmatrix} \begin{bmatrix} W(i, k) \end{bmatrix} \begin{bmatrix} B_{ij} \end{bmatrix} \begin{bmatrix} B_{ij} \end{bmatrix} \begin{bmatrix} B_{ij} \end{bmatrix} \]

and solved by conventional linear approaches such as linear least squares or nonlinear least-squares algorithms [26].
Figure 2: Computation of the distance error between TOA and TOAD stations.

Since errors in (13) may be correlated, this equation can be expressed as

\[ E[e_i^2] \leq E[(e_{R_i})^2] + E[(e_{R_u})^2] + E[(e_v)\hat{e}_i^2]. \]  

(15)

Figure 2 displays the errors involved in the computation of the distance between two estimated positions: \(Q_u\) and \(Q_v\). In this figure, \(e_u\) and \(e_v\) are the modules for the error involved in each position, and \(\alpha_u\) and \(\alpha_v\) are the phases of these errors. According to Figure 2,

\[ \hat{W} = \sqrt{B1 + (W \sin(\alpha_u) + e_v \sin(\alpha_i) - e_u \sin(\alpha_u))^2}, \]

\[ \hat{W} = \sqrt{e_i^2 + e_v^2 + W^2 + B2 - 2e_v e_u \cos(\alpha_v - \alpha_u)}, \]

(16)

where \(B1\) denotes \((W \cos(\alpha_v) + e_v \cos(\alpha_v) - e_u \cos(\alpha_u))^2\), \(B2\) denotes \(2W[e_v \cos(\alpha_v - \alpha_u) - e_u \cos(\alpha_u - \alpha_u)]\).

Thus, the error in the distance computation is the following:

\[ E[(W - \hat{W})^2] = E[(W)^2] + E[(\hat{W})^2] - 2E[W \hat{W}], \]

(17)

\[ E[(W - \hat{W})^2] = E[(W)^2] + E[e_i^2] + E[e_v^2] + W^2 \]

\[ + E[2W(e_v \cos(\alpha_v - \alpha_u) - e_u \cos(\alpha_u - \alpha_u)) \]

\[ - 2e_v e_u \cos(\alpha_v - \alpha_u)] - 2E[W \hat{W}], \]

(18)

\[ E[(W - \hat{W})^2] = E[W^2] + E[e_i^2] + E[e_v^2] + E[W^2] - 2E[W \hat{W}], \]

(19)

\[ E[(W - \hat{W})^2] = E[e_i^2] + E[e_v^2] + 2E[W^2] - E[W \hat{W}], \]

(20)

Finally, (20) can be rewritten as

\[ E[(W - \hat{W})^2] = E[e_i^2] + E[e_v^2] - 2E[W \hat{W}], \]

(21)

where \(\hat{W}_e\) stands for the bias of the distance estimator, that is, \(W - E[\hat{W}]\). This bias could be positive or negative, so neither upper nor lower bounds can be set to (21). Therefore, assuming that \(\hat{W}\) is an unbiased estimator of \(W\), (21) may be expressed as

\[ E[(W - \hat{W})^2] = E[e_i^2] + E[e_v^2]. \]

(22)

In accordance with (21), we can rewrite (15) as

\[ E[e_i^2] \leq (E[e_i^2] - 2R_{ij} \hat{W}_e) + (E[e_v^2] - 2R_{kj} \hat{W}_e) \]

\[ + (E[e_i^2] + E[e_v^2]) - 2R_{ij} \hat{W}_e, \]

(23)

where \(e_i\) and \(e_k\) stand for the positioning errors of the TOA and TOAD stations, respectively. Equation (23) can be rewritten as

\[ E[e_i^2] \leq 2(E[e_i^2] + E[e_v^2] - 2R_{ij} \hat{W}_e). \]

(24)

Equation (24) provides a way of relating the MSE of differences in distance (i.e., the values of matrix \(T\)) to the MSE of the position of the TOAD station. Under the unbiased assumption made for (22), we finally obtain

\[ E[e_i^2] = 2(E[e_i^2] + E[e_v^2]). \]

(25)

4. TOAD PERFORMANCE ASSESSMENT

4.1. Procedure and scenarios

This section provides an empirical analysis of TOAD performance. Montecarlo simulations were carried out to characterize the TOAD positioning error. Real data was not used in this study since it conditions the results with a specific hardware/software implementations, and the purpose of the paper is to study the performance expected for TOAD.

The simulated scenario consisted of four access points placed at the corners of a square-shaped simulation area and two stations, one of which used TOA positioning, whilst the other used the TOAD positioning algorithm. The simulations were performed as follows. First of all, the two stations were uniformly placed in the simulation area. The TOAD station then computed its position using the TOA technique. The TOAD station used the differences in distance taken from the TOA procedure and estimated its position. This procedure was repeated for 1000 random positions in the case of the TOAD station, whilst the TOA station was kept in the same position. Finally, the whole procedure was run for 1000 random positions for the TOAD station. The Gauss-Newton nonlinear least-squares method [27] algorithm was used to compute the position of the two stations. The measurements used to compute the position were degraded by the communication channel and thermal noise at receivers. No other sources of error, such as those derived from the measurement system, are included. Dilution of precision due to the geometry of the access points or the TOA stations is also beyond the scope of this paper and will be the subject of further research.
Two basic scenarios are accounted for: line of sight (LOS) and non-line of sight (NLOS). The ranging error model that applies to each scenario is extracted from [27] and is computed as

$$e_d = (d - \hat{d}) = W_G \ast \text{Gaussian}(0, \sigma) + W_E \ast \text{exponential}(1/\lambda),$$

(26)

where $d$ is the actual distance, $\hat{d}$ is the estimated distance, Gaussian$(0, \sigma)$ stands for a Gaussian variable of the zero mean and standard deviation of $\sigma$, exponential$(1/\lambda)$ is an exponential random variable with an average of $1/\lambda$, and $W_G$ and $W_E$ are the gains for the Gaussian and exponential channel components. The values for the parameters in (26) proposed in [27] are displayed in Table 1. As can be seen, the ranging error in the LOS scenario is white noise, where $\sigma$ is the root MSE (RMSE) of the ranging error. In the case of LOS, $\sigma$ was multiplied by two until 1.7408 was reached. Therefore, the ranging error in the NLOS scenario involves an average that is different to zero, which means that the ranging error RMSE must be increased if it is to be compared with equivalent figures in the LOS scenario.

The values shown in Table 1 are proposed for use in UWB location systems. The literature available about indoor ranging models in other technologies is scarce. Hence, the TOAD positioning algorithm was evaluated using different values for the RMSE of the ranging error. In the case of LOS, $\sigma$ was multiplied by two until 1.7408 was reached. Therefore, the TOAD positioning algorithm was evaluated using an RMSE of the ranging error that varied from millimeters to meters. The same approach was applied to NLOS. However, in this case the RMSE of the ranging error was modified by means of the $\lambda$ parameter. The reason for not changing $\sigma$ was that the effect of tuning this parameter is seen in the LOS scenario. Furthermore, the particularity of NLOS is the inclusion of the exponential term in the ranging error calculation. Thus, values that range from millimeters to meters were also taken for the RMSE of the ranging error in NLOS scenarios. Finally, various distances between access points were simulated to evaluate the dependence of the algorithm on the distance to the access points. Based on current WLAN network deployments, three distances were explored: 10, 20, and 30 meters.

### 4.2. Performance evaluation

In the two scenarios, the RMS TOA error shows a linear dependence on the ranging error and achieves an excellent performance: less than 1.5 and 2 times the ranging error for LOS and NLOS scenarios, respectively. This technique would not appear to be sensitive to the separation between access points in LOS scenarios. In the NLOS scenarios, distance between access points shows little impact on TOA error. As expected, the dependence of RMS TOA error on the access point distance is more noticeable if the distances between the access points are shorter. In such cases, ranging errors are more likely to constrain the position calculation algorithm.

The performance obtained by TOAD is shown in Figure 3. This figure plots the evolution of the RMS of the positioning error made by the TOAD algorithm and the standard two-way-based TOA technique against the RMS of the ranging error in LOS and NLOS scenarios. The figures between brackets indicate the distance between access points.

When TOAD positions were calculated, divergence was detected in the Gauss-Newton method in some situations, which resulted in clear outliers [26]. In contrast, TOA positioning using the Gauss-Newton approach is more likely to converge and, in fact, divergences in the values of the positions were extremely rare. The reason for this dual behavior is the error introduced by the known positions. The Gauss-Newton algorithm applied to the TOA technique computes positions using perfectly known signal-transmitter positions (i.e., the position of the access points assumed to include no error). However, the TOAD algorithm uses the estimated TOA position to locate customers. It introduces an additional error that makes the Gauss-Newton algorithm more sensitive to the ranging error and hence less likely to converge. This degradation in the performance of the Gauss-Newton algorithm is more noticeable when distances between access points are shorter, since it is more likely that ranging errors and distances to the access points become comparable magnitudes.

As expected, the TOAD algorithm follows the linear dependence on the ranging error shown for the TOA technique. However, the error of the TOAD algorithm seems to be higher than the error achieved by the TOA technique, since a greater number of noisy measurements are used to compute the position. However, there are several differences between the LOS and NLOS scenarios. In the case of LOS, the RMSE of TOAD increases quickly from very low values of the ranging error. The results for the RMS error in the case of the NLOS scenario are much more surprising, even more so if the limitations introduced above for the Gauss-Newton algorithm applied to TOAD are taken into account. In this scenario, the Gauss-Newton algorithm seems to be less sensitive to the ranging error. In the case of the scenario in which the access points are separated by 10 meters, the convergence issue is still present but starts to be noticeable at higher ranging error values. In scenarios in which the distance between access points is greater (i.e., 20 and 30 meters), convergence is much smoother as the ranging error increases, which indicates that TOAD performance is

| Scenario | Gaussian parameters | Exponential parameters |
|----------|---------------------|------------------------|
| LOS      | $W_G = 1; \sigma = 0.0068$ meters | $W_E = 0; \lambda = 1$ meters$^{-1}$ |
| NLOS     | $W_G = 0.26; \sigma = 0.0129$ meters | $W_E = 0.74; \lambda = 8.433$ meters$^{-1}$ |
better in NLOS than in LOS scenarios. In fact, the RMSE of the TOAD algorithm is very close to the figures achieved with the TOA technique. This is due to the exponential noise component of the ranging error present in NLOS scenarios. The TOAD algorithm is able to mitigate this component, because exponential noise always yields positive values and is likely to generate errors of a similar magnitude. The computation of the differences in distance involves subtracting terms that are thus affected by similar noise values and hence reduces the RMSE of the algorithm. As a result, the TOAD positioning algorithm performs better in NLOS scenarios than in scenarios with access points in sight.

As seen in Figure 3, the outliers given by the Gauss-Newton algorithm make the RMS error figures higher, thus distorting the performance results. Therefore, the outliers that were subsequently detected were removed from the results, which explains why the use of other nonlinear system equation algorithms is able to provide valid positions under the same conditions and further improves the results. The filter criterion is the following: positions with an RMSE higher than the distance between access points are filtered. Note that this is a conservative approach, since it doubles the error expected from the Cell-ID.

Figure 4 plots the percentage of TOAD locations that diverge. As shown, the most severe filtering is applied to the scenarios whose access points are placed 10 meters apart: 12 and 9% of the positions in the LOS and NLOS environments, respectively. Figure 4 shows less aggressive outlier filtering with greater distances between the access points: less than 4 and 1.5% of positioning processes do not converge in the LOS and NLOS scenarios, respectively.
More realistic figures on TOAD performance are obtained if TOAD accuracy is normalized by the RMS TOA error. Figure 5 plots the normalized RMS for TOAD error for which the positioning processes that diverge (see Figure 4) have been filtered. The figures between brackets indicate the distance between the access points. The results show the excellent performance of the TOAD technique in terms of accuracy, which is even greater according to the scarce requirements demanded by the technique. RMS errors for the lowest ranging errors are slightly higher than those achieved using the TOA technique. In fact, it is expected that most of the environments provide ranging errors of less than 0.1 meters (see the reference scenarios in Table 1). Under these ranging errors, the TOAD positioning algorithm increases the RMSE derived from the TOA technique by only 10 to 20%. Note also that at these ranging errors, the Gauss-Newton algorithm works perfectly and only a few outlayers are reported. This is the result of having a location that is almost as accurate as TOA, but in which it is only necessary to listen to the air interface. Consequently, TOAD improves the scalability of TOA location systems, and there is thus an increase in the location traffic that the network is able to carry.

The accuracy of the TOAD algorithm differs drastically in LOS and NLOS scenarios when RMS ranging errors rise above 0.1 meters. In the case of LOS, the RMSE of TOAD starts to increase until the presence of outlayers is noticeable, and the filter starts working. Figure 5 shows that at this stage the RMSE of TOAD is at most 1.6 times the RMSE of TOA. Beyond this point, the greater the ranging error is, the more the detected and filtered outlayers and, hence, the RMSE of TOAD tend to decrease (up to less than 1.4 times the RMS TOA error). In the case of NLOS scenarios, the behavior is the opposite. The higher the ranging error, the lower the RMSE of TOAD. This is due to the fact that the NLOS ranging error has a bias (i.e., it does not have a zero mean). The TOAD algorithm benefits from the fact that the TOA station is the source of all the TDOA measurements, which are used to reduce the exponential noise in the ranging error. It is therefore possible to obtain a greater degree of accuracy than that obtained using the TOA technique: up to 0.9 and 0.67 times the RMS TOA error in scenarios with access points 10 and 30 meters apart, respectively. In fact, this good performance is also shown in Figure 4, in which lower outlayer percentages are shown in NLOS scenarios. The good performance of TOAD in NLOS scenarios is a very important feature since NLOS is the constrained scenario and the most frequent one. Therefore, this improvement on the accuracy will impact noticeably on the average accuracy of the location system. Better results are expected when tracking algorithms are used rather than pure positioning algorithms such as the Gauss-Newton nonlinear least-squares algorithm.

According to the data in Figure 5, the RMSE of TOAD in NLOS scenarios can be rewritten as a linear expression such as

$$\text{RMS}_{\text{TD}} = (\alpha \cdot \text{RMS}_{\text{Ranging}} + \beta) \cdot \text{RMS}_{\text{TOA}}.$$  \hspace{1cm} (27)

Table 2 shows the values for the parameters of (27) in the simulated NLOS scenarios, after a linear regression had been performed. In this table, $R^2$ stands for the coefficient of determination. As can be seen, most of the variability of the data included in Figure 5 can be explained by (27) in combination with the data in Table 2. LOS scenarios do not allow this linear approach to be used, as shown in Figure 5, but polynomial approximations can be followed until similar $R^2$ figures are reached.

### 5. CONCLUSIONS

This paper presents a positioning algorithm that takes advantage of TOA techniques that are based on two-way procedures (e.g., those based on measuring the RTT between the client and the base station or the bearer). This new algorithm, which has been named TOAD, is based on listening to the TOA positioning of a neighboring terminal and then turning the TOA measurements into TDOA measurements. This procedure allows the stations to position themselves without injecting traffic into the network. However, this is achieved to the detriment of accuracy.

An analytical model for the technique is included in the paper. Montecarlo simulations were run to evaluate the performance of the technique. The results on TOAD performance demonstrate the benefits of using this technique: the RMSE of TOAD increases by less than 60% of the RMS of the ranging error in line-of-sight conditions, only listening to the location processes in the area surrounding the TOAD station. The loss of accuracy is lower in the case of non-line-of-sight conditions and involves an increase by less than 40%. Better results are obtained when distances between access points are greater than 20 meters. Thus, the scalability of a location

![Figure 5: Normalized average of the RMS of the positioning error for the TOAD algorithm with outlayers filtered.](image-url)

**Table 2: Parameters for the linearization of percentiles of the RMSE of TOAD.**

| Distance between APs | $\alpha$   | $\beta$   | $R^2$  |
|----------------------|------------|-----------|--------|
| 10 m                 | -0.1275    | 0.1649    | 0.9505 |
| 20 m                 | -0.1630    | 1.1479    | 0.9446 |
| 30 m                 | -0.2564    | 1.1350    | 0.9279 |
REFERENCES

[1] M. Oguz, “Evaluation of location determination technologies towards satisfying the FCC E-911 ruling,” in Next Generation Wireless Networks, S. Tekinay, Ed., chapter 5, Kluwer Academic, Norwell, Mass., USA, 2000.

[2] CGALIES, “Report on implementation issues related to access location information by emergency services (E-112) in the European Union,” 2002.

[3] 3GPP TS 23.271, “Functional Stage 2 Description of Location Services (LCS,R6),” 2004.

[4] A. Küpper, Location-Based Services: Fundamentals and Operation, John Wiley & Sons, Hoboken, NJ, USA, 2005.

[5] S. Goebbels, M. Siebert, M. Schinnenburg, and M. Lott, “Simulative evaluation of location aided handover in wireless heterogeneous systems,” in Proceedings of the 15th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC ’04), vol. 2, pp. 1080–1084, Barcelona, Spain, September 2004.

[6] S. Soliman, P. Agashe, I. Fernandez, A. Vayanos, P. Gaal, and M. Olijca, “gpsOne™: a hybrid position location system,” in Proceedings of the 6th IEEE International Symposium on Spread Spectrum Techniques and Applications, vol. 1, pp. 330–335, Parsippany, NJ, USA, September 2000.

[7] S. Venkatraman and J. Caffery Jr., “Hybrid TOA/AOA techniques for mobile location in non-line-of-sight environments,” in Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC ’04), vol. 1, pp. 274–278, Atlanta, Ga, USA, March 2004.

[8] D. Porcino, “Performance of a OTDOA-IPDL positioning receiver for 3G-FDD mode,” in Proceedings of the 2nd International Conference on 3G Mobile Communication Technology, pp. 221–225, London, UK, March 2001.

[9] B. Ludden and L. Lopes, “Cellular based location technologies for UMTS: a comparison between IPDL and TA-IPDL,” in Proceedings of the 51st IEEE Vehicular Technology Conference (VTC ’00), vol. 2, pp. 1348–1353, Tokyo, Japan, May 2000.

[10] J. Borkowski and J. Lemplainen, “Practical network-based techniques for mobile positioning in UMTS,” EURASIP Journal on Applied Signal Processing, vol. 2006, Article ID 12930, 15 pages, 2006.

[11] I. Martin-Escalona, F. Barcelo, and C. Manente, “A field study on terrestrial and satellite location sources for urban cellular networks,” in Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM ’06), pp. 1–5, San Francisco, Calif, USA, November 2006.

[12] I. Martin-Escalona and F. Barcelo, “Optimization of the cost of providing location services in mobile cellular networks,” in Proceedings of the 15th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC ’04), vol. 3, pp. 2076–2081, Barcelona, Spain, September 2004.

[13] M. Spanoudakis, A. Batistakis, I. Prigouoris, A. Ioanidis, S. Hadjieftymiades, and L. Merakos, “Extensible platform for location based services provisioning,” in Proceedings of the 4th International Conference on Web Information Systems Engineering Workshops (WISE ’03), pp. 72–79, Rome, Italy, December 2003.

[14] S. S. Soliman and C. E. Wheatley, “Geolocation technologies and applications for third generation wireless,” Wireless Communications and Mobile Computing, vol. 2, no. 3, pp. 229–251, 2002.

[15] M. Ciurana, F. Barceló, and S. Cugno, “Multipath profile discrimination in TOA-based WLAN ranging with link layer frames,” in Proceedings of the 1st ACM International Workshop on Wireless Network Testbeds, Experimental Evaluation and Characterization (WNTECH ’06), vol. 2006, pp. 73–79, Los Angeles, Calif, USA, September 2006.

[16] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil, “LANDMARC: indoor location sensing using active RFID,” Wireless Networks, vol. 10, no. 6, pp. 701–710, 2004.

[17] M. Youssef and A. Agrawala, “The Horus WLAN location determination system,” in Proceedings of the 3rd International Conference on Mobile Systems, Applications and Services, pp. 205–218, Seattle, Wash, USA, June 2005.

[18] R. Yamasaki, A. Ogino, T. Tamaki, T. Uta, N. Matsuzawa, and T. Kalo, “TDOA location system for IEEE 802.11b WLAN,” in Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC ’05), vol. 4, pp. 2338–2343, New Orleans, La, USA, March 2005.

[19] A. Hatami and K. Pahlavan, “Performance comparison of RSS and TOA indoor geolocation based on UWB measurement of channel characteristics,” in Proceedings of the 17th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, pp. 1–6, Helsinki, Finland, September 2006.

[20] K. Yu and I. Oppermann, “Performance of UWB position estimation based on time-of-arrival measurements,” in Proceedings of the International Workshop on Ultra Wideband Systems; Joint with Conference on Ultra Wideband Systems and Technologies (UWST & IWUWBS ’04), pp. 400–404, Kyoto, Japan, May 2004.

[21] M. Brunato and R. Battiti, “Statistical learning theory for location fingerprinting in wireless LANs,” Computer Networks, vol. 47, no. 6, pp. 825–845, 2005.

[22] L. Tsung-Nan and L. Po-Chiang, “Performance comparison of indoor positioning techniques based on location fingerprinting in wireless networks,” in Proceedings of the International Conference on Wireless Networks, Communications and Mobile Computing (WirelessCom ’05), vol. 2, pp. 1569–1574, Maui, Hawaii, USA, June 2005.

[23] Widyanaw, M. Klepal, and D. Pesch, “Influence of predicted and measured fingerprint on the accuracy of RSSI-based indoor location systems,” in Proceedings of the 4th Workshop on Positioning, Navigation and Communication (WPNC ’07), pp. 145–151, Hannover, Germany, March 2007.

[24] L. A. Ibraheem and J. Schoebel, “Time of arrival prediction for WLAN systems using prony algorithm,” in Proceedings of the 4th Workshop on Positioning, Navigation and Communication (WPNC ’07), pp. 29–32, Hannover, Germany, March 2007.
[25] D. Kang, Y. Namgoong, S. Yang, S. Choi, and Y. Shin, “A simple asynchronous UWB position location algorithm based on single round-trip transmission,” in Proceedings of the 8th International Conference Advanced Communication Technology (ICACT ’06), vol. 3, p. 4, Phoenix Park, Korea, February 2006.

[26] C. Mensing and S. Plass, “Positioning algorithms for cellular networks using TDoA,” in Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP ’06), vol. 4, pp. 513–516, Toulouse, France, May 2006.

[27] B. Denis and N. Daniele, “NLOS ranging error mitigation in a distributed positioning algorithm for indoor UWB ad-hoc networks,” in Proceedings of the International Workshop on Wireless ad-hoc Networks, pp. 356–360, Oulu, Finland, May-June 2004.