Automatic Switching Between Indoor and Outdoor Position Providers

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***Abstract*—In which way may an application switch instantly and reliably between an indoor and an outdoor positioning provider as a user enters and exits buildings? In this work we present a robust switching algorithm, utilizing the dynamic accuracy estimation of each position provider as a reliability indication. Our algorithm offers a fast automatic switch between the indoor and the outdoor provider, in a transparent way for the user. We also present experimental results, using GPS outdoors and a Bluetooth provider indoors. This technique was tested in our lab and was afterwards installed at the Hospital of Perugia, Italy, in the context of the Ambient Assisted Living (AAL) Virgilius project, where users can navigate with a smartphone. This study is also a result of the research done in the context of the AAL EDLAH project, for optimizing the selection of the most adequate positioning technology. Accurate position estimations are used as input for the EDLAH object detection module.**

***Keywords*—Indoor and Outdoor Detection, Indoor Positioning, Mobile Phones, GPS Availability, Bluetooth.**

I. Introduction

Indoor positioning is a topic that has gained great attention over the last years. Numerous mobile applications are utilising the location of the user. Outdoors positioning has been ahead, with GPS (Global Positioning System) being the dominant technology of the field. On the other hand, no universal standard has dominated the field of indoor positioning, where a big variety of alternatives has been proposed.

A technology which has been widely used during the last years is the Bluetooth Low Energy (BLE) technology. It has a low energy consumption, while maintaining a communication range similar to that of its predecessor, Classic Bluetooth. Several manufacturers produce Bluetooth beacons, that can be used for location applications, among their other utilities. Bluetooth beacons function with batteries and are small in size, thus they offer flexibility in the way they can be deployed in a building. Each beacon broadcasts a self-contained packet of data periodically. The packets contain an identifier of each beacon, so that the receiver can distinguish them. The Received Signal Strength Indicator (RSSI) can be used to estimate the distance between the mobile device and the transmitting beacon [1][2][3]. Due to their low cost and low consumption, a dense network can be deployed. Having a dense deployment can lead to reliable distance estimations from, at least, the closest beacons.

An important challenge for applications that need to offer positioning globally, both indoors and outdoors, is to have an efficient mechanism of switching between positioning providers. An example scenario can be the task to navigate a user to a hospital with GPS, and automatically switch to BLE when the user enters the building, in order to guide him to the specific room he wishes to go to , as in the Virgilius project. Another scenario may be to navigate users in University campuses or conference centres, where both indoor and outdoor positioning is required. In these scenarios, the outcome of the positioning module may be used to feed a navigation module, whose results rely on the accuracy and the responsiveness of the position estimations, regardless of the changes of environment (indoors/outdoors). Moreover, localizing a user accurately can assist other modules, such as the object localization module [4] created in the context of the of EDLAH project. The goal of this module is to assist older persons to locate an object that they might have lost, such as keys or glasses, at their house. A BLE beacon is attached to these objects, from which the distance to the user can be inferred, as described in [4]. As users move inside their house or in their yard, their estimated positions and the estimated distance from the beacons are used to infer the location of the lost object.

Lately, several studies [5][6][7][8][9][10] have focused on the $Indoor/Outdoor$ (IO) $detection$ problem. This problem is studied not only specifically for selecting the most appropriate provider for positioning, but to serve in a broader domain of context-aware applications. One of the existing techniques for IO detection is to use GPS and its drop in confidence or inability to obtain a fix in order to conclude that the user is indoors, as in [5][6].

The use of GPS quality has also been used for a positioning provider switching study [7]. In their work, Saengwongwanich et al. [7], present an indoor/outdoor switching methodology which utilizes the fact that receptions of at least four GPS satellites are needed in order to calculate the user's position in three dimensions. The algorithm uses the GPS position estimations when 4 or more satellites are visible, whereas the indoor provider (WiFi in their work) is trusted otherwise.

This work was co-funded by the State Secretariat for Education, Research and Innovation of the Swiss federal government and the European Union, in the frame of the EU AAL projects EDLAH (aal-2012-5-062, contract No INT2012.0054) and Virgilius (aal-2011-4-046, contract No INT2011.0048).

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Another method is to use the light sensor of the mobile device (as in [8][9]) alongside to other signals such as the cell signal and magnetic intensity, and utilize the difference in luminosity of indoor and outdoor environments, for IO detection. Lastly, IO detection utilizing embedded digital cameras in mobile phones and image processing techniques has been also proposed [10].

The rest of this paper is organized as follows. In Section II, we shortly present the indoor positioning method that was used for the experimental part of this work. In Section III, we present the idea of the proposed switching algorithm. Measurements and experimental results are reported and discussed in Section IV. Finally, conclusions drawn along with future directions are presented in Section V.

II. Indoor positioning method

The switching logic that is presented in a following chapter is generic, and provider independent. Nevertheless, for the testing implementation and the measurements of this study, the BLE technology is used as an indoor provider, and more specifically, the algorithm presented in [11] is utilized. Also, GPS technology is used as the outdoor provider. Following, we briefly present the indoor provider that is used.

For the indoor BLE provider, Bluetooth beacons are used. Each beacon periodically transmits a packet containing its identity. The mobile device that is to be localized receives these packets from the beacons in range. From the RSSI received from each beacon a distance estimation can be inferred.

Having obtained an estimation about the distance of the mobile device from each beacon, we proceed to the position estimation. From the list of beacons that are detected, only a set of the closest beacons are used for the calculation. In [11], it is shown that keeping the four closest beacons minimizes the estimation error.

Assuming that the mobile device is inside the coverage area (inside the outer polygon defined by the beacons' placement), the estimated position will also be inside the quadrilateral defined by the four closest beacons. Let $[e_1, e_2, e_3, e_4]$ be the estimated distances from the 4 closest beacons, while $[lat_1, lat_2, lat_3, lat_4]$ and $[lon_1, lon_2, lon_3, lon_4]$, the corresponding latitude and longitude of their positions. The latitude Lat_{est} and longitude Lon_{est} of the estimated position are calculated as follows:

$$Lat_{est} = \frac{\sum_{i=1}^{4} \frac{lat_i}{e_i}}{\sum_{i=1}^{4} \frac{1}{e_i}} \ , \ Lon_{est} = \frac{\sum_{i=1}^{4} \frac{lon_i}{e_i}}{\sum_{i=1}^{4} \frac{1}{e_i}} \tag{1}$$

The inverse value of the distance estimation from each beacon is used as a weight, in order to perform a weighted average of the positions of the closest beacons, that will give the estimated position. In order to have a more reliable distance estimation, we average the latest estimated distances from each beacon. In this way, we partially cope with the instability of the RSSI.

The position prediction is limited to the area that is defined by the polygon that the beacons' positions define. Thus, it is indispensable for this positioning algorithm that beacons are placed in such a way so that they surround all the area that is desired to be covered. For the deployment of this study, and in order to record the experimental results that are later presented, common areas of the building of Centre Universitaire d'Informatique of the University of Geneva were used. A zigzag pattern was used for placing the beacons in corridors and big halls. The same logic was used at the deployment of the Hospital in Perugia.

III. Switching methodology

The algorithm proposed in this study is intended to be used with any indoor or outdoor provider. The experimental implementation for this study uses GPS as an outdoor provider, and Bluetooth as the indoor one, since these were the technologies selected for the final deployment, at the Hospital of Perugia. It is noteworthy that the same logic may support a multi-provider approach. Thus, the logic may support cases where several indoor areas use different indoor technologies (BLE, WiFi, etc.), or if it is desired not to restrict the outdoor provider to GPS, but also use others, such as the Cell-ID. Nevertheless, in our implementation a single provider was used for each environment (indoors and outdoors).

The crucial parameter of the switching algorithm is the dynamic accuracy estimation that each provider should give. This claimed accuracy of each provider is utilised in order to compare the providers' reliability. The position estimations from the GPS provider contain an estimation of the accuracy, that can be used as the level of confidence of this estimation. On the other hand, in the following subsection the dynamic accuracy estimation concerning the indoor provider used is discussed, before proceeding to the detailed presentation of the algorithmic logic of switching.

A. Dynamic accuracy estimation

The field of calculating a dynamic accuracy estimation for indoor positioning techniques is very challenging. There have been studies [12][13] that use an observed correlation between the positioning error and the number of visible access points, in order to provide dynamically an estimation about the certainty of the estimated position. Nevertheless, these approaches do not refer to a dense indoor deployment, such as the indoor provider used at the experimental part of this study, but refer to public WiFi access points that can provide a rough position estimation (indoors or outdoors) with a precision of a few tens of meters. Thus, to have a more representative dynamic accuracy estimation, an empirical method is used, that is presented below. It should be pointed out, that this method is an open subject of research, with a view to be further optimized.

An empirical way was used for estimating the certainty over a position estimation, for the Bluetooth positioning method proposed in [11]. As described in [11], the beacons are deployed in a zigzag pattern. We chose the distance estimation

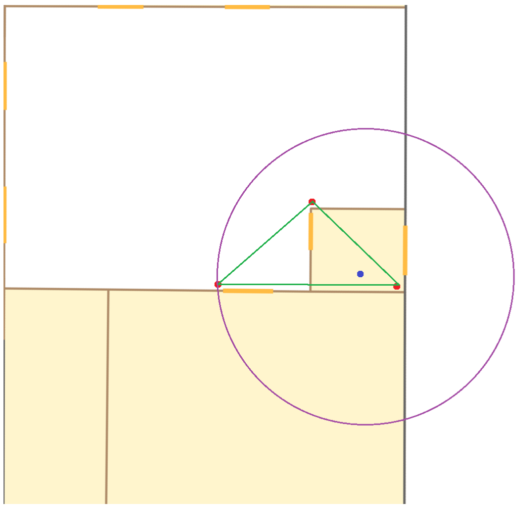

Fig. 1. Position of the user (in blue) inside the beacon area (in green), and accuracy circle (in purple), as infered from the estimated distance from the 3 closest beacons (in red)

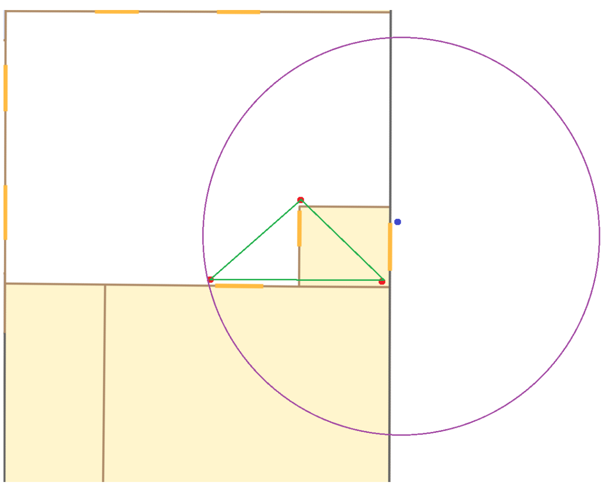

Fig. 2. Position of the user (in blue) outside the beacon area (in green), and accuracy circle (in purple), as infered from the estimated distance from the 3 closest beacons (in red)

from the third closest beacon to be the value of the claimed accuracy of the estimated position. A user that moves inside the area that the beacons define will be inside the triangle that the three closest beacons define. A circle having as center the estimated position and as radius the distance to the third beacon will include the triangle of the three closest beacons, as in Figure 1. When the user goes outside the area that the beacons define, as in Figure 2, the distance estimation from the third beacon will give a rough approximation of how far the user is from the beacon area. Even when the user exits the building, thus the beacons' area, the position estimations remain inside this area, since the way the positions are estimated is by averaging the positions of beacons. Nevertheless, the estimations of the distance from each beacon will get high values, and thus, the claimed accuracy (distance from the third closest beacon) will indicate the poor quality of the estimation, as the user moves away from the beacon area.

B. Behaviour of indoor and outdoor providers

The accuracy estimation of the indoor provider is also needed in order to have a measure of comparison with the GPS accuracy estimation. The accuracy of GPS takes small values (meaning that the accuracy is good) in open spaces outdoors, while it has really big values inside buildings. Using the distance estimation from a beacon (the third closest in our case), we get the inverse behaviour, that is having small values when the user moves indoors among the beacons and big values as he leaves the building. These measures form indications about being indoors or outdoors. The crucial step is the creation of a robust algorithm that switches quickly and reliably from one provider to the other.

It is worth mentioning at this point, some challenges of the task of switching. Initially, it is worth investigating the behaviour of the position estimations and of the dynamic accuracy estimation at the border regions of indoors/outdoors areas. In order to be able to exemplify, we mention in this example BLE as the indoor provider and GPS as the outdoor one.

When a user moves outdoors, towards the entrance of a building, the GPS accuracy may start degrading and the user may start receiving Bluetooth signal receptions. In cases like this, if the application receives position estimations from both providers, and returns to the user the one with the best claimed accuracy, the result may be a totally inconsistent series of positions. This happens because the most reliable provider can change continuously between Bluetooth and GPS, in these border regions. A continuous switching, back and forth, between providers can significantly deteriorate the user experience, and all functionalities that might be related with the location estimation. For example, a recalculation of the trip in a navigation module may be triggered continuously, if the provider selection is unstable. On the other hand it is desirable that the switch occurs quickly, but still reliably. With this view, we now present the switching algorithm.

C. Switching algorithm

In this subsection, the switching algorithmic logic is presented, with the assistance of the flow chart of Figure 3. We assume that position estimations from both indoor and outdoor providers are available to the application. The application uses the flag $currentProvider$, which stores the provider that is trusted at each moment. Without loss of generality, we present a generic solution for two providers. Let IN and OUT be these two providers, which implies that the $currentProvider$ may receive these two values. Moreover, the application stores the accuracies of the last position received from each provider, namely $lastIN$ and $lastOUT$ (an implied action in Figure 3). At each new position estimation received from the current provider, the position is returned to the application. When the received position estimation is not from the current provider, the last accuracies of each provider ($lastIN$ and $lastOUT$) are compared. If the current provider's accuracy is worse than

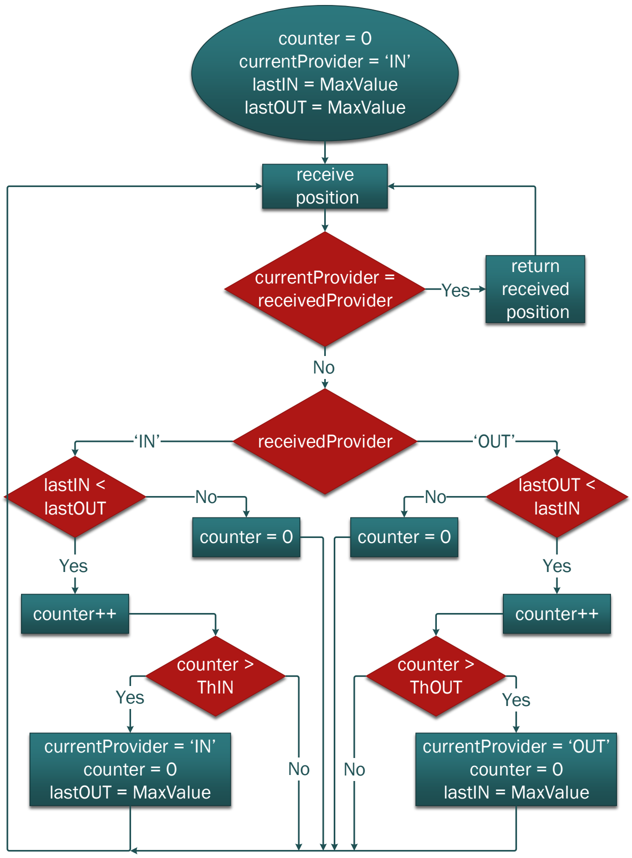

Fig. 3. Flow chart of switching algorithm

the accuracy of the other provider, then a $counter$ is incremented by one, otherwise the $counter$ is set to zero. When the counter reaches a threshold value, the $currentProvider$ changes value, from IN to OUT or inversely. The counter reaching a threshold signifies that several consecutive position estimations of the $currentProvider$ were less reliable than those given by the other provider. Requesting a number of good receptions greater than a threshold, guarantees that the new provider is reliably better than the previous one. If there are not several consecutive good readings but sporadically a few, the $currentProvider$ remains unchanged.

The specific values of the thresholds used should be appropriately tuned, according to several factors. Firstly, the frequency that position estimations are given from the indoor provider is an important factor. Commenting our experimental experience, we note that the indoor Bluetooth provider returns one position approximately every one second. This frequency is similar to the frequency with which positions are normally obtained by GPS. Furthermore, the density of the deployment and the range of the beacons influence the threshold selection. Lastly, there is a trade-off in selecting the threshold values, between the level of certainty with which a switch should be triggered and how quickly a switch should occur.

Apart from the main algorithmic logic presented in the flow chart (Figure 3), more details should be carefully examined. The algorithm should not get stuck to a provider at any point. For example, consider a scenario $IN = BLE$ and $OUT = GPS$, in which a user exits a building having BLE as $currentProvider$. Assume that the accuracy of GPS position estimations that she receives outdoors is consistently bad (due to environmental conditions). In this case, if the last Bluetooth position estimation received has a better claimed accuracy than what GPS can achieve under these circumstances, $currentProvider$ will be stuck to BLE, and no position estimation will be returned to the application ever since. To avoid this, we propose an additional mechanism that checks the number of consecutive position estimations that are not provided by the current provider, and changes the $currentProvider$ when these consecutive receptions exceed a threshold.

As mentioned before, in cases where the two providers have distinct frequencies of providing position estimations, the threshold values of the described algorithm as well as the threshold of consecutive position estimations from a provider of the above mentioned additional mechanism, should be carefully tuned.

IV. Measurements

The switching algorithm was tested in the building of the Centre Universitaire d'Informatique of the University of Geneva. Initially, in Figure 4, we present an example of the way the claimed accuracy of the two providers change as a user moves, exiting from a building. As the user starts indoors, she moves close to the beacons and thus, we observe that the estimated accuracy of the Bluetooth provider gets low values (good accuracy). As the user approaches the exit of the building, she starts getting some GPS readings, that have poor accuracy. At the border regions of indoor/outdoor areas, the accuracy may fluctuate until the user distances herself from the building. When the user passes to the outdoor area (after the red dashed line), the GPS accuracy improves and, at the same time, the accuracy of Bluetooth degrades. We observe that it takes a few seconds to receive a number of reliable readings from the new provider, before the $currentProvider$ changes (brown dashed line). This time depends on the threshold of new reliable readings that has been set. This threshold tunes the trade-off between delay of switching and robustness of switching. The comparison of different settings of parameter values is out of the scope of this work, as it depends on many factors, such as the technologies used, the environment and the preferences of the user over the trade-off previously mentioned.

In Figure 5, we present the position estimations that an application will receive, using the proposed algorithm. The grey segments represent the true trajectory of the user. From checkpoints 1 to 3, the user moves inside the building. From checkpoints 3 to 5, the user is outside the building, but under a rain shelter, highlighted in light purple. In accordance to the related bibliography [8][9], we refer to this segment of the path as semi-outdoor part. The fact that in semi-outdoor environments the area above the user is covered significantly degrades the position estimations given by GPS, and constituently, its claimed accuracy. For this reason, when we make a binary distinction (indoors/outdoors) in this work, we will only include the truly open spaces as outdoor environments, and not the covered areas (semi-outdoor). As a consequence, we only consider the path from checkpoints 5 to 7 to be outdoors.

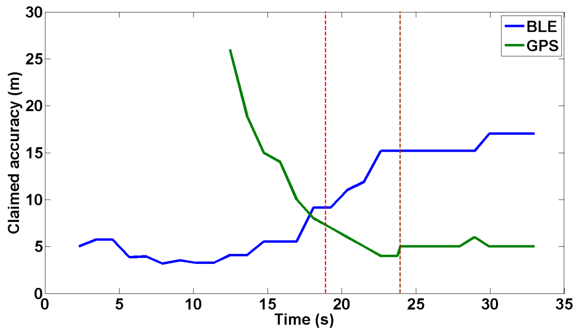

Fig. 4. Claimed accuracies of Bluetooth (blue line) and GPS (green line), during a movement from indoor to outdoor environment. The dashed lines indicate the moment that the user went outdoors (red dashed line), and the moment the provider switched (brown dashed line).

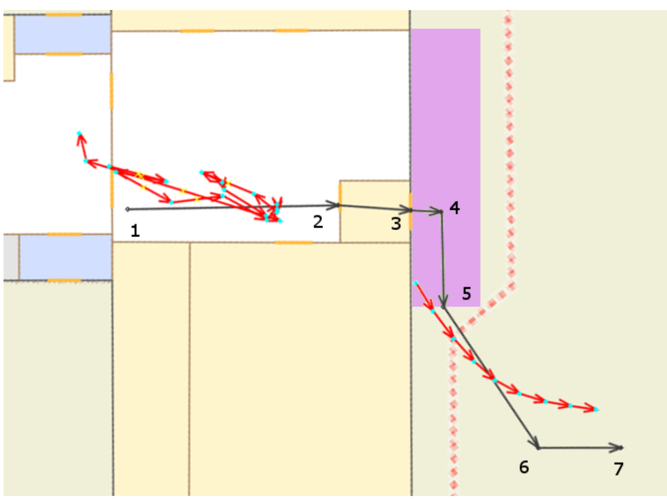

Fig. 5. Estimated positions using the switching algorithm, are shown in red (indoors and outdoors). The true trajectory of the user appears in grey.

With the trajectories in red color, we see the estimated positions that the user receives using the automatic switching. Initially, when the user is indoors, the Bluetooth provider is giving position estimations that suggest a trajectory towards the exit of the building. When the user moves in the semi-outdoor area that is not equipped with beacons, the estimated positions remain inside the building. This happens because the Bluetooth provider gives position estimations only inside the area where beacons are deployed. When the user passes checkpoint 5, GPS estimations start becoming much more accurate. At the same time, as the user distances herself from the beacons of the building, the claimed accuracy of Bluetooth worsens. The moment that the automatic switching occurs, indicating GPS as the $currentProvider$, the position estimations of GPS are provided to the user, as seen by the red trajectory at the outdoor part.

TABLE I
DELAY OF PROVIDER SWITCHING

	Mean switch delay (s)	*σ of delay (s)*
Outwards	6.72	2.1
Inwards (checkpoint 5)	9.04	0.95
Inwards (checkpoint 3)	3.43	1.05

The distance from checkpoint 1 to 7 (outwards) and from 7 to 1 (inwards) was covered 10 times, in order to report an average behaviour. In Table I, the delay with which the switching occurs is reported. For the outward trip we report the mean difference in time between the moment the user passes from checkpoint 5 and the moment that the $currentProvider$ changes, as well as the standard deviation. Similarly, we provide the same statistics for the inward trip, measuring this time the time difference not only regarding passing checkpoint 5 (entering the semi-outdoor area), but also passing checkpoint 3 (entering the building), since this is when the user enters the beacons area. It should be mentioned that the algorithm's threshold of requested consecutive good readings was set to 5. The correct switch occurs always, and has a very low delay. Considering that 5 good readings are requested, and that the Bluetooth provider has an update frequency of one second, we see that the switching is very responsive.

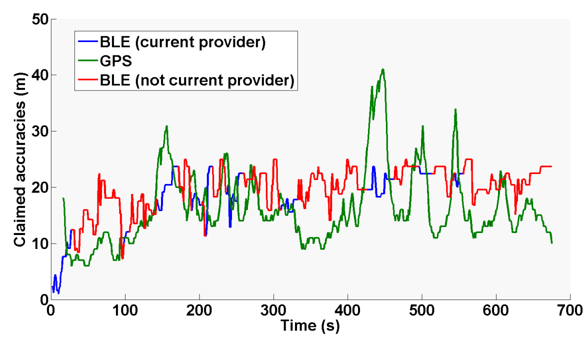

Fig. 6. Claimed accuracies of GPS (green line) and BLE (blue when BLE is the current provider, red otherwise), received at the limit of indoor/outdoor areas.

To offer a better understanding of the behaviour of the claimed accuracies and of the challenges of the proposed switching algorithm, we conducted the following experiment of a border case scenario. A user moved from checkpoint 1 to checkpoint 5 (referring to the checkpoints, as they appear in Figure 5), and then stayed at checkpoint 5, that is the limit of indoor/outdoor areas, for 10 minutes. The measurements were done during the lunch break time, with crowds of people passing by, influencing the receptions, as in a real life scenario. In Figure 6, we can observe the fluctuation of the claimed accuracies of the two providers through time. In green, we see the GPS accuracy. The accuracy of Bluetooth appears in blue when Bluetooth is the $currentProvider$, and with red otherwise. It can be easily observed that the claimed accuracies of the providers significantly fluctuate at the limit of indoor/outdoor areas. During the time of this experiment, the $currentProvider$ changed 19 times. We see that instant jumps from one provider to the other are avoided, and the median time of staying at the same provider is 20 seconds. On the other hand, if only the latest claimed accuracy were to be used, the $currentProvider$ would have changed 40 times, and would often be switching back and forth between the two providers, at consecutive seconds.

V. Conclusions and Future Work

A simple and effective algorithm for automatic switching between indoor and outdoor positioning providers was presented. The algorithm can be tuned according to the properties of the technologies used and the requirements of the application.

For battery saving reasons, geofencing could be used to activate and deactivate providers. For example, when a user is outdoors, the BLE could be inactive until the user enters an area around the building that supports a BLE positioning provider. Thus, it is only next to the building that both providers will be active. In this way, the proposed responsive automatic switch occurs when the user actually enters the building, and also, battery life is increased as both providers stay active only in areas where a switch may occur.

Moreover, we intent to investigate in detail the concept of the dynamic accuracy estimation for indoors providers. It is worth investigating for the optimal measure that can dynamically give an estimation of certainty over a position estimation. A potential measure can be evaluated a posteriori, comparing it with the actual positioning error committed by the provider.

The current study works as a solid base for the rest of the research modules of the two European projects, EDLAH and Virgilius. The robustness and responsiveness of the selection of the most appropriate provider improves the quality of position estimations that are fed to the object localisation module of EDLAH. Furthermore, a fast automatic switching between indoor and outdoor providers facilitates the goal of Virgilius towards a continuous user-friendly navigation, in any environment.

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