Π3: Overview of location techniques

Preface

The scope of this deliverable is the classification, analysis and evaluation of existing mobile location techniques. Several techniques have been studied including those that have already been standardized for cellular networks (GSM/UMTS) and others that have been presented in the literature. The main principles and characteristics including the underlying positioning algorithm, the accuracy achieved, as well as problems and limitations are outlined in this report and an extensive list of related references is provided. Emphasis is laid on location techniques applicable in wireless access networks, such as GSM, UMTS and WLAN, excluding satellite based techniques. Classification is based on the type of measurements employed in the positioning process. The rest of this report is structured as follows. Section 1 provides introductory remarks, while location techniques based on Angle of Arrival, Time of Arrival and Received Signal Strength measurements are analyzed in Sections 2, 3 and 4, respectively. Hybrid location techniques are described in Section 5 and advanced techniques, based on filtering and statistical processing, are discussed in Section 6. Section 7 highlights positioning issues related to propagation conditions followed by a list of location techniques evaluated in outdoor or indoor environments, in the Annex.

1. Introduction

A wide variety of location techniques has been proposed so far, each one presenting certain advantages, as well as drawbacks. To deal with the issue of required investment on the network side and the modernization of terminals, all Location Based Services (LBS) technology roadmaps begin with low cost and low accuracy techniques (e.g. Cell Identity based) and evolve in the long term towards Assisted Global Positioning System (A-GPS), the best performing mobile location technique in terms of accuracy and reliability.

However, A-GPS terminals are still expensive, with limited market penetration and there will be a relatively long period of time for which commercial GSM or GSM/UMTS devices will not be equipped with GPS receivers. Furthermore, many LBS may not even require the high accuracy provided by GPS. Even if GPS equipped terminals proliferate in the near future, satellite based techniques will still suffer from time-to-first-fix delay, excessive battery consumption and accuracy degradation related to satellite visibility problems occurring indoors and in urban canyon conditions. Therefore, other mobile positioning solutions with higher degree of applicability are in demand in order to complement satellite positioning systems. Such positioning methods are often considered as short term solutions or as fallback solutions in hybrid schemes based on A-GPS. One way to categorize mobile location techniques is according to the measurements employed and the underlying processing algorithm.

2. Angle of Arrival

Signal Angle of Arrival (AoA) information, measured at the Base Station (BS) using an antenna array, can be employed to perform terminal positioning. Assuming two-dimensional geometry, AoA measurements at two BSs are sufficient to provide a unique location. Each AoA measurement determines a Line of Bearing (LoB) of the terminal's signal. This is illustrated in Figure 1, where the terminal location is determined as the point of intersection of two LoBs. By using more measurements, the location estimate becomes more unambiguous. The uncertainty in AoA measurements results in accuracy degradation that is proportional to the distance between the terminal and each BS. The AoA method is entirely network-based and requires BSs to be equipped with sophisticated antenna arrays. This method performs best in rural areas, where line-of-sight (LOS) paths between the mobile terminal and the BSs are prevalent. The major error source is multi-path propagation due to reflections, which cause large differences between the measured AoA and the real LOS AoA [1].

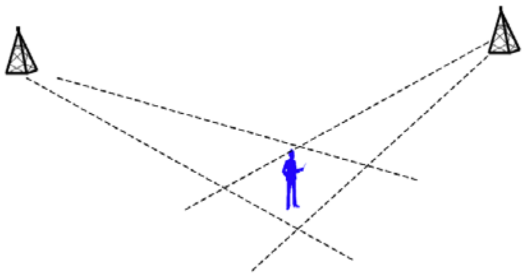

Figure 1: Positioning with AoA technique.

3. Time of Arrival

Timing information, namely the Time of Arrival (ToA), can also be used for localization purposes. ToA information is available in GSM through the Timing Advance (TA) [2] and in UMTS through the Round Trip Time (RTT) parameter [3]. In GSM, the TA parameter is known by the serving cell and it is directly proportional to the distance between the serving cell and the mobile terminal so it can be used to increase the accuracy of the pure Cell-ID method. However, the resolution of the parameter is poor (>550m) so it is beneficial only in case of large cells. In UMTS, the RTT can be used equally to enhance the Cell-ID method. Because of the wider bandwidth used in UMTS networks, the resolution of RTT (80m) is much better than the resolution of TA. Additional improvement is possible in the case of sectored cells, where directional antennas are used. This technique is depicted in Figure 2, for the TA parameter.

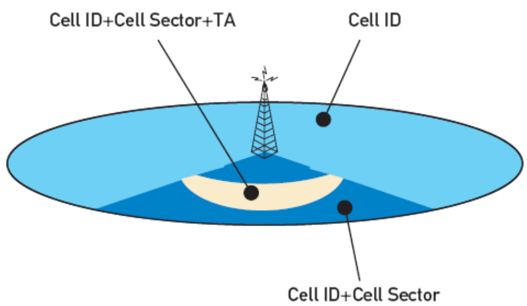

Figure 2: Positioning with Cell-ID and TA parameter [4].

ToA information is also employed in a technique based on triangulating the propagation time delay between the mobile terminal and at least three BSs, as shown in Figure 3. To support this method, additional hardware components called Location Measurement Units (LMUs) need to be installed into the network. The UpLink Time of Arrival (UL-ToA) is one of the standardized methods in GSM [5]. The UL-ToA location technique is based on measuring the ToA of a known signal sent by the mobile at three or more BSs. The method is purely network-based and works with existing mobile terminals without any modifications. The used signal in the positioning process is an access burst, which is generated by forcing the mobile to perform an asynchronous handover [5]. If a suitable reference time is available in asynchronous networks, such as GSM (and UMTS-FDD), the ToA location can also be applied in the downlink direction as mobile-assisted or mobile-based technique. This approach increases signaling load and requires that the terminal has adequate measurement and reporting capabilities. The accuracy of ToA method depends on the existence of a LOS path between the terminal and the BS. In areas where LOS conditions are often unavailable e.g. in urban environments, the ToA values can differ substantially from the actual values, thus contributing to large errors in the location estimate.

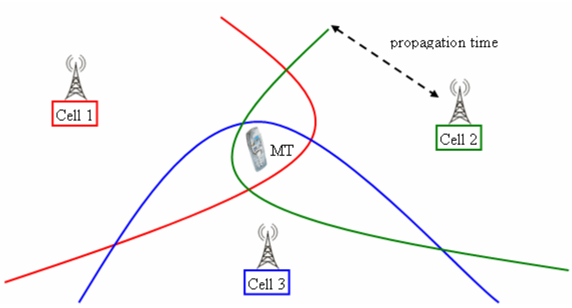

Figure 3: Positioning based on triangulating ToA measurements.

Timing measurements can also be used by the terminal to calculate differences between the signals sent by the nearby BSs, known as Time Difference of Arrival (TDoA) measurements. A TDoA value defines a hyperbola with the two BSs as the foci and at least three hyperbolae are required to uniquely identify the terminal position [6]. This technique is also standardized in GSM [5], [7] named Enhanced Observed Time Difference (E-OTD) and in UMTS known as Observed Time Difference of Arrival (OTDoA) [8]. Both solutions can be either terminal-based or terminal-assisted. In UMTS networks, idle periods can be used to improve hearability. During an idle period the serving NodeB ceases its transmission and thus, enables the NodeBs further away to be measured. The usage of idle periods improves the accuracy of OTDoA but at the same time, decreases the capacity of the network. This technique is known as Idle Period DownLink OTDoA (IPDL-OTDoA) [9].

4. Received Signal Strength

Received Signal Strength (RSS) measurements have also been utilized in order to determine the terminal's position. Such measurements are collected by the terminal as part of its standard functionality to assist in the handover process. Network type and topology influence the number of cells, from which the mobile terminal is capable of extracting RSS measurements. In GSM, for example, the mobile terminal measures continuously the signal strength of the serving and up to six neighboring cells.

There are two approaches followed in this category. In the first one, a proper propagation model (e.g. Hata model [10] or a propagation model calibrated to best fit the specific environment in the area of interest) is used to translate RSS values to distances from the respective neighboring BSs. Then through standard trilateration techniques position is determined. This is shown in Figure 4. The distance from each BS defines a circle around it, with radius equal to the distance calculated through the propagation model, on which the terminal is possibly located. With the distances from the serving and the available neighboring cells known, a trilateration method is employed in order to determine the location of the terminal. However, errors occur regarding the radius of the circle. There are three sources of error affecting the radii of these circles, including the validity of the employed propagation model, the truncation and quantization of RSS values according to access network specifications and most importantly the disturbance of RSS values due to fast fading and shadow fading. In the absence of these errors the radius of each circle can be calculated precisely. If at least three radii are known then a single point, which corresponds to the location of the terminal, can be determined. Due to these errors, the most probable terminal position is actually calculated by using estimation techniques, such as Maximum

Likelihood Estimation (MLE) and optimization techniques, such as Least Squares (LS).

The propagation model can be empirical, semi-empirical or statistical and also compensate for the directionality of the antenna's radiation pattern [11], [12], [13]. Moreover, a method presented in [14] does not require a known and accurate propagation model in order to perform positioning. There are also simpler ways to estimate the mobile terminal's position, without employing a propagation model. For example, the mobile location can be calculated as the weighted average (weighted by the RSS values) of the cell locations.

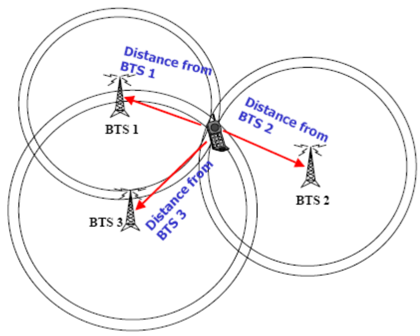

Figure 4: Positioning with RSS measurements using a propagation model.

The second approach, known as fingerprint technique, employs a database of fingerprints measured a priori inside the area where the terminal is to be located. Each fingerprint contains signal information from the BSs or WLAN Access Points (AP) detected at certain locations. Positioning is performed by matching the signal information of the request fingerprint, received by the terminal, to the signal information of the reference fingerprints. The signal information usually refers to RSS measurements from neighboring GSM cells. This is the concept of the Database Correlation Method (DCM) presented in [15]. However, power delay profiles [16] or Received Signal Code Power (RSCP) values [17] of the detected UMTS cells can also be employed. In [18] measurements from multiple networks were combined in order to form the fingerprints. To overcome the cumbersome task of collecting the fingerprints on site, the output from network planning tools has been used to artificially generate the required fingerprints as in [19].

5. Hybrid

In the previous sections, location techniques utilizing certain measurements obtained from a specific network (or access technology) were presented. However, it is also possible to combine measurements from multiple networks or location estimates from multiple techniques and thus improve the final location estimate.

In [20] an algorithm called Selective Fusion Location Estimation (SELFLOC) is presented. The main idea is to exploit multiple wireless technologies or algorithms. The elementary algorithms studied in the paper are triangulation, K-nearest neighbour and smallest M-vertex polygon. The wireless technologies used are WLAN and Bluetooth. The final location estimate is obtained as a weighted average of elementary location estimates. The weights can be calibrated in the offline phase to yield better performance. Also, it is pointed out in the paper that the information coming from multiple wireless technologies or algorithms should be uncorrelated. Similar elementary algorithms are used in [21] as well. The access techniques are WLAN and Bluetooth. The final location estimate is the centroid of the polygon resulting from elementary location estimates. In the case presented in the paper, the midpoint of two position estimates is used, since only two wireless technologies are available.

A potential UMTS location technique especially in rural and suburban areas, where a LOS connection between the terminal and the serving BS is often present, is AoA-RTT hybrid in which even one BS is enough for location estimation. It is a network-based method that alleviates the hearability problem since a single BS, equipped with an antenna array, can make the necessary measurements. The location estimate accuracy of this technique is limited by the beamwidth of the antenna array and RTT resolution. As with AoA method, the location error will increase proportionally to the distance between the terminal and the BS.

In UMTS, the OTDoA measurements will be available in every terminal and deployment of antenna arrays will enable AoA measurements without extra costs. The performance of both OTDoA and AoA techniques is decreased due to NLOS conditions. Even though the errors in AoA measurements due to NLOS conditions are correlated to the errors affecting the timing measurements involving the serving BS, they are useful for the location procedure. Using the OTDoA-AoA hybrid terminal positioning is feasible even in highly NLOS. The accuracy of the hybrid is better than OTDoA or AoA alone and coverage is increased [22], [23].

In [18], measurements from multiple networks are combined before calculating separately position estimates in each network. The method presented is based on fingerprinting and the fingerprint vectors themselves consist of RSS measurements from multiple networks. The networks used in the study are GSM and UMTS, but the approach is applicable to other networks as well. In [24], a combination of measurements from GSM and WLAN networks is used outdoors.

6. Advanced Location Techniques

The aforementioned techniques perform positioning in a *static* manner, i.e. they make no assumptions regarding the terminal's motion and dynamics. Time processing of noisy measurements collected by the terminal, in the form of filtering, can alleviate the positioning errors and increase accuracy by incorporating proper mobility models. Filtering, including the well studied Kalman filters [25] commonly used in satellite based positioning, can be applied in the raw measurements or in the coarse position estimations domain. In the case of raw measurements, the performance of the underlying positioning algorithm is greatly improved by estimating the system's state, i.e. the terminal's motion, from noisy observations. Different variants of Bayesian filters [26] have been discussed in the literature, including Kalman Filter [27], Extended Kalman Filter (EKF) [28], [29] and Particle Filter [30].

In the case of coarse position estimations derived from any positioning technique, filtering is employed in order to eliminate high positioning errors that are not corresponding to the terminal's dynamics. These are also known as post processing techniques that generate a smoothed location sequence to reflect the terminal's mobility pattern more accurately. Popular post processing techniques include Kalman filters [31], [32], [33] and Particle filters [34]. Map matching is also employed as a post processing technique to increase the accuracy by matching the terminal's trajectory to a set of candidate road segments of a digital road map or indoor floor plan [35], [36]. In [18] map matching has been used as the final processing step following Kalman filtering.

7. Indoor vs Outdoor

Standard location techniques, based on different types of measurements, have been applied to both indoor and outdoor positioning. However, there are many factors affecting the performance, in terms of the accuracy achieved, in each case. For example, the radio wave propagation environment is more complicated indoors than outdoors, since concrete walls result in severe signal attenuation and create NLOS conditions. Moreover, the accuracy requirement for the location estimate is often higher indoors, since the area itself is usually smaller. Furthermore, some techniques that work well outdoors (e.g. AoA) are far less applicable for indoor positioning. In [37], it is pointed out that in indoor positioning, the number of people inside a room can cause unpredicted RSS fluctuations. More specifically, the variance of the signal level measurements was observed to be about 4dBm in empty office compared to about 8dBm in busy office. Also, floors affect signal levels a lot causing a power reduction between 15dBm and 35dBm. An analytical model for analysing the accuracy of an indoor positioning system has been developed in [38].

Indoor positioning using WLAN can be based on various measurements. Typically, localization is accomplished by using RSS measurements [39], [40]. However, approaches utilizing time measurements (TDoA) have been presented as well [41]. Most studies address WLAN indoor positioning, but outdoor evaluations have been carried out as well. For example in [42] it is pointed out that especially when fingerprint-based location techniques are used in metropolitan scale, an important metric for the performance is the accuracy of positioning versus the calibration overhead. An important result is that the positioning accuracy does not increase when the distance between consecutive fingerprints is lowered below 10 meters.

On the other hand, outdoor positioning techniques can be further split into categories based on the type of terrain in which they are deployed e.g. urban, sub-urban and rural areas. Each of these environments has specific features that influence the performance of the location technique. Urban areas usually include street canyons, causing radio waves to propagate from transmitter to receiver via indirect paths. This deteriorates the accuracy of location techniques based on trilateration, which assume that the distance between transmitter and receiver is proportional to the propagation loss.

Typically, cellular networks (GSM/UMTS) are used in outdoor positioning where larger areas are covered, while WLAN networks are used in indoor positioning. This is because WLAN networks have smaller cell sizes and there is available infrastructure in many buildings. However, this is not always the case. Apart from [42] where WLAN positioning has been evaluated outdoors, there are also studies considering the use of cellular access networks for indoor positioning. For example, in [43] high positioning accuracy is attained with a fingerprint-based technique in a GSM network. Contrary to normal GSM fingerprints, which utilize signal levels of 6 neighboring cells, the system presented in the paper utilized measurements from up to 35 cells by using a SonyEricsson GM28 GSM modem.

In the Annex several location techniques available in literature have been tabulated for easy reference, based on whether these are applied indoors or outdoors. The underlying positioning algorithm, the access network (GSM/UMTS/WLAN), the trials area and the accuracy/precision achieved, are listed as well. Accuracy of the location estimate indicates the geometric distance between the true location (obtained through GPS) and the estimated location of the terminal in meters. Precision indicates how often the location estimate can be obtained with certain accuracy. Precision can be stated as a percentage value, e.g. 67^{th} and 95^{th} percentile expressing the accuracy achieved in 67% and 95% of the cases, respectively.

Annex

Location techniques applied outdoors

Reference	Algorithm	Access Network	Trials Area	Accuracy & precision
Pettersen et al, 2002 [44]	Cell ID + TA	GSM	outdoors, 5000-10000 samples, 30 different serving cells	urban: 450 m / 50 %; suburban: 670 m / 50 %; rural (flat): 2625 m / 50 %; rural (valley): 2825 m / 50 %
Murray et al, 2002 [45]	Cell ID, Cell ID + TA, Cell ID + TA + RXLEV	GSM	outdoors, urban and suburban (Tallinn, Estonia)	67 % Cell ID: urban: 320 m suburban: 640 m Cell ID+TA: urban: 290 m suburban: 400 m Cell ID + TA + RXLEV: urban: 200 m suburban: 430 m
Lin et al, 2005 [14]	Cell ID, weighted centroid	GSM (1800 MHz)	outdoors, Taipei, Ericsson TEMS, 2.1 km × 1.6 km; 1251, 1688, 2254 samples	Cell ID (50, 67, 95 %) 141.8, 197.6, 353.8 m (route 1); 224.5, 277.8, 422.6 m (route 2); 197.7, 257.3, 478.2 m (route 3); Centroid: 107.6, 139.6, 251.3 m (route 1); 134.9, 189.7, 314.2 m (route 2); 114.9, 143.5, 298.4 m (route 3)
Cheng et al, 2005 [42]	centroid (basic, weighted), fingerprint-based (radar, rank), particle filter (signal strength, response rate)	WLAN	outdoors, Seattle: downtown, Ravenna neighbourhood, Kirkland suburb, #APs per scan: 2.66, 2.56, 1.41, APs/km^2: 1030,1000, 130	13-60 m (depending on algorithm and trial area)

Kunczier et al, 2004 [46]	fingerprint-based (Bayesian)	GSM	outdoors, Vienna, 282 measurement locations, 5 m spacing	20 m / 67 %, 50 m / 90 %
Laitinen et al, 2001 [15]	fingerprint (RXLEV)	GSM	outdoors, 3 urban trials, 1 suburban trial; 389, 3604, 1240, 766 locations	urban: 44, 90m/67%, 90%; suburban: 74, 190 m /67%, 90%
Zimmermann et al, 2004 [19]	fingerprint (RXLEV, synthetic; LMS & EXP)	GSM	outdoors, Stuttgart (urban, suburban/rural): 10 km^2, 109 cells; 50 km^2, 43 cells;	LMS, urban: 98, 282 m / 67, 95 %; EXP, urban: 83, 192 m / 67, 95 %; LMS, suburban: 602, 1023m/67,95%; EXP, suburban: 607, 1021 m/67,95%
Wertz et al, 2002 [47]	fingerprint (RXLEV, synthetic)	GSM	outdoors, Stuttgart, urban, 6 km^2	Falsified loss: 115, 270 m / 67, 95%; Hata-Okumura: 115, 530 m / 67, 95%; COST 231 WI: 65, 150 m / 67, 95%; 3D IRT: 65, 250 m / 67, 95%
Borkowski et al, 2005 [17]	fingerprint	UMTS	outdoors, Tampere, urban, 2 km^2, NEMO	70, 130 m / 67, 90%; 90, 195 m / 67, 90%; 90, 180 m / 67, 90% (routes 1, 2, 3)
Kemppi et al, 2006 [18]	fingerprint (RXLEV, RSCP, AP SS), Kalman filtering, map-matching	GSM, UMTS, WLAN	outdoors, urban (Helsinki), suburban (Espoo), indoor (Otaniemi); NEMO, TEMS, Netstumbler	GSM+UMTS: 58, 157 m / 67, 95 %; 60, 162 m / 67, 95 %; 65, 196 m / 67, 95 %; 66, 162 m / 67, 95 %; (urban1, urban2, surban1, surban2); WLAN indoor: 3, 6.7 m / 67, 95 %
Komar et al, 2004 [37]	fingerprint	WLAN	outdoors, 60 locations, 10 samples per location, 2 m spacing, 240 m^2	6.537 m / mean
Lattunen et al, 2006 [24]	fingerprint (RXLEV, AP SS)	GSM, WLAN	outdoors, suburban (Otaniemi)	GSM+WLAN: 37, 131 m / 67, 95 %; 52, 234 m / 67, 95 %;
Borkowski et al, 2004 [3]	Cell ID + RTT	UMTS	outdoors, simulations	16-440 m
Porcino et al, 2001 [9]	OTDOA-IPDL	UMTS	outdoors, simulations	rural: 17, 27 m / 67, 95 %; suburban: 18, 36 m / 67, 95 %; urbanA: 86, 193 m / 67, 95 %;

				urbanB: 68, 156 m / 67, 95 % bad urban: 113, 224 m / 67, 95 %
Ahonen et al, 2003 [16]	fingerprint (multipath profile)	UMTS	outdoors, 1 km^2, 24 sites (1-3 cells per site), simulations	25, 140 m / 67, 95 %

Location techniques applied indoors

Reference	Algorithm	Access Network	Trials Area	Accuracy & precision
Kotanen et al, 2003 [48]	signal strength (propagation model)	WLAN	indoors, 4 WLAN APs, 32 locations, 120 samples per location, 3 m spacing,	2.6 m / mean
Komar et al, 2004 [37]	fingerprint-based	WLAN	indoors, 30 locations, 100 samples per location, 1.2 m spacing;	8.144 m / mean (1 AP), 4.767 m / mean (2 APs), 2.244 m / mean (3 APs)
Youssef et al, 2003 [49]	fingerprint (probabilistic), radar	WLAN	indoors, 67.97 m × 25.94 m, 110 locations, 1.52 m spacing, 300 samples per location, 4 WLAN APs per location (avg)	proposed: 2.13 m / 90 %, radar: 2.13 m / 38 %
Elnahrawy et al, 2004 [39]	various area-based and point-based algorithms	WLAN	indoors, 2 buildings: 60.96 × 24.38 m, 286 locations; 68.58 × 43.89 m, 253 locations	> 3.05 m / 50 %, 9.14 m / 97 %
Yamasaki et al, 2005 [41]	TDOA	WLAN	indoors, storehouse, 40 × 70 m, 11 APs, 28 locations, 30 samples	2.4 m / 67 %
Gwon et al, 2004 [20]	triangulation, K-nearest neighbour, smallest M-vertex polygon	WLAN & Bluetooth	indoors, 39.83 m × 25.60 m, 1.422 m spacing, 4 WLAN APs (207 locations, 40 samples per location and per direction), 3 Bluetooth APs (71 locations, 25 samples per location and per direction)	1.5-9 m (depending on algorithm, system and mobility)
Pandya et al, 2003 [21]	triangulation, nearest neighbour, smallest polygon	WLAN & Bluetooth	indoors, 32.2 m × 25.7 m 3 WLAN APs, 3 Bluetooth APs, 49 locations, 50 samples per location and per direction	2-18 m (depending on algorithm and system)
Hii et al, 2005 [50]	fingerprint-based & TDOA	WLAN & acoustic	indoors	1,234 m, 2,8798 m / mean (acoustic, Ekahau)

				1.8997 m, 1.8094 m / mean (acoustic, Ekahau)
Otsason et al, 2005 [43]	fingerprint (wide signal strength, K – nearest neighbor)	GSM, WLAN	indoors, 2 office buildings & one private house, spacing 1-1.5 m, 2 samples per location, 284, 234, 111 samples	WLAN (50, 90 %): 4.40, 10.27 m; 2.49, 4.94 m; 3.11, 5.80 m; GSM (50, 90 %): 4.98, 18.74 m; 4.41, 9.43 m; 3.66, 7.02 m

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