# Enabling Seamless Positioning for Smartphones

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***Abstract*— Smart devices are attractive platforms for researchers to collect data coming from several sensors due to their small size, low cost, and the fact that they are already carried routinely by most people. The capability of smart devices to be used as the target of a positioning system has been already demonstrated in previous works. However, most of them rely on a single technology, or they are specific to the environment or user. In this paper we tackle these constraints by presenting a novel seamless positioning system which fuses the sensors information provided by a portable smart device to perform real time location without interruption and regardless the environment where the user is moving. We have tested the system with a commercial smartphone in a three floor building and its surroundings fusing the GNSS, WiFi and barometer as frequently used sensors, and the proximity contactless technologies as occasionally used sensors. The obtained positioning accuracy mainly depends on the indoor path-loss awareness and on the markers density, showing that without using markers but dynamically estimating the path-loss exponents we obtain an error of less than 2 m for 90 % of cases.**

## I. Introduction

Man has always felt the need to position himself using the sun and the stars as the only reliable reference systems for many centuries. Today, with the advent of global navigation satellite systems (GNSS) global positioning in the earth's surface is a successfully overcome problem. Nonetheless, local positioning in indoor environments is still a matter of active research, since GNSS signals get severely degraded in this type of environments due to multipath and attenuation losses, and thus they cannot be used to track people or objects with acceptable accuracy [1]. Many local positioning systems (LPS) have been developed during the past two decades based on different technologies that include radio-frequency [2]–[5], vision cameras [6] and magnetic [7], among others. After all this research effort, it is becoming clear that none of these technologies clearly outperforms the others, and we expect now a new tendency to design systems that combine some of them to benefit from their complementary strengths.

In this paper we propose a seamless positioning engine for the fusion of the sensors information provided by a smartphone, intended to perform real time location without interruption and regardless the environment where the user is moving. The capability of smartphones to be used as the mobile node in privacy-oriented systems, where this node is in charge of computing its own position, has been already demonstrated in several works. Hence, in [8] a privacy-oriented system based on the use of Bluetooth beacons is described, where a Nokia N70 device is positioned with an accuracy of 2-3 m. Also, accuracies below 4 m have been reported in [9] by using the magnetometer of a HTC Nexus One in several corridors of two buildings. All these works rely on a single technology, though. There are also some recent works that propose the fusion of the information provided only by the different built-in sensors of a smartphone. This is, for example, the case of the system proposed in [10], that implements a Kalman filter to combine the information obtained from the WiFi transceiver and the built-in accelerometer and digital compass of a Samsung Nexus S, obtaining accuracies between 2.4 and 4.1 m. A similar system is proposed in [11], that uses Hidden Markov Models to combine the information provided by the WiFi transceiver, the accelerometer and the compass of a Nokia N8, to achieve accuracies around 3 m in a real office environment. In both cases, the system has been designed to operate in a calibrated environment and it is very sensitive to changes in this environment, since the WiFi positioning system is based on the comparison on the measured RSS values with those previously gathered in a fingerprint database.

To the authors knowledge, the seamless positioning engine presented in this paper is the first system to combine a wide diversity of information provided by different sensors of a single and commercially available smartphone with the aim to perform seamless positioning both outdoors and indoors without fingerprinting. The main improvements of this system with respect to previous directly related works can be summarized as follows:

- The WiFi positioning engine is not based on fingerprinting, what gives the system the capability to work in uncalibrated environments.
- The information provided by the smart device sensors is combined by means of an unscented Kalman filter (UKF), a filter that is more accurate than an extended Kalman filter (EKF) and easier to implement than a Gauss second-order filter [12].

This system would be the ideal platform for location based services (LBS) that provide the user with personalized information depending on his geographic location [13]. The proposed engine would easily allow the extension of all those services that are currently being provided outdoors to indoor environments such as hospitals, museums, train stations, airports, malls and many others that could undoubtedly benefit from this type of services.

## II. The Seamless Positioning Engine

Nowadays, the smartphones already integrate a GNSS receiver, a WiFi transceiver, a camera, and shortly, most of them will integrate other sensors such as the barometer and the proximity contactless technology NFC. The aim of this paper is to develop a framework that seamless estimates the user position by fusing the so called signals of opportunity (SoOP) which are transmitted for non-localization purposes, but may be exploited to this end. In fact, this work is thought as a modular system for commercially available smartphones where SoOP coming from new technologies can be easily added.

Bayesian filters, which use a probabilistic framework to perform reasoning, are a theoretically sound way to combine multiple and different SoOP. Bayes filters probabilistically estimate a dynamic system's state from noisy observations. They represent the state at time $t_k$ by random variables $\mathbf{x}_k$. At each point in time, a probability distribution over $\mathbf{x}_k$, called *belief*, represents the uncertainty. Bayes filters aim to sequentially estimate such beliefs over the state space conditioned on all information contained in the observations [14]. In this paper, the state is the user's location, $\mathbf{x}_k = [x_k, y_k, z_k]^T$, while the SoOP provide observations about the state. Among the different Bayes filters, Kalman filters are the most widely used. They are optimal estimators, assuming the initial uncertainty is Gaussian, the observation model and system dynamics are linear functions of the state, and the measurement and process noise distributions are Gaussian. However, the lack of linearity in the models that relates most of the SoOP to the user's location implies the usage of a suboptimal solution, where the most common is to use the EKF. Nevertheless, we selected the UKF since it better captures the higher order moments caused by the non-linear transformation and avoids the computation of Jacobian and Hessian matrices [12]. Furthermore, the overall number of computations performed by the UKF are the same order as the EKF, and much lower than solutions such as the particle filter which better represents the belief but needs a number of computations unacceptable for most smart devices.

Consider the following non-linear system, described by the *dynamic* and *measurement* models with additive noise:

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}) + \mathbf{w}_{k-1} \quad (1)$$

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{v}_{k-1} \quad (2)$$

where $\mathbf{w}_k$ and $\mathbf{v}_k$ are the process and observation noise which are both assumed to be zero mean multivariate Gaussian noise with covariance $\mathbf{Q}_k$ and $\mathbf{R}_k$, respectively. The function $f$ can be used to compute the predicted state from the previous estimate and similarly the function $h$ can be used to compute the predicted measurement from the predicted state.

On the one hand, the dynamics of the system can be represented as

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \dot{\mathbf{x}}_{k-1}\Delta t + \mathbf{w}_{k-1} \quad (3)$$

where $\Delta t = (t_k - t_{k-1})$ is the time step and $\dot{\mathbf{x}}_k$ is the first derivative of the state, in this case, the user's velocity. Finally, $\mathbf{w}_k$ is assumed to be a zero-mean Gaussian variable with covariance matrix $\mathbf{Q}_k$. The values of $\mathbf{Q}_k$ depend on the dynamic of the target, in this paper a walking person. In practice, $\mathbf{Q}_k$ is a diagonal matrix whose in-diagonal elements represent the variance of the user's position and velocity [15].

On the other hand, the function $h$ depends on the SoOP. In the WiFi case the measurement model, called $h^w$, can be represented as

$$\mathbf{z}_k^w = \alpha - 10n\log_{10}(||\mathbf{x}_k - \mathbf{AP}||) + \mathbf{v}_{k-1}^w \quad (4)$$

where $\mathbf{z}_k^w$ is the RSS measured value; $\alpha$ is a parameter that remains constant in those scenarios where the antennas gain and the power transmitted from the access points are also constant, a situation typically found in most WiFi WLANs [16]; $\mathbf{AP}$ is the position of the WiFi access point; and $n$ is the path-loss exponent corresponding to the actual propagation environment. In free space $n = 2$, however in practice, depending on the environment the path-loss exponents ranging from 1,5 to 4,5 [16], [17]. In this paper we analyze the performance using the path-loss exponent values under two different situations: (i) setting fixed values for the path-loss exponents sampling values ranging from 1,5 to 4,5 according to this rule: the stronger the RSS measured value (assuming a closer position to the antenna) the smaller the path-loss exponent value (assuming lower reflections and diffractions), and (ii) dynamically estimating the path-loss exponent values following the algorithm proposed in [4]. By using this algorithm we found the path-loss exponents that best fit the propagation environment between the receiver (user's smart device) and each WiFi access point in range at each time interval. $\mathbf{v}_k^w$ represents the RSS noise and it can be assumed to be zero-mean Gaussian variable with covariance matrix $\mathbf{R}_k^w$. In practice, we have $h_i^w$ with $i = 1, 2, \dots M_k$ functions, where $M_k$ is the number of WiFi access points in range at each time step $t_k$. Accordingly, $\mathbf{R}_k^w$ is a diagonal matrix whose in-diagonal elements represent the variance of the measurements coming from each WiFi access point. The benefit of using this SoOP is that WiFi signals predominate inside buildings where GNSS signals are blocked.

In the GNSS case, the measurement model, called $h^g$, can be represented as

$$\mathbf{z}_k^g = \mathbf{x}_k + \mathbf{v}_{k-1}^g \quad (5)$$

where $\mathbf{z}_k^g$ is the GNSS position estimation reported by the built-in GNSS receiver. $\mathbf{v}_k^g$ represents the GNSS noise which can be assumed to be zero-mean Gaussian variable with covariance matrix $\mathbf{R}_k^g$. In practice, $\mathbf{R}_k^g$ is a diagonal matrix whose in-diagonal elements represent the variance of the measurements coming from the satellites, and its value depends on the number of satellites in line-of-sight. The more satellites with good GDOP (Geometric Dilution of Precision), the more reliable the GNSS data. We benefict form the GNSS data only in open areas where it accurately reports the user's position

In the barometer case, the measurement model, called $h^b$, can be represented as

$$\mathbf{z}_k^b = p_0 \cdot \left(1 - \frac{\lambda}{T_0} x_k\right)^{\frac{g}{\lambda R_{air}}} + \mathbf{v}_{k-1}^b \tag{6}$$

where $\mathbf{z}_k^b$ is the air pressure, $T_0 = 288,15\ K$ is the temperature at sea level, $\lambda = -0{,}0065\ K/m$ is the temperature gradient, $p_0 = 1013{,}25\ mbar$ is the pressure at sea level, $R_{air} = 287\ m^2(s^2K)^{-1}$ is the atmosphere gas constant, and $g = 9{,}8\ m/s^2$ is the earth gravity. $\mathbf{v}_k^b$ represents the air pressure noise which can be assumed to be zero-mean Gaussian variable with covariance matrix $\mathbf{R}_k^b$. This model is not exact because it assumes some variables as constants, and it does not take into account other factors such as humidity, weather, or the presence of air conditioning systems. However, we do not use the absolute but the relative altitude. The estimated relative altitude is used to infer any building floor change.

Finally, in the contactless technologies cases using NFC tags and QR codes, the measurement model, calle $h^c$, can be represented as

$$\mathbf{z}_k^c = \mathbf{x}_k + \mathbf{v}_{k-1}^c \tag{7}$$

where $\mathbf{z}_k^c$ is the position of the NFC tag or QR code. $\mathbf{v}_k^c$ represents the observation noise which can be assumed to be zero-mean Gaussian variable with covariance matrix $\mathbf{R}_k^c$. As the SoOP gather by the contactless technologies have to be read at few centimeters from the tag or code, in practice, $\mathbf{R}_k^c$ is a diagonal matrix whose in-diagonal elements are lower than 1 m. These proximity contactless technologies work anywhere and they can update the location algorithm with accurate position information.

As shown in Figure 1, and it is well described in [12], once the dynamic and measurement models, and their noise covariace matrices are described, the UKF is straightforward to implement. Notice that the initial values of the state covariance matrix, $P_0$, depends on the initial state confidence. UKF main advantage is their computational efficiency (same as EKF and lower than particle filters), better linearization than EKF (accurate in the third-order Taylor series expansion), and derivative-free (no Jacobian and Hessian matrices are needed) [12].

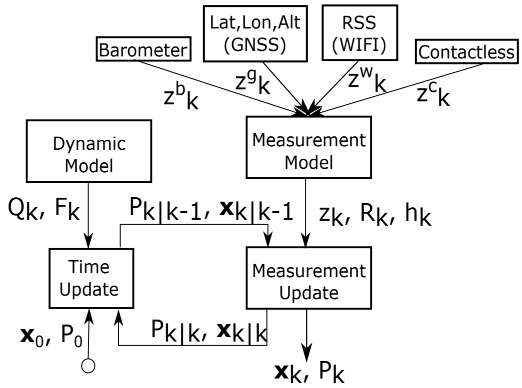



Fig. 1. Flowchart of the processing block

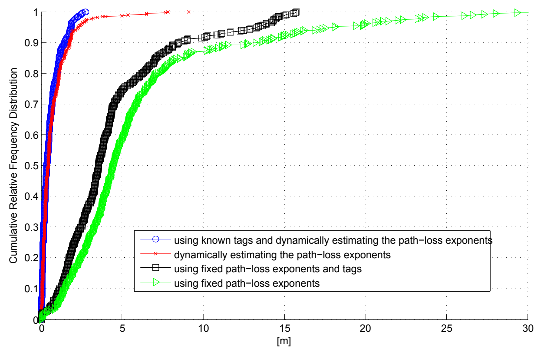



Fig. 3. CRFD of the position error in different situations

## III. Experimental Results

The seamless positioning engine has been developed on Android, a mobile operating platform which nowadays controls most of smartphones. As a way to verify its behaviour under a real environment it has been tested using the GNSS, WiFi and barometer as frequently used sensors, and the proximity contactless technologies as occasionally used sensors.

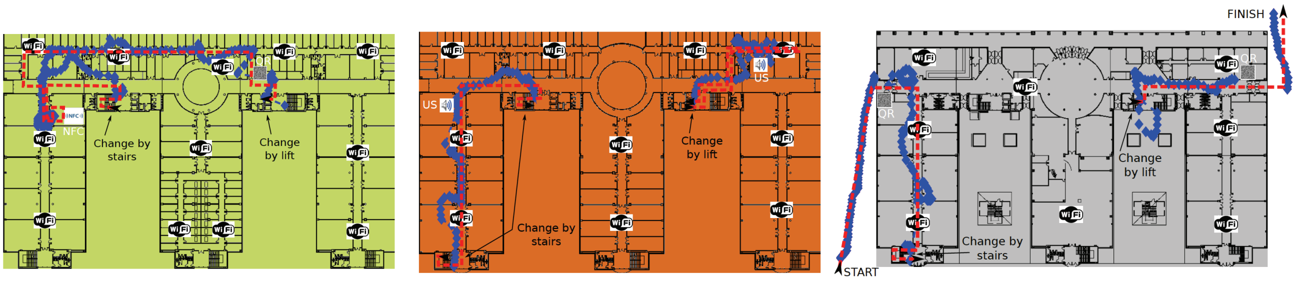
### A. *Experimental Setup*

For the experimental evaluation we conducted real trials at the building of the Higher Technical School of Telecommunications (ETSIT) in the city of Valladolid, whose floor map is shown in Figure 2. This three floor building is 125 m long and 75 m wide. In the experiments the target is a person who carries the Galaxy Nexus GT-i9250 smartphone. It incorporates the broadcom BCM4330 single chip device providing with integrated IEEE 802.11 a/b/g, the Bosch BMP180 digital barometric pressure sensor as barometer, the CSR GSD4t as internal satellite signal tracking engine, and the NXP PN533 NFC controller. As WiFi access points we used the Trapezee MP372 already deployed at the ETSIT building which send a beacon frame each 100 ms at constant power on frequency channels 1, 6 and 11 (around 2.412, 2.437 and 2.462 GHz, respectively). The building has approximately one WiFi access point each 900 $m^2$.

The path shown in Figure 2 tries to cover all the situations that a user can face up when walking inside a building. The path contains outdoor to indoor and indoor to outdoor transitions, floor changes by stairs and lift, and wide and narrow corridors. Figures 2 (a), (b) and (c) show the actual path in red slash, the estimated positions in blue diamonds, and the position of the WiFi access points, QR codes, and NFC tags deployed in the ETSIT ground, first, and second floors.

### B. *Results and Discussion*

For the evaluation of the error distribution, we compared the obtained positions with a ground truth measured using marks in the walking path. The cumulative relative frequency distributio (CRFD) of the positioning errors is presented in




(a) Second Floor (b) First Floor (c) Ground Floor

Fig. 2. Path followed carrying the smartphone at the ETSIT building. In red slash the actual path, in blue diamonds the estimated positions.

Figure 3. The proposed engine is able to obtain positions errors of less than 8 m for 90 % of the samples when using fix path-loss exponents and a few markers such as the QR codes and NFC tags which once in a while update the estimated position. This error increases up to 12 m for 90 % of samples without using the markers. We compared these two CRFDs to the one obtained by dynamically estimate the path-loss exponents that best fits the propagation environment in real time only using the actual RSS measurements, following [4], in both cases with and without markers. When the path-loss exponents are dynamically estimated the positions errors are lower than 2 m for 90 % of samples. These results show the importance of the path-loss exponents values when working with RSS measurements.

## IV. Conclusions

In this paper we have presented an UKF scheme for the real time fusion of the SoOP provided by a smartphone sensors to guarantee a seamless positioning system. The GNSS signal provides a good three-dimensional position estimation in open areas, while the WiFi RSS provides a good two-dimensional estimation in indoor environments. The barometer provides a good estimation of the relative altitude profile indoors, thus, this sensor extends the indoor positioning to 2.5 dimensions. Additionally, the markers such as the QR codes and NFC tags can be used, once in a while, to accurately update the estimated position. This engine is thought as a modular system, therefore, new SoOP which can be related to the user position can be easily added, such as map information, user acceleration, rate of turn or magnetic north.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## References


[1] P. Zandbergen, "Accuracy of iPhone Locations: A Comparison of Assisted GPS, Wifi and Cellular Positioning," *Transactions in GIS*, vol. 13, no. s1, pp. 5–25, 2009.

[2] J. Werb and C. Lanzl, "Designing a Positioning System for Finding Things and People Indoors," *IEEE Spectrum*, vol. 35, no. 9, pp. 71–78, 1998.

[3] K. Whitehouse, C. Karlof, and D. Culler, "A Practical Evaluation of Radio Signal Strength for Ranging-Rased Localization," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 11, no. 1, pp. 41–52, 2007.

[4] S. Mazuelas, A. Bahillo, R. M. Lorenzo, P. Fernández, F. Lago, E. García, J. Blas, and E. J. Abril, "Robust Indoor Positioning Provided by Real-Time RSSI Values in Unmodified WLAN Networks," *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, no. 5, pp. 821–831, Oct. 2009.

[5] A. Bahillo, S. Mazuelas, R. M. Lorenzo, P. Fernández, J. Prieto, R. J. Durán, and E. J. Abril, "Hybrid RSS-RTT Localization Scheme for Indoor Wireless Networks," *EURASIP J. Adv. Signal Process*, vol. 2010, pp. 17:1–17:12, Feb. 2010. [Online]. Available: http://dx.doi.org/10.1155/2010/126082

[6] V. Willert, "Optical Indoor Positioning using a Camera Phone," *Proceedings of the 2010 International Conference on Indoor Positioning and Indoor Navigation*, 2010.

[7] J. Chung, M. Donahoe, C. Schmandt, I.-J. Kim, P. Razavai, and M. Wiseman, "Indoor Location Sensing Using Geo-Magnetism," *Proceedings of the 9th International Conference on Mobile Systems, Applications and Services (MobiSys'11)*, pp. 141–154, 2011.

[8] S. P. Subramanian, J. Sommer, S. Schmitt, and W. Rosenstiel, "SBIL: Scalable Indoor Localization and Navigation Service," *Proceedings of the 3rd International Conference on Wireless Communication and Sensor Networks*, pp. 27–30, 2007.

[9] K. P. Subbu, B. Gozick, and R. Dantu, "Locateme: Magnetic-fields-based indoor localization using smartphones," *ACM Trans. Intell. Syst. Technol.*, vol. 4, no. 4, pp. 73:1–73:27, Oct. 2013.

[10] T. Gallagher, E. Wise, B. Li, A. Dempster, C. Rizos, and E. Ramsey-Stewart, "Indoor Positioning System based on Sensor Fusion for the Blind and Visually Impaired," *Proceedings of the 2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN'12)*, pp. 1–9, 2012.

[11] J. Liu, R. Chen, L. Pei, R. Guinness, and H. Kuusniemi, "A Hybrid Smartphone Indoor Positioning Solution for Mobile LBS," *Sensors*, pp. 17 208–17 233, 2012.

[12] S. Julier, J. K. Uhlmann, and H. F. Durrant-Whyte, "A New Method for the Nonlinear Transformation of Means and Covariances in Filters and Estimators," *IEEE Trans. Automat. Contr.*, vol. 45, no. 3, pp. 477–482, 2000. [Online]. Available: http://dblp.uni-trier.de/db/journals/tac/tac45.html#JulierUD00

[13] S. Steiniger, M. Neun, and E. Alistair, "Foundations of Location Based Services," *CartouCHe1-Lecture Notes on LBS*, vol. 1, 2006.

[14] D. Fox, J. Hightower, L. Liao, D. Schulz, and G. Borriello, "Bayesian Filters for Location Estimation," *IEEE Pervasive Computing*, pp. 24–33, 2003.

[15] C. F. Wakim, S. Capperon, and J. Oksman, "A Markovian Model of Pedestrian Behavior." in *SMC (4)*. IEEE, 2004, pp. 4028–4033. [Online]. Available: http://dblp.uni-trier.de/db/conf/smc/smc2004-4.html#WakimCO04

[16] X. Li, "Rss-based location estimation with unknown pathloss model." *IEEE Transactions on Wireless Communications*, vol. 5, no. 12, pp. 3626–3633, 2006. [Online]. Available: http://dblp.uni-trier.de/db/journals/twc/twc5.html#Li06

[17] K. Pahlavan and A. H. Levesque, *Wireless Information Networks*. New York: Wiley, 1995.