An approach to increase the scalability of location systems in WLAN networks

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ABSTRACT
This paper presents a software layer designed to reduce the consumption of network resources and, at the same time, the amount of location traffic being carried by indoor location systems that are able to use a variety of location techniques. This new layer in the user equipment selects the optimum technique depending on the request, i.e. the location technique that fulfils the required quality of service (QoS) and minimizes the resource operating expense. The factors used to compute resource consumption in WLAN networks are defined and quantified. Simulation is used to assess the impact of including the software developed in a network that supports several technologies, namely A-GPS, WLAN fingerprinting and inertial MEMS. Performance analysis shows how the application layer improves performance in terms of use of resources and percentage of successful location services (LCS).

General Terms
Algorithms, management, measurement, performance, design, reliability, verification

Keywords
Location middleware, indoor location, A-GPS, WiFi fingerprinting.

1. INTRODUCTION
Today, several location techniques are ready for deployment in indoor environments: fingerprinting, time of arrival (TOA), assisted GPS (A-GPS), ultra wideband, etc. Each of them provides a given quality of service (QoS) in terms of accuracy, response time, availability and consistency [1]. There are also a variety of location-based services (LBS), each of which requires different QoS depending on their purpose. Thus, the capabilities of location systems for carrying location requests coming from different LCS depend directly on the features of the location techniques implemented in them [2]. Hybrid techniques are proposed as a way of overcoming the drawbacks of using a single location technique as standalone. They are based on combining measurements taken with different techniques to exploit the advantages of each one [3-7]. Using these kinds of techniques enhances the QoS offered by the system and allows more LCS to be carried. However, the QoS figures obtained by these kinds of techniques are often much better than is required for many LBS, which can lead to an inefficient use of network resources.

Four techniques have been proposed to obtain the location in indoor scenarios in the framework of the IST LIAISON project [8]: WIFI fingerprinting, coupling between WIFI fingerprinting and inertial MEMS, coupling between A-GPS and WIFI fingerprinting, and coupling between A-GPS and MEMS. Table 1 shows the QoS obtained with some of these techniques, in which FP stands for fingerprinting and WIFI-FP/MEMS, A-GPS/MEMS stand for hybrid approaches that couple these techniques and *Exc* means *Excellent*.

Table 1. QoS of the location techniques implemented

	WIFI-FP	**A-GPS**	**WIFI-FP / MEMS**	**A-GPS / MEMS**
Accuracy	Good	Exc. (outdoors) Poor (indoors)	Good	Good
Response time	Good	Good	Exc.	Exc.
Availability	Good	Exc. (outdoors) Poor (indoors)	Excellent	Good
Consistency	Good	Medium	Good	Medium

2. SYSTEM DEFINITION
2.1 System definition
The network resources consumed by a location system belong to the infrastructure of the underlying cellular network on which the location service is running. As a result, the resources used for location purposes are not available for other types of traffic. The software layer presented here (MILCO, Middleware for Location Cost Optimization) is a middleware that manages all location processes and aims to reduce resource usage as long as the QoS requested is fulfilled. Other proposals for location middleware are

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focused on technology independence, system integration and quick LCS development [9-11], but not on the efficient use of resources. A middleware is presented in [12] for maximizing the coverage of location systems. It consists of a database supplying beacon positions and a client in the user equipment which computes the position combining the beacon measurements with the positions provided. What differences this software layer from those systems is that this middleware aims to minimize the consumption of resources at the time the time the availability is maximized. The software presented in this paper is implemented as a new application layer inside the user terminal's protocol stack and follows the main lines presented in [13, 14].

Figure 1 shows the location system architecture, including MILCO. Each time a location request reaches the location system, it is delivered to the user terminal, where the request is handled. MILCO then analyzes the requirements included in the location request (e.g. the QoS or latency required) and gathers all the facilities provided by the user terminal (e.g. the location techniques implemented). MILCO selects the location technique that best fits the request, i.e. the one that is expected to achieve the requested QoS and minimizes the spent resources. Finally, MILCO uses the user terminal's facilities to determine the user's position and forwards the result to the location service (LCS) client that requested it.

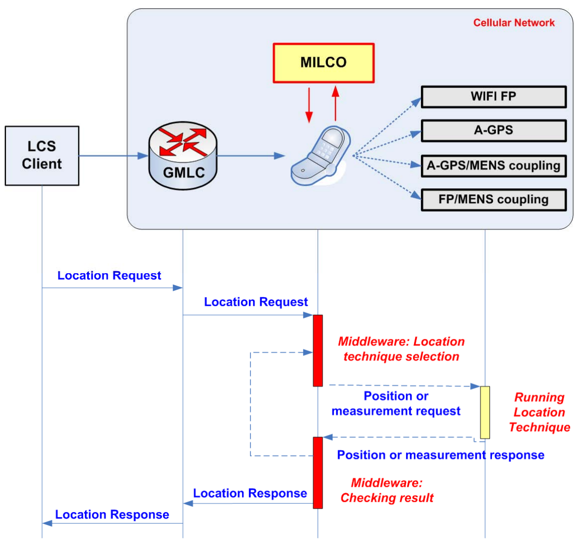


Figure 1. System architecture

MILCO performs in a three-step fashion: filtering, technique selection and result management. The filtering stage aims to filter out any location technique that is not suitable for the request. Location techniques may be marked as unsuitable for three reasons: there is an incompatibility (i.e. either the network or the user terminal cannot implement the technique), the location technique is unable to achieve the QoS requested (e.g. the maximum accuracy achieved by the technique is worse than that requested), or there is an input module that can handle the request without running a location technique. The second stage is the location-technique selection. In this stage, the proposed layer selects the optimum location technique from the remaining set (i.e. after filtering). This is achieved by means of a cost function (i.e. corresponding to a certain criterion), which ranks the resource consumption of each location technique. Finally, the third stage manages the results, i.e. chooses the procedures for handling the failures and for maintaining a database with the previous location measurements and calculations, etc. The default behavior on location failure is to execute another location technique.

2.2 Cost function

The cost function is the core module. It ranks appropriate location techniques for the request according to the amount of resources used, i.e. the greater the amount of resources the technique consumes the lower it is ranked. This rank is used to select the optimum location technique, i.e. the one that uses the fewest resources. The cost function is composed of several factors, which are used to quantify network-resource usage. Thus, it is defined as

$$Z(LT_i, t) = f(\alpha_1, \dots, \alpha_n; z(LT_1), \dots, z(LT_n); t), \quad (1)$$

where $Z(LT_i)$ represents the resources spent by the i^{th} location technique (i.e. LT_i), f stands for some function, α_j and $z_j(LT_i)$ are, respectively, the weight and value of the j^{th} factor applied to the location technique LT_i and t is the time at which the resource-consumption is going to be calculated. Several functions (f) can be used to calculate resource usage. For simplicity's sake and without loss of generality, a simple additive function with m factors is proposed to evaluate the performance of the module. This is defined as

$$Z(LT_i, t) = \sum_{j=1}^{m} \alpha_j(t) \cdot z_j(LT_i, t). \quad (2)$$

The cost factors define the grade of service variables that are used to quantify the suitability of using a specific location technique at a certain time. Factors included in this paper for illustrative purposes are described below.

2.2.1 Probability of success

This cost factor aims to compute the probability that a location technique will achieve the QoS requested. Two histograms are built according to the results obtained over time (past), one for accuracy and one for the response time. The successful probability is thus calculated as

$$z_1(LT_i, t) = \Pr\{Acc(LT_i, t) \le ACC\} \cdot \Pr\{rtime(LT_i, t) \le RTIME\}, \quad (3)$$

where z_1 is the successful probability, $Acc(LT_i,t)$ and $rtime(LT_i,t)$ are, respectively, the accuracy and response time of the i^{th} location technique, while ACC and RTIME are the requested accuracy and response time, respectively.

In order to increase the effectiveness of the system, the accuracy and response-time histograms are built locally in an area called *SP_CELL*. The smaller the *SP_CELL* areas the more accurate the calculation of the successful probability, although more hardware resources are needed to store this data. Accordingly, we decided that using *SP_CELL* to match the coverage area of an access point was a good trade-off between these parameters.

As MILCO will be functioning in a constrained environment (indoors, with possible changes in the layout of the furniture, electric noise, etc.), in which signal conditions and consequently the QoS offered by location techniques may change drastically, the histogram computation follows a non-linear approach. Hence, recent samples are favored since they are more likely to be correlated with future positions rather than older positions. Accordingly, the weights of each sample are computed as

$$\alpha_1(n) = \begin{cases} A \cdot \log(n) + g_{\min}, & 1 \le n < M \\ g_{\max}, & M \le n \le N \end{cases}, \qquad (4)$$

where g_{min} and g_{max} are the minimum and maximum gains respectively, M is the number of weighted samples and N is the maximum number of samples used to compute the histogram. A is a scale factor that results from the *gmin*, *gmax* and M parameters. Note that the histogram has a maximum size (N). This approach saves memory in the user terminal. The higher N is, the more accurate the expected results. If a new sample is added to a histogram with N samples, the oldest sample is removed to make room for the new one. All the remaining samples are shifted one position and their weights are then recalculated.

2.2.2 Energy consumption

This cost factor places constraints on the use of techniques according to the energy consumption and the remaining battery in the terminal. The energy consumption is highly dependent on the hardware and algorithms used. However, in order to allow a performance evaluation to illustrate the presented approach, a rough estimation including several obvious dependencies is displayed in Table 2. N_{AP} and N_{SAT} stand for the number of access points and satellites involved in the positioning process.

Table 2. Energy consumption

Location technique	Energy-consumption factor
WLAN fingerprinting	10 + N_{AP}
MEMS	1
Assisted GPS	10 + N_{SAT}

The figures in Table 2 only account for the energy that each location technique consumes. However, the quantification of this factor should depend on the remaining battery of the terminal, since highly demanding location techniques could make the battery of the terminal run out in a relatively short time, making any kind of location impossible. The cost function weights this factor according to the estimated battery life as

$$\alpha_2(t, t_0) = \alpha_2(t_0)\left[1 - \log\left(\frac{Battery(t)}{Battery(t_0)}\right)\right]^{3/2}, \qquad (5)$$

where t_0 indicates the starting time, i.e. the time at which the battery is completely recharged, and *Battery(t)* indicates the remaining battery in the terminal at time t.

2.2.3 Expected accuracy

This factor is computed as the average accuracy expected for each location technique. In principle, this should be a static cost factor, since the expected accuracy comes from the previous performance analysis of the location technique. However, there are techniques whose accuracy depends on the time that has elapsed. For instance, MEMS depends on the distance traveled since the last positioning with another technique (i.e. the time that has elapsed since the last positioning). Accordingly, this cost factor updates its values along the time for these time-dependent techniques, while other techniques such as WLAN-FP or A-GPS present constant values for this cost factor.

3. SIMULATION AND SCENARIOS

Simulation was selected as a tool for quantifying the performance of the proposed approach in several scenarios. The simulator used is—an adapted version of the one used in [13], which was customized to model an indoor WLAN network. The propagation pattern follows the Okumura-Hata model for indoor scenarios, with path-loss slope and zero-meter losses set to 3.5 and 40 dB, respectively. The SIR is calculated according to [15]. Table 3 shows the main parameters of the propagation pattern according to current industry equipment.

Table 3. Parameters of the propagation pattern

Parameter	Value
Minimum SIR	-9 dB
Sensitivity of the stations	-65 dBm
Maximum MS transmission power	17 dBm
Minimum MS transmission power	0 dBm
AP transmission power	17 dBm
Handoff threshold for received power	-62 dBm
Handoff threshold for SIR at reception	-6 dB

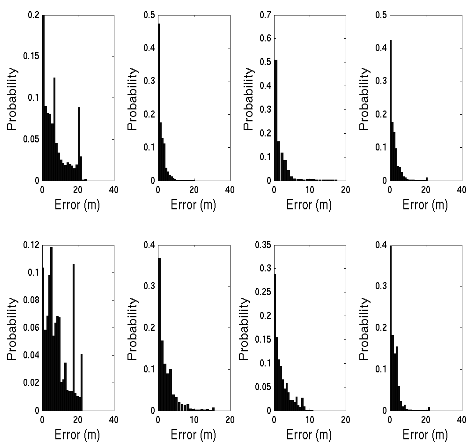
The simulation layout represents a square-shaped corridor where users move through freely. The corridor is 4m wide. The access points placed outside the corridor simulate those that are in rooms connected to the corridor or on other floors of the building. The scenario is populated with a single pedestrian user. More users are not needed in this preliminary evaluation, since the performance is implemented in the mobile station and is thus user-oriented. The user speed (in both directions, x and y) follows a normal random variable, with mean and standard deviation of 0.6 m/s and 0.18 m/s, respectively. The value of the user speed in both directions is updated once per second. This scenario is then simulated with 9, 16, 25 and 36 access points. The access points (APs) are uniformly spread along a square-shaped simulation area. In accordance with Table 3, each AP achieves 63 meters of coverage at minimum throughput.

Table 4. Parameters of the propagation pattern

Scenario name	Number of APs	Minimum coverage	Maximum coverage
Scenario_1	9	0 AP	1 AP
Scenario_2	16	0 AP	2 APs
Scenario_3	25	2 APs	4 APs
Scenario_4	36	4 APs	4 APs

Table 4 shows the expected coverage in terms of access points that is expected from each scenario. As can be seen, the target scenario is *Scenario_3*, in which the stations receive a signal from at least 2 and up to 4 APs. More than 4 APs are not considered since such network planning in actual WLAN deployments is unlikely. *Scenario_4* is included as an example of an over-covered network. *Scenario_1* and *Scenario_2* are examples of constrained scenarios, in which only part of the network infrastructure is working (degraded service). Note that minimum coverage is computed according to analytical models. However, simulation involves factors that are not included in the analytical calculation. For instance the power control algorithm in the mobile station may lead to coverage figures below the expected minimum.

Four location techniques are considered in the simulated model: WLAN fingerprinting (FP), A-GPS as a standalone technique and A-GPS/MEMS and FP/MEMS couplings. Only 2D positioning is considered. Figure 2 shows the accuracy of the WLAN-FP technique according to the number of available access points obtained from [8]. The first and second rows of images in the Figure stand for the error module in the *x* and *y* coordinates, respectively. Figure 3 shows the accuracy expected from MEMS in a light indoor scenario, according to [8]. The system couples MEMS with another technique as long as the accuracy of the position from this other technique is better than 4 meters. Thus, the results are expected to be slightly conservative, since in real scenarios MEMS could be used in a few more positioning processes. A-GPS operates differently. To reduce the complexity of implementing the whole satellite map, the simulator computes the availability of GPS satellites to estimate the signal availability, according to the kind of scenario: A-GPS is likely to give a position in light indoor scenarios (i.e. close to windows) and no position at all in deep indoors. Accordingly, the simulator provides availability for A-GPS satellites uniformly distributed from 2 to 4 satellites if the user is less than 1 meter from the edges of the simulation area. Otherwise, no satellites are assumed to be received in the user terminal. Expected accuracy values for all the techniques are provided in Table 5. Response times for WLAN fingerprinting, MEMS and A-GPS are exponentially distributed, with average values of 2, 0.5 and 1 seconds, respectively. These values were proposed in keeping with the author's experience, since actual values are really hardware-dependent.



a) b) c) d)

Figure 2. Accuracy of WIFI-FP with a) 1 to d) 4 APs in sight

The cost function includes the cost factors presented in Section 2. The weight of the factors in the cost function (α_i in Eq. 2) is set to 1 for the successful probability and expected accuracy. The weight of the energy consumption ($\alpha_2(t_0)$ in Eq. 5) is set to 3. Accordingly, the cost function can produce values from 0 to 5. This overweighting of the energy consumption allows the most suitable technique to be used as long as there is enough energy available in the user equipment and this equipment switches to a technique that uses less power when the power has nearly run out. It must be noted that the station handles incoming traffic until its battery runs out. In such conditions, the station is switched off for 5 seconds, after which it is turned back on, completely recharged. The time the station spends between switching off and on includes the network reassociation process. Table 5 shows the values for the expected accuracy cost factor, according to [8], where *d* stands for the distance traveled since the last positioning made with WLAN-FP or A-GPS. Regarding MEMS, note that Table 5 shows only the error incurred by the measurement system. Consequently, the actual positioning error of MEMS will increase with the accuracy of the initial position used by this technique.

Table 5. Expected accuracy values

Technique	Expected accuracy factor	
WLAN-FP	12.2766 m (1 AP) 3.1982 m (3 APs)	3.4058 m (2 APs) 3.9329 m (4 APs)
MEMS	$1.65 + 0.2825 \cdot d$ meters	
A-GPS	3 meters (only on covered areas)	

A single location service was included to illustrate the performance. The time between service requests is 5 seconds and the requested accuracy is 6 meters. Simulations were carried out not accounting for the response-time requirement in the QoS computation. This approach is taken because customers perceive more degradation in the QoS when accuracy requirements are not fulfilled than when response-time limits are exceeded. Additionally, most of the time used by the LCS is expected to be spent in dialog with the network, not on executing the technique. Thus, the impact of the response time on the QoS results would be similar for all the location techniques. To limit the number of executions per location service, the cost function is run twice, at most. Therefore, an LCS request is considered unsuccessful if none of the techniques provide sufficient accuracy in these two cost-function executions.

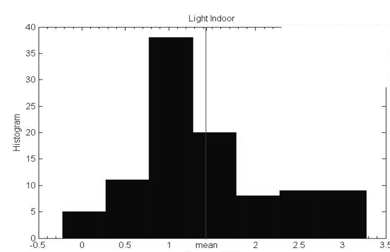


Figure 3. Accuracy of MEMS in light indoor scenario

4. PERFORMANCE EVALUATION

This section presents the performance results that can be expected from the proposed layer in a location system. Its performance is compared with the performance achieved using only WLAN-FP and only A-GPS. MEMS is not evaluated as standalone, since this technique must be assisted by WLAN-FP or A-GPS (the error drifts with the distance covered and MEMS needs correction updates from other location techniques).

Figure 4 presents the location traffic carried in the scenarios proposed. Two situations may lead to a location request not being carried: the station being in a position without radio network coverage and the station being in a *recharging* condition, i.e. the station being shutdown and thus unavailable for network communication. WLAN fingerprinting and MILCO handle more than the 80% of traffic and thus provide a good ratio of carried traffic. However, MILCO achieves higher ratios and its performance is more stable due to better battery management, which reduces the number of blocking situations in dark areas (i.e. without coverage) in the network. Figure 4 shows that, in all scenarios, the traffic carried by MILCO is higher than that carried by WLAN fingerprinting used as standalone. This is mainly due to the support of MEMS. Although A-GPS performs poorly as standalone (because it performs in an indoor environment), it should be noted that a single A-GPS position can help the MEMS to provide accurate locations for a certain time.

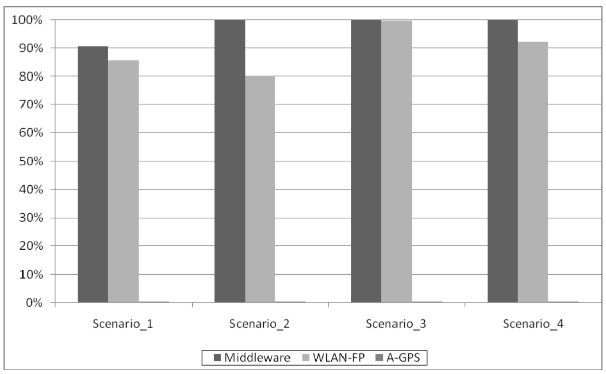


Figure 4. Carried location traffic

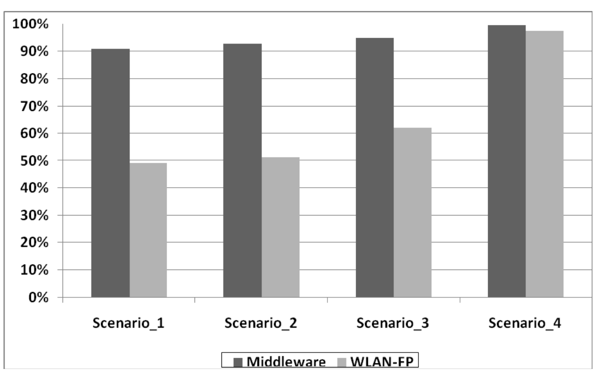


Figure 5. Percentage of successful LCS from carried traffic

Figure 5 shows the percentage of successfully handled traffic. Results for A-GPS are not included since traffic carried by this technique as standalone is only marginal. As shown, under excellent coverage conditions (i.e. *Scenario_4*), the solutions provide almost the same ratio of successfully handled LCS. However, reducing the number of APs available has a detrimental effect on the figures provided by the WLAN fingerprinting solution. MILCO, on the other hand, is not as sensitive to a reduction in the number of access points. This is because it is able to use MEMS when WLAN fingerprinting is not available. In fact, the lack of WLAN fingerprinting is partially solved by A-GPS. As seen in Figure 5, in the most constrained scenario MILCO successfully handles 91% of carried traffic versus 49.1% achieved by WLAN fingerprinting as standalone. This result shows the benefits expected in situations in which the integrity of the network cannot be guaranteed.

Figure 6 displays the average accuracy (in centimeters; lower figures denote greater accuracy) in each scenario for WLAN fingerprinting and MILCO solutions. In the first three scenarios MILCO outperforms WLAN, while in *Scenario_4* WLAN fingerprinting provides better accuracy. However, the LCS client requests positioning errors that are lower than 6 meters and in this scenario both figures fall below this threshold. The higher error in this scenario for MILCO is a consequence of the use of MEMS technique, which provides less accurate positions than WLAN fingerprinting and A-GPS. This use of MEMS provides enough accuracy and also reduces battery consumption. Figure 6 also shows how the performance of WLAN fingerprinting location worsens as the number of APs is reduced (as expected).

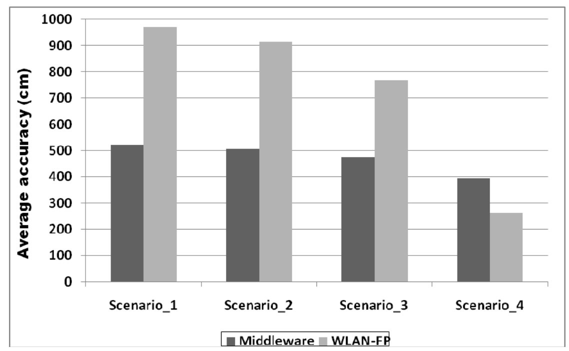


Figure 6. Accuracy achieved by MILCO and WIFI-FP

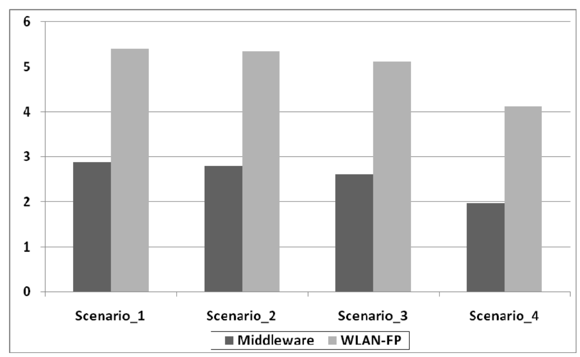


Figure 7. Average cost reported by the cost function (all LCS)

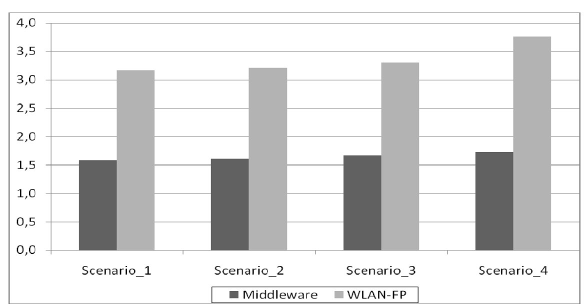


Figure 8. Average cost reported by the cost function (for successful LCS only)

Figures 7 and 8 show the cost quantified by the cost function when MILCO is used and the equivalent for systems in which only WLAN fingerprinting is used. Figure 7 accounts for all the LCS, while Figure 8 only displays the cost of successful LCS. In both cases, MILCO reduces the cost of providing LCS. Along with the higher successful LCS ratio, this indicates that MILCO achieves what was expected. The cost is reduced by more than 46% in all scenarios, which is a significant saving of resources. Accordingly, extended battery lifetime is expected, in addition to improved system performance. Better results are displayed in Figure 8, in which costs are reduced by more than 50% in all the scenarios. Figure 7 shows that, as expected, the cost increases with the lack of available access points, since unsuccessful LCS involves several techniques being run. Figure 8 shows the opposite: more constrained scenarios incur a lesser cost. This is because an estimation of the technique's performance shows that MILCO reduces the use of A-GPS and WLAN fingerprinting, which are the most costly techniques.

5.CONCLUSIONS

This paper presents a new software layer in the user terminal. This layer works like a middleware and manages several location techniques in order to maximize benefits. This middleware-like layer is based on a cost function, which aims to quantify the resources used by each location technique at a specific time. Three cost factors are implemented to illustrate the performance (but others could also be considered): successful probability, energy consumption and expected accuracy. The first estimates the performance of the location technique in a defined region and forecasts whether the location technique will be able to cope with the QoS requirements. Energy consumption favors those techniques that need less energy to be executed. Decisions relating to battery power depend on the power remaining in the terminal. The latter cost factor sorts the techniques according to their expected accuracy, i.e. the nominal accuracy that they should achieve.

Simulations were run to evaluate the performance of the proposed layer. The simulator implemented the radio link of a WLAN network and provided propagation models, power control algorithms, etc. that are suitable for such networks. Performance evaluation proves that the proposed approach is able to give a successful position for more than 91% of the carried LCS, even in highly constrained scenarios with only 1 AP in sight. In addition, the resources used (i.e. the cost) of providing such LCS is drastically reduced in comparison to the techniques used as standalone. Average accuracy provided by MILCO is worse than that achieved with standalone techniques but better than required by the service, with the benefit of using fewer resources to fulfill the service requests. At the same time, the performance of the proposed layer is stable in the different scenarios.

6. ACKNOWLEDGEMENTS

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