

Smart Position Selection in Mobile Localisation

Carlos Martínez de la Osa, Grigorios G. Anagnostopoulos, Michel Deriaz

Information Science Institute

GSEM/CUI

University of Geneva

Geneva, Switzerland

Email: {carlos.martinez, grigorios.anagnostopoulos, michel.deriaz}@unige.ch

Abstract—Which technology should be used in order to be able to locate oneself in any kind of scenario? This has been a recurrent question in the last years. It has become evident that, until now, there is no dominant indoor positioning solution based on a single technology. Outdoors, positioning systems based on satellites have given excellent results. However, a global solution for both kinds of scenarios does not exist. In our study, this problem is dealt with by creating an algorithm able to evaluate positions received from different technologies and choose the most trustworthy one. As a result, we are able to improve the overall accuracy of the user's position estimation, compared to the ones the different technologies would have given if used independently. In this way, the user is offered a simple solution to have an accurate position in all environments, in a transparent way. The main challenge of using different technologies at the same time is usually the battery consumption. A solution for dealing with this aspect is also proposed in this document. This research has been done in the context of the Ambient Assisted Living (AAL) Enhanced Daily Living and Health (EDLAH) project, where older people can track their lost objects, which requires them to be positioned in a very accurate way.

Keywords—Indoor localisation; Outdoor localisation; Position selection; Heterogeneous positioning; Battery saving.

I. INTRODUCTION

The ability to position people indoors has become a very important focus of research in the last years. An example of this are the requirements given in the European project EDLAH, that motivates this research, where the goal is for users to be able to locate some of their lost objects in a map of their house. It is also required to position these users in a very accurate way using their mobile devices.

Outdoor positioning is now excellent with the establishment of Global Positioning System (GPS), but the number of applications that demand positioning abilities in all environments is increasing rapidly. On the other hand, it appears that, until now, there is not a dominant solution based on a single technology able to offer better results than the rest for these cases.

One of the commonly used technologies for positioning in indoor environments is the Wi-Fi signal [1][2]. This approach takes advantage of the fact that most buildings have several Wi-Fi access points, in order to provide Internet access, so the hardware required is already installed. On the other hand, usually the access point network is not dense enough to facilitate a satisfactory precision of localisation. Another technology

widely used during the last years is the Bluetooth Low Energy (BLE) technology [3][4]. It has a low energy consumption, while maintaining a communication range similar to that of its predecessor, Classic Bluetooth. Some other approaches combine these methods with the inertial sensors of the device used to improve the accuracy and the experience of the user in between position estimation receptions [5][6].

An important challenge for applications that need to offer positioning globally, both indoors and outdoors, is to have an efficient mechanism that decides which position provider should be used. In our study, we face this problem by creating an algorithm able to gather positions received from different technologies, evaluate them and choose the most trustworthy one, therefore improving the overall accuracy of the user's position estimation. A similar approach to this solution can be found in [7], where the concept "Quality of Position" is presented.

This is one of the problems that must be faced in the EDLAH project, where the users must be located with high precision in their own flat, as well as outdoors in a garden or common area, in order to find their lost objects. These objects have been previously identified with a BLE beacon that allows a mobile device to compute the distance to them, as described in [8].

In this work, the position providers offered by Google in the Android operative system have been used, both GPS and Cell-ID based position provider [9]. Also, the BLE positioning solution presented in [3], where a grid of BLE beacons is deployed. This allows the position of the user to be inferred from a weighted average of the Received Signal Strength Indication (RSSI) values, which were received from the different beacons in range. In this case, the position estimation is limited to the area that is defined by the polygon that the beacons' placement creates. This way if the beacons are placed in an indoors environment, the position estimation will only be calculated indoors.

There exist also several studies about power saving in mobile positioning, giving an overview of current localisation technologies and a classification of techniques for improving the energy efficiency by evaluating some of the most promising approaches [10][11][12].

The rest of this paper is organised as follows. In Section II, we present the position selection algorithm and the concepts of position estimation and position trust. Experimental results and their corresponding analysis are shown in Section III. In Section IV, we present a theoretical model for battery saving. Finally, future work directions along with conclusions drawn are presented in Section V.

II. POSITION SELECTION

The core of this research is based on the existence of position providers. Conceptually, position providers constitute the lowest layer of a location based service. They transform raw sensor data into position estimations. In our system, these estimations are sent to higher level layers.

A. Position estimation

Firstly, it is necessary to establish the attributes that a position estimation must have in order to be suitable for the algorithm. These are:

- Latitude
- Longitude
- Accuracy
- Provider name
- Timestamp

The two basic parameters that a position must have are the latitude and longitude coordinates, as they allow the identification of a specific point in the geographic coordinate system.

As the position is not exact, but an estimate, it is needed to have an idea of the quality of that estimation. This is given by the dynamic accuracy estimation (referred in this paper as accuracy), which is generally described as the radius of 68% confidence of the position. In other words, if a circle centred at the position's latitude and longitude is drawn, and with a radius equal to the accuracy, then there is a 68% probability that the true position is inside the circle. This is because it is assumed that location errors are random with a normal distribution, so the 68% confidence circle represents one standard deviation. In practice though, location errors do not always follow such a simple distribution.

Moreover, the name of the provider that estimated the position must be delivered in order to give the user and the system information about the technology used. This is specially important for the battery saving algorithm, as it makes it possible to differentiate between different providers. Finally, the timestamp of when the position was recorded is also required, which is basic to have an idea of how recent each estimation is.

Additionally, the position estimation might also contain information about the altitude, the speed, the bearing of the user, etc. These are given to upper layers, but are out of the scope of this research.

B. Position trust

We define the position trust as an internal parameter of the algorithm utilized to determine which of the available positions is the best at each moment. The calculation of the trust is based on three parameters:

- Accuracy: as stated before, it is described as the radius of 68% confidence of the position, in meters. As explained, this error is also an estimation, because the system does not know what the exact real position of the person is. The accurate modelling of the accuracy estimation is vital for the correct behaviour of our approach. Generally, this estimation is based on some of the received characteristics of the raw data of the technology used. In GPS and the Cell-ID provider it is given by Android, while in the BLE provider we base this estimation on the strength of the received Bluetooth signal and the number of Bluetooth beacons in sight.
- Recency: in seconds, the difference between the timestamp obtained when the position was estimated and the actual timestamp at that moment.
- Priority: optionally, a value from 1 to 10, with 1 being the highest priority that can be assigned by the user to the different technologies used when initialising the algorithm. This is utilised in case the user prefers specific providers above others, even if the algorithm would choose a different position estimation if this priority would not exist. If priorities are not assigned, this parameter will not be taken into account in the selection process.

The trust of the position will be inversely proportional to the accuracy, which is given as the estimated error committed in the measurement, in meters. Therefore, the smaller the error, the bigger the trust. The trust will also be inversely proportional to the recency of the position, thus the newer the position, the higher the trust. If the user has given priorities to the different providers, this value will also be taken into account when calculating the trust. This will be inversely proportional to the value of the priority. Following, in (1), (2) and (3), the way that the trust is calculated, as well as the restrictions of the weight values are presented.

$$trust = \frac{w_1}{accuracy} + \frac{w_2}{recency} + \frac{w_3}{priority} \quad (1)$$

$$w_1 + w_2 + w_3 = 1 \quad (2)$$

$$w_i \geq 0, i \in \{1, 2, 3\} \quad (3)$$

The values w_1 , w_2 and w_3 correspond to the weight, or the importance, given to the accuracy, the recency of the position and the priority of the provider used, respectively. These weights can be tuned, following (2) and (3), in order to obtain the most adequate results for each scenario or preference of the user.

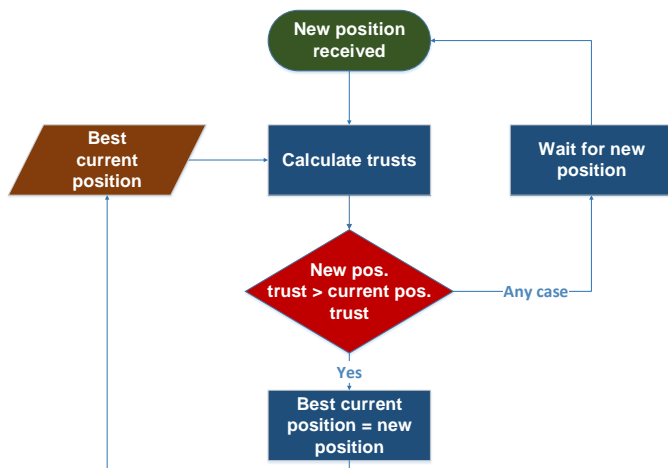


Figure 1. Flow chart of the position selection algorithm

C. Position selection

Each time that one of the position providers sends a new position estimation, its trust will be calculated and compared with the recalculated trust of the last best position estimation. If the trust of the new position is better, the algorithm will save it as the best possible position estimation at the moment and it will be returned to the user as an output. If the previous position estimation still has a better trust, then no update occurs. It is important to note that the trust of the last best position estimation will be recalculated every time a provider offers a new position. This is done because the recency of the previous position estimation must be updated and, therefore, its trust will decrease. The procedure's logic can be visualised in Figure 1.

III. RESULTS

We will now proceed to show the results achieved by using the position selection algorithm in our test environment at the University of Geneva. Concretely, the algorithm is tested using three different position providers: GPS, Cell-ID positioning, and a BLE provider. The first two providers are the ones provided by Google in Android mobile devices, while the BLE one has been developed by our group. The position selection algorithm, in the following example, has been configured using $w_1 = w_2$ and $w_3 = 0$ in (1). This means that, when calculating the trust of a position estimation, one meter in the accuracy is penalized the same way as one second in the recency of the estimation. This setup would be the logical solution for a user that is moving at a speed of one meter per second. In this example, the priorities are not taken into account. As an example, a position that was taken one second ago with an accuracy of one meter, will have the same trust as a position calculated right now with an accuracy of two meters. In this situation, the algorithm will choose the newer position estimation.

To measure the results of the algorithm, we have created a tool that allows us to record the actual real position of

a user, as he or she is moving, at the same time that the estimated positions are being calculated. Therefore, we can later calculate the error committed in the position estimations of a moving or static user. In our case, we have selected a path that mixes different types of scenarios. The user started the trip in an indoors area with no BLE coverage (and being indoors the GPS coverage is almost non-existent), followed by an indoors zone with BLE coverage. Later, the path continues outdoors with no BLE coverage and finishes again indoors with BLE coverage. The goal of this procedure is to test how the algorithm handles the changes between areas where one technology has much better accuracy than others.

TABLE I. RESULT FOR DIFFERENT POSITION PROVIDERS

Provider name	Mean error (m)	SD (m)	SR
GPS	13.7	11.68	41.01%
Cell-ID	31.69	20.07	62.96%
BLE	6.51	15.2	21.78%
GPStoBLE	5.76	7.53	39.57%
Our solution	4.84	6.42	45.34%

A list of the results can be seen in Table I. These have been extracted using a Samsung Galaxy S4 device. The results have been taken from five different position providers: standalone GPS, standalone Cell-ID position provider, standalone BLE position provider, GPStoBLE and our solution. GPStoBLE is a position provider previously created in our research group, that is specifically designed to switch between the BLE provider and GPS. It takes into account the specific characteristics of both providers and waits until several good readings of one of the providers are received to decide which of the two will be used.

In Table I, for each of these providers, the mean error committed in the estimations is shown, measured as the distance between the estimated position and the real one, in meters. Additionally, the standard deviation of the error is also specified, in order to offer a better idea about the dispersion of the results. Lastly, a parameter defined as Success Rate (SR), can be observed related to the estimated accuracy claimed by the providers. It indicates the percentage of the times that the real position was inside the area delimited by the circle with the estimated position as a center and a radius equal to the accuracy. As described in Section II, this value is expected to be close to 68%. Nevertheless, it is observed that this is not true for most of the providers, which means that the estimation of the accuracy should be improved in these cases.

Looking at the data obtained, it is directly seen that the standalone solutions are more inaccurate than the other two. Furthermore, the BLE and GPS solutions do not offer coverage everywhere. For example, even if the total error committed by the BLE position provider is relatively low, the error outdoors is unaccounted for as the provider is not estimating positions. Nevertheless, the user would not be able to position himself at that moment. It is notable that our solution, which is not provider specific, has a better performance compared to the one specifically designed for BLE and GPS, due to the introduction of a third position provider (Cell-ID) in areas

where none of the previous ones have coverage. The superior performance is also due to the removal of bad estimations, because when a new position is received with a bad accuracy, the algorithm will most likely keep using the previous position estimation as it would have more trust. The visual difference between the real path followed by the user and the one estimated by our solution can be observed in figures 2 and 3.

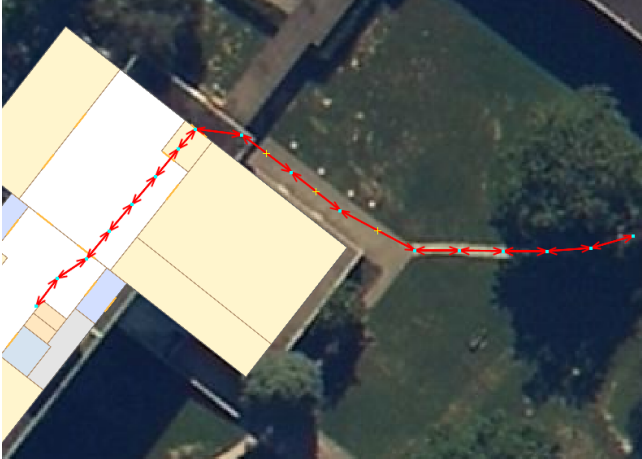


Figure 2. Real path followed by the user



Figure 3. Estimated path by our solution

Lastly, a parameter optimization step is made, in order to find a better parameter tuning for our algorithm. In Table II the results of five different setting of w_1 and w_2 , are exemplified. The parameter w_3 , representing the weight of the priority given to each provider, is again set to zero. Values were given following (2) and (3). The values vary from 0.3 to 0.7 for both parameters. Higher or lower than that, the algorithm starts giving poor results. If the accuracy has a weight lower than 0.25 the algorithm will start giving only new positions, taking very little into account the estimated error committed. Similarly, if w_2 is very low, the algorithm will offer a position update only when it receives a more accurate position, even if the saved one was taken a long time ago.

TABLE II. RESULT FOR DIFFERENT ALGORITHM WEIGHTS

w_1	w_2	Mean error (m)	SD (m)	SR
0.3	0.7	4.84	6.37	46.28%
0.4	0.6	4.81	6.36	47.44%
0.5	0.5	4.84	6.42	45.35%
0.6	0.4	4.90	6.55	40.46%
0.7	0.3	4.92	6.68	38.60%

It is appreciated how slightly better results are obtained for $w_1 = 0.4$ and $w_2 = 0.6$. This means that the estimations are closer to the real path of the user when the recency of the updates is given slightly higher importance than the estimated accuracy. This result might also be due to the accuracy estimation not having a 68% confidence as it should, but significantly lower in most of the cases.

IV. BATTERY SAVING

One of the downsides of this approach and, in general, of all heterogeneous positioning solutions, is that the device needs to have activated all technologies and be subscribed to their corresponding position providers at all times, which translates into an elevated battery consumption. For this reason, it is here presented a theoretical model on how to apply battery saving techniques to the solution presented in this paper. This model is based on controlling the switching, on or off, of the different position providers depending on how they are needed. There are no experimental results offered for this model yet, as it is an ongoing work in our group.

The algorithm applied in this case checks, on every position update, the trust of the position estimations offered by the different active providers. The main idea of the algorithm is to classify providers as reliable when they offer a number of trustworthy positions in a row, and, in a similar way, classify them as unreliable if they give a number of untrustworthy position estimations in a row.

The algorithm is iterated every time there is a position update. It checks the trust of the position received, if this trust is higher than a predefined trust value, a specific counter for this provider is increased. The counter is reset to zero every time the trust is lower than this value. When the algorithm detects that the counter is higher than a confidence threshold, it means that the provider has given several trustworthy positions in a row, so it is classified as a reliable position provider. If the system detects that there are several reliable providers at the same moment, it deactivates the ones with the highest power consumption.

Similarly, when a reliable provider gives a series of untrustworthy positions in a row, it is classified as not reliable and, if it is the only active provider at that moment, the rest of the providers will be reactivated again in order to find positions with higher trust. This logic can be visualised in Figure 4.

Besides, if the only provider used at a given moment consumes a high amount of power, a timer will be activated so that every given amount of time, providers that have a lower battery consumption are reactivated to check if they became

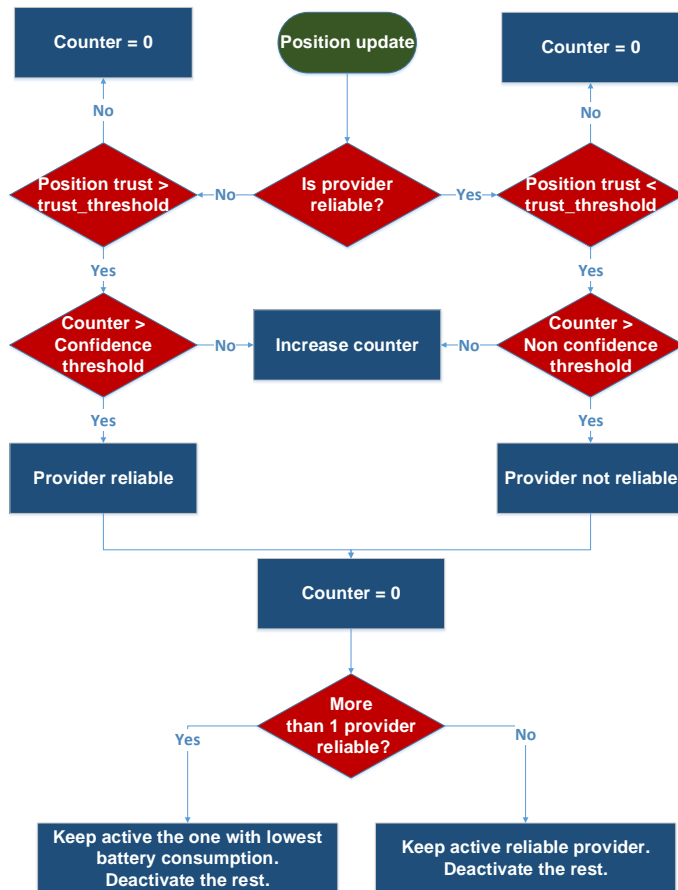


Figure 4. Flow chart of the battery saving algorithm

trustworthy and use one of them instead of the one with high battery consumption demand.

In order for this algorithm to be effective, it is important that, when defining a new provider, a parameter which indicates the energy consumption rate of this technology is specified. This parameter does not need to be a quantitative measure, but may just be a qualitative description. As an example, in our system, GPS is marked as High Consumption, while the BLE position provider is marked as Low Consumption.

The confidence thresholds that define when a provider is reliable or not, as well as the timer set for high power consumption providers, are meant to be tuned by the user of the algorithm. It is evident that there exists a trade-off between battery consumption and position accuracy. Having very low values on these parameters will imply a high amount of activating and deactivating providers, but it will also mean that more position estimations of different providers are received, improving the chances of getting more accurate estimations, but also increasing the battery consumption. On the other hand, higher values will imply less changes of providers, less battery consumption, and, most likely, less accuracy.

V. CONCLUSION AND FUTURE WORK

A switching algorithm between different mobile position providers has been presented along with a battery saving logic. It has been demonstrated how our solution has been able to improve the results previously achieved in our group, which used to rely on position providers based on a single technology, or a switching logic designed for specific providers. The proposed solution is technology independent, since the algorithm simply requires some basic parameters in the position estimation, which offers substantial flexibility for the future addition of new position providers based on other technologies.

The requirements for the project EDLAH have been fulfilled, as the accuracy is improved in all environments, according to the available technologies. This way, the object localization module has a more reliable position estimation input.

Future work in this area involves testing other configurations of the algorithm by adjusting the different weights and thresholds involved. One of the possibilities is the addition of machine learning techniques to optimise the algorithm parameters trying to minimise the average error in the estimation. Additionally, the battery saving theoretical model will be implemented in order to extract results and conclusions from its use.

ACKNOWLEDGEMENTS

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 project EDLAH (aal-2012-5-062).

REFERENCES

- [1] S. Mazuelas *et al.*, "Robust indoor positioning provided by real-time rssi values in unmodified wlan networks?" *J. Sel. Topics Signal Processing*, vol. 3, pp. 821–831, 2009.
- [2] M. Lee and D. Han, "Voronoi tessellation based interpolation method for wi-fi radio map construction." *IEEE Communications Letters*, vol. 16, no. 3, pp. 404–407, 2012.
- [3] G. G. Anagnostopoulos and M. Deriaz, "Accuracy enhancements in indoor localization with the weighted average technique," in *SENSORCOMM 2014*, 2014, pp. 112 – 116.
- [4] Z. Jianyong *et al.*, "Rssi based bluetooth low energy indoor positioning," in *IPIN 2014*, 2014.
- [5] L. Liew and W. S. H. Wong, "Indoor positioning method based on inertial data, rssi and compass from handheld smart-device," 2014, pp. 48 – 52.
- [6] U. Shala and A. Rodriguez, "Indoor positioning using sensor-fusion in android devices," 2011.
- [7] E. Metola and A. Bernardos, "Poster an embedded fusion system for location management," vol. 104, pp. 233–237, 2012.
- [8] G. Ionescu, C. M. de la Osa, and M. Deriaz, "Improving distance estimation in object localisation with bluetooth low energy," in *SENSORCOMM 2014*, 2014, pp. 45 – 50.
- [9] Google, "Android Location Strategies," <http://developer.android.com/guide/topics/location/strategies.html>, 2015, [Online; accessed 24-June-2015].
- [10] T. Graf, "Power-efficient positioning technologies for mobile devices," *Berlin University of Technology*, Jul, 2012.
- [11] T. Nakagawa *et al.*, "Variable interval positioning method for smartphone-based power-saving geofencing," in *Personal Indoor and Mobile Radio Communications (PIMRC), 2013 IEEE 24th International Symposium on*, Sept 2013, pp. 3482–3486.

- [12] K. Lin, A. Kansal, D. LyMBERopoulos, and F. Zhao, "Energy-accuracy aware localization for mobile devices," in *ACM MobiSys 2010*, 2010.