An integrated WLAN and GPS Localization for Urban Canyon Environments using Sparse Data Processing

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BIOGRAPHY

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ABSTRACT

This paper proposes a novel localization system for urban canyon environments through the marriage of Wireless Local Area Networks (WLAN) and the Global Positioning System (GPS). In the proposed technique, the wireless device receives GPS and WLAN signals simultaneously. If the GPS signals are sufficient for positioning, an Extended Kalman Filter (EKF) is used to provide a coarse location of the user. Otherwise, WLAN signals are used for coarse localization. Then, Access Points (APs) are selected for fine localization based on Fisher criterion. To obtain the fine location of the user, a Sparse Kalman Filter (SKF) is applied on the received online measurement and recorded WLAN radio map. The proposed method has been implemented on a real wireless device and the results show that the localization error has been reduced to 5 meters. [1]

INTRODUCTION

Although the US Global Positioning System (GPS) revolutionized outdoor navigation by providing a free global service for outdoor location-awareness [1], [2], it is fundamentally constrained by Line-Of-Sight (LOS) signal propagation between satellites and GPS receivers. This limits the ubiquity of GPS operation in urban canyon and indoor environments. To overcome this problem, GPS receivers have been integrated with inertial navigation systems such as accelerometers and gyroscopes, magnetometers, with various signals of opportunity (SOP), etc. [2]-[4]. In addition, some works have been directed toward modifying GPS measurements in urban canyon environments. One of the proposed solutions is Doppler smoothing. This technique applies a consistency modification between pseudoranges and pseudorange rates. To this end, more accurate

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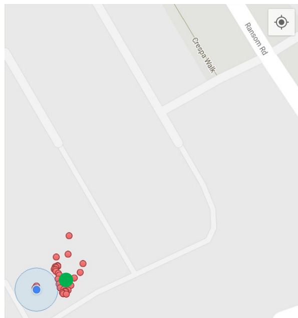
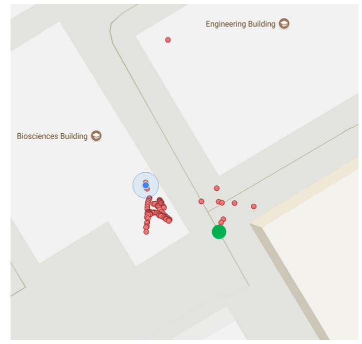
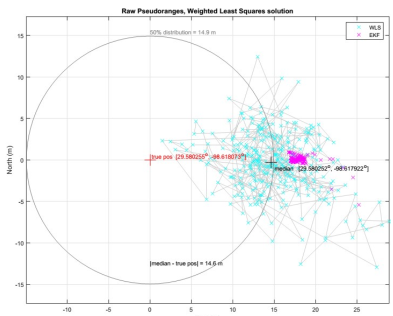


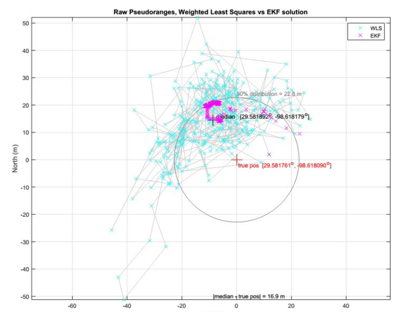
(a) Open-sky position estimates



(b) Urban canyon position estimates



(c) Open-sky position estimate spread



(d) Urban canyon position estimate spread

Fig.1 – Performance comparison of GPS in open sly and urban canyon environments. The green circles indicate the true location. The cyan and magenta dots show the WLS and EKF estimates, respectively.

pseudoranges are obtained and thus, the localization error is reduced. However, our experimental results showed that considerable localization error remains even after pseudorange smoothing is applied. WLAN signals are useful types of SOPs [5], [6]. WLAN transmitters, called Access Points (APs), are densely deployed in indoor and urban environments, and allow for an acquisition of sets of location-distinct wireless measurements called fingerprints. Such fingerprints are typically rearranged in a radio-map database which associates a fingerprint vector with a single location on the map [7]. Although WLAN signals are typically useful for indoor localization [8]-[10], penetration of these signals outdoors provides abundant information. Even in some outdoor areas, WLAN APs are installed outside buildings to provide WLAN network coverage.

In this paper, a novel localization method is proposed for the fusion of WLAN (WiFi) and GPS measurements for an integrated WLAN/GPS operation in urban canyon environments. The novelty is achieved by extending sparse dynamical processing for the integrated operation of the proposed hybrid system. In the extended solution, the Kalman Filter is constrained to render sparse solution as the user travels in a gridded area. The proposed localization system has been deployed on a tablet platform (Google Nexus 9) suitable for experimenting with GPS measurements [11]. Android tablets allow for WLAN measurement extraction, so both sets of measurements from WLAN and GPS are available. The operation of the proposed approach has been evaluated in a typical urban canyon environment, the campus of the University of Texas at San Antonio. The proposed solution allows continuous localization in the sense that localization will be available both outdoors and indoors in a dense urban environment and the user does not need to switch between devices or applications.

In what follows, we first illustrate the behavior of GPS measurements in urban canyon environments and then, experimentally show that Doppler smoothing is not an effective localization procedure in urban canyon environments. Afterwards, our proposed localization system is detailed following by numerical results in a real environment with a real device.

BEHAVIOUR OF PSEUDORANGE AND DOPPLER IN URBAN CANYON ENVIRONMENT

The GPS receiver on an urban canyon environment is highly affected by the presence of several urban-based errors such as multipath, interference, signal masking, and poor constellation geometry. This entails an important loss of precision in the navigation solution.

To compare the localization accuracy of GPS in open-sky and urban canyon environments, an experiment has been conducted. Fig. 1 shows the location estimates of a GPS receiver at a UTSA parking lot (opensky environment) and between buildings at the UTSA engineering area (urban canyon environment).

To quantify the quality of the measurements, we compared the spread of position estimates through Weighted Least Square (WLS) and Extended Kalman Filter (EKF). The EKF is the solution to the following dynamical model for a static receiver as:

$$\underbrace{\begin{pmatrix} x[l+1] \\ y[l+1] \\ z[l+1] \\ cb[l+1] \\ c\dot{b}[l+1] \end{pmatrix}}_{\mathbf{x}_{l+1}} = \underbrace{\begin{pmatrix} \mathbf{I}_{3\times3} & \mathbf{0}_{3\times2} \\ \mathbf{0}_{2\times3} & \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \end{pmatrix}}_{\mathbf{A}_{l+1}} \underbrace{\begin{pmatrix} x[l] \\ y[l] \\ z[l] \\ cb[l] \\ c\dot{b}[l] \end{pmatrix}}_{\mathbf{x}_{l}} + \underbrace{\begin{bmatrix} \mathbf{I}_{3\times3} & \mathbf{0} \\ \mathbf{0} & \begin{bmatrix} c & \\ & c \end{bmatrix} \end{bmatrix}}_{\mathbf{B}} \underbrace{\begin{pmatrix} w_x[l+1] \\ w_y[l+1] \\ w_z[l+1] \\ w_b[l+1] \\ w_{\dot{b}}[l+1] \end{pmatrix}}_{\mathbf{w}_{l+1}} \tag{1}$$

$$\underbrace{\begin{pmatrix} \rho_1[l] \\ \vdots \\ \rho_N \\ \dot{\rho}_1[l] \\ \vdots \\ \dot{\rho}_N[l] \end{pmatrix}}_{\mathbf{y}_l} = \underbrace{\begin{pmatrix} \mathbf{h}(\mathbf{x}_l) \\ \mathbf{g}(\mathbf{x}_l) \end{pmatrix}}_{\mathbf{C}_1} - \begin{pmatrix} cb_1[l] \\ \vdots \\ cb_N[l] \\ c\dot{b}_1[l] \\ \vdots \\ c\dot{b}_N[l] \end{pmatrix} + \underbrace{\begin{pmatrix} \epsilon_{\rho_1} \\ \vdots \\ \epsilon_{\rho_N} \\ \epsilon_{\dot{\rho}_1} \\ \vdots \\ \epsilon_{\dot{\rho}_N} \end{pmatrix}}_{\mathbf{v}_l} \tag{2}$$

$$\begin{aligned} &\mathbf{h}(\mathbf{x}_l) = \|\mathbf{p}_i[l] - \mathbf{p}_u[l]\|_2 + c(b[l] - b_i[l]) \\ &\mathbf{g}(\mathbf{x}_l) = (\mathbf{v}_i[l] - \mathbf{v}_u[l])^T \frac{\mathbf{p}_i[l] - \mathbf{p}_u[l]}{\|\mathbf{p}_i[l] - \mathbf{p}_u[l]\|} + c(\dot{b}[l] - \dot{b}_i[l]) \\ &\mathbf{\Sigma}_{\tilde{x},0} = diag([100\ \ 100\ \ 100\ \ 30\ \ 3]), \\ &\mathbf{\Sigma}_{\tilde{w}} = \begin{pmatrix} \mathbf{0}_{2\times2} & \mathbf{0}_{2\times2} \\ \mathbf{0}_{2\times2} & \mathbf{Q}_{clk} \end{pmatrix}, \\ &\mathbf{Q}_{clk} = \begin{pmatrix} S_b\Delta t + S_{\dot{b}}\frac{\Delta t^3}{3} & S_{\dot{b}}\frac{\Delta t^2}{2} \\ S_{\dot{b}}\frac{\Delta t^2}{2} & S_{\dot{b}}\Delta t \end{pmatrix}, \\ &S_b = h_0/2, S_{\dot{b}} = 2\pi^2 h_{-2}, \\ &h_0 = 2\times10^{-19},\ h_{-2} = 2\times10^{-20} \\ &\mathbf{\Sigma}_{\tilde{v}} = \text{ is upated based on the uncertainty in the pseudorange measurements at each epoch.} \end{aligned} \tag{3}$$

Fig. 1a and Fig. 1b depict the spread of location estimates of WLS and EKF in open sky and urban environments, respectively. The spread of errors for the estimated location reaches 15 m for the open sky environment and 60 m in urban canyon environments. Fig. 1c and Fig. 1d show the spread of errors for location estimates. The localization error has been increased up to 45 m in urban canyon areas.

To modify the GPS pseudorange measurements, we experimented with pseudorange modification through Doppler smoothing [3]. In Doppler smoothing, current pseudorange measurements is estimated by forming the differences of previous measurements across time. Doppler smoothing defines a threshold for the expected difference between the current measured pseudoranges and expected pseudoranges estimated from previous measurements. Let $T_i[l]$ be a metric that evaluates the difference between the current measurement for satellite i and the expected measurement based on previous information divided by corresponding state and measurement noise covariance matrices as follows:

$$T_i[l] = -\frac{|\rho_i[l] - \hat{\rho}_i[l|l-1]|}{(B\Sigma_{\tilde{w}}B^T + \Sigma_{\tilde{v}})_i} \tag{4}$$

where $(\cdots)_i$ denotes the i-th diagonal component. If this difference exceeds the thresholds η_1, the pseudorange measurements are modified through a weighted combination of the current pseudorange, previous pseudoranges and pseudorange rates as below:

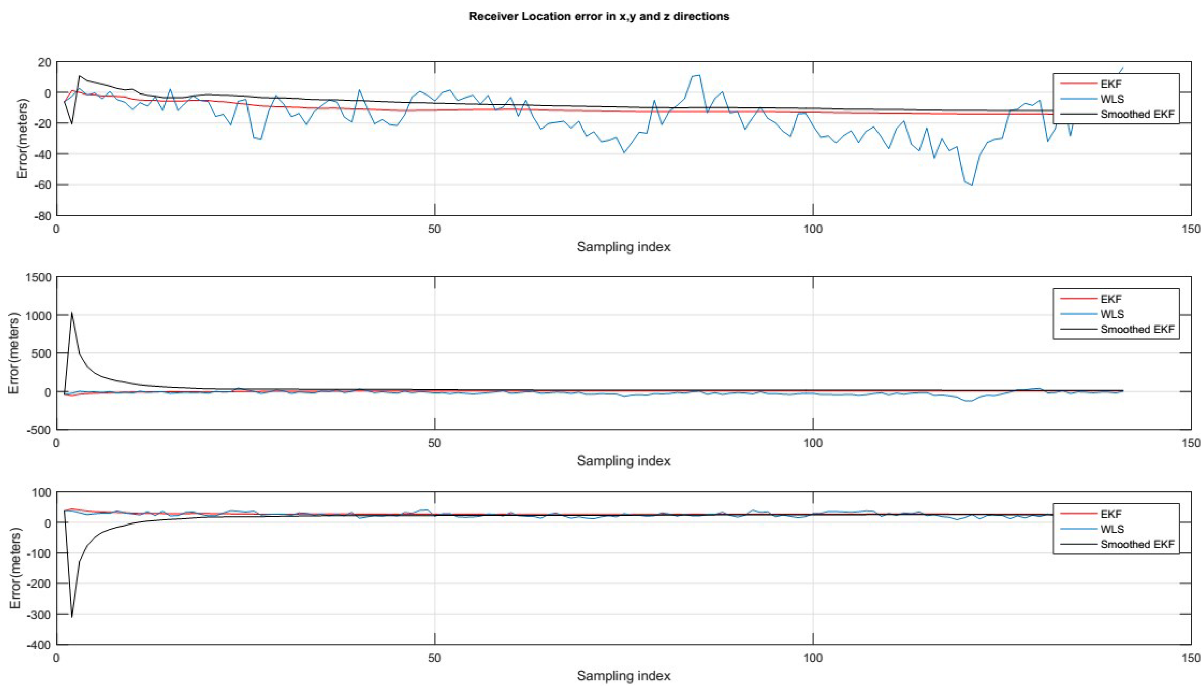


Fig.2 – Localization error comparison between WLS, EKF, Smoothed EKF.

$$\alpha_i[l] = -\frac{1}{\eta_2 - \eta_1}(T_i[l] - \eta_1) + 1 \quad (5)$$

$$\rho_i[l] = \alpha_i[l]\rho_i[l] + (1 - \alpha_i[l])(\rho_i[l-1] + \dot{\rho}_i[l-1]\Delta t) \quad (6)$$

where Δt is the duration of each epoch. This technique has been applied on our collected data and compared with the Weighted Least Squares (WLS) [11] and Extended Kalman Filter (EKF) based (1)-(3). Fig. 2 shows the localization error comparison between WLS, EKF and EKF with smoothed pseudoranges (Smoothed EKF). In this experiment, $\eta_1 = 2$ and $\eta_2 = 4$ as suggested in [13]. The results illustrate that although the smoothed EKF reduces the error, the enhancement is not substantial and is not able to enhance the GPS localization accuracy appreciably.

PROPOSED LOCALIZATION SCHEME

The localization result of stand-alone GPS shows limited accuracy performance. Therefore, the localization scheme should be tailored to the environment based on available SOPs. To provide more accurate and reliable localization, the GPS can be assisted with the courtesy available measurements in the area. WLAN (WiFiis a widely available signals not intended for localization that can however be exploited for localization purposes. In the rest of this paper, we elaborate on a novel localization scheme in which GPS and WiFi measurements are integrated to provide more accurate localization. It is assumed that outdoor positioning with unobstructed sky uses GPS for the positioning, and localization in areas without GPS coverage is based solely on WLAN. In urban canyon areas with mixed signal availability, GPS signals are available but distorted by multipath propagation.

The conceptual diagram of the proposed solution is shown in Fig. 3. This solution consists of two phases. In the offline phase, wireless signals are surveyed on a grid of locations, called Reference Points (RPs), and WLAN Received Signal Strengths Indicator (RSSI) measurements are recorded at each RP. Fig. 4 depicts the view of the self-developed WiFi recorder application. The application records RSSI data along with MAC addresses of the available APs.

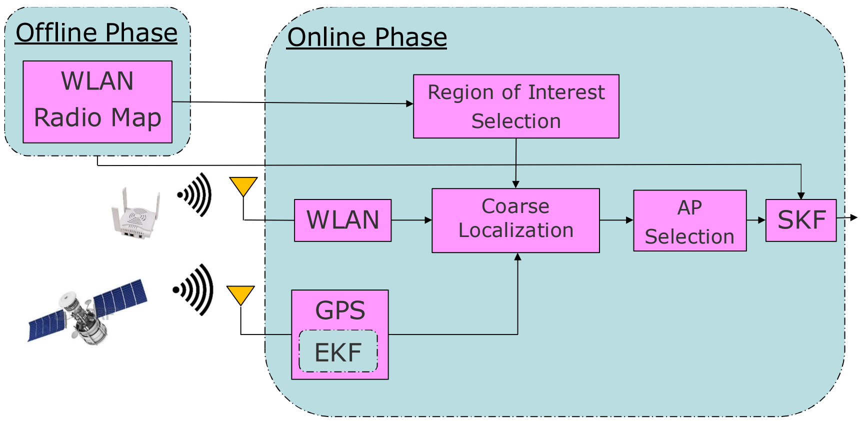


Fig.3- Diagram of the proposed localization scheme

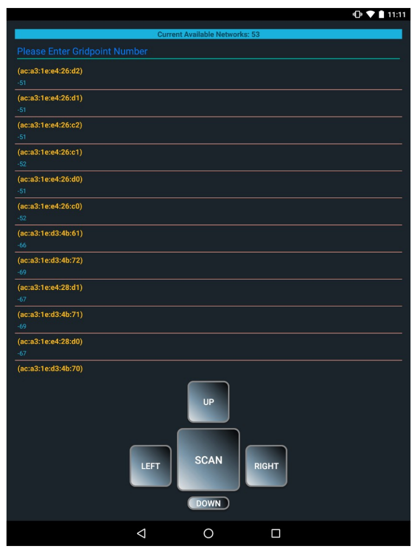


Fig. 4 – View of WiFi recorder Android application

Overall, the following process is used for the offline WLAN fingerprinting stage. The WLAN fingerprint measurements are RSSI which are recorded for the visible APs at each RP. As mentioned earlier, the whole set of fingerprints for all RPs is called the radiomap of the environment. The radiomap can also be obtained by recording the WiFi signals on a coarser grid and interpolating on finer grids [8].

Coarse Localization using GPS

In the online phase, the user receives GPS measurements along with online WiFi RSS. GPS provides a rough estimate of the location of the user by selecting an area (cluster) consisting of several RPs, where the user is most probably located. Since the single point solution of GPS is unreliable, we perform EKF on the GPS measurements. If the user is static, the EKF with constant position model is applied, and if the user is moving the EKF with constant velocity model refines the GPS estimate. The decision over the user's motion is defined with the Inertial Measurement Units (IMU) of the embedded sensor in the device. The EKF is based on the dynamical model in (1)-(3). A subset of K closest RPs is chosen as the coarse location of the user. The subset of RPs that fall into the user's estimated coarse location are then used for finer localization using WLAN. Tighter integration of GPS and WLAN measurements is also possible and will be explored in a future work.

Coarse Localization using WLAN

If GPS is not available, coarse localization is performed through WLAN measurements instead. To this end, an AP indicator vector I_i, $i = 1,...,L$ is assigned to each AP. The AP indicator is a binary vector in which each AP receives a 1 or 0. An AP receives 1 if its measurements during fingerprinting is greater than threshold γ for at least 90 % of the time and 0 otherwise:

$$\mathcal{T}_j^i = \left\{m \in \{1,\ldots,M\} \,|r_j^i(t_m) \geq \gamma\right\}. \qquad (7)$$
$$\forall i = 1,\ldots,L, \quad \forall j = 1,\ldots,M,$$

$$I_j^i = \begin{cases} 1 & |\mathcal{T}_j^i| \geq 0.9T \\ 0 & \text{otherwise} \end{cases} \quad i = 1,\ldots,L, \qquad (8)$$

where $r_j^i(t_m)$ is the recorded fingerprints at time t_m. The AP indicator vector for online measurements is defined similarly. The distance between an RP and online measurements is obtained through the difference between their AP indicator vectors as

$$\mathbf{H}(\mathbf{p}_j, \mathbf{p}_{j'}) = d_H(\mathbf{I}_j, \mathbf{I}_y) = \sum_{i=1}^{L} |I_j^i - I_y^i| \qquad (9)$$
$$\forall j \in \{1,2,\ldots,M\}.$$

For coarse localization, RPs with the least distance are selected for coarse location of the user.

AP Selection

Not all APs are useful for localization as some may induce a bias towards some RPs. Therefore, an AP selection procedure should be performed. The AP selection procedure should maximally differentiate between RPs and also renders the least variance of the measurements. The following score is evaluated for each AP according to the above requirements:

$$\zeta^i = \frac{\overbrace{\sum_{j=1}^{N}(\psi_j^i - \bar{\psi}^i)^2}^{\text{the differentiability of APs across RPs}}}{\underbrace{\frac{1}{T-1}\sum_{\tau=1}^{T}\sum_{j=1}^{N}(r_j^i(t_\tau) - \psi_j^i)^2}_{\text{the variance of readings for AP } i}} \qquad (10)$$
$$i = 1,\ldots,L, \quad \bar{\psi}^i = \frac{1}{N}\sum_{j=1}^{N}\psi_j^i$$

where ψ_j^i is the average of radio map at point j and AP i. A subset of APs with the highest scores are selected for localization.

Fine Localization

Once the coarse location of the user is obtained, WiFi fingerprints along with online measurements are utilized to provide an estimate of the user location with a finer granularity. The fine localization is performed through the Sparse Kalman Filter (SKF) [14]. We use the idea of sparsity intertwined with Kalman Filtering to impose the sparsity on the state of Kalman Filter. Here, the state of the model is not the true location of the user, but rather the closest RP that the user is located at. The sparse dynamical model is defined as follows:

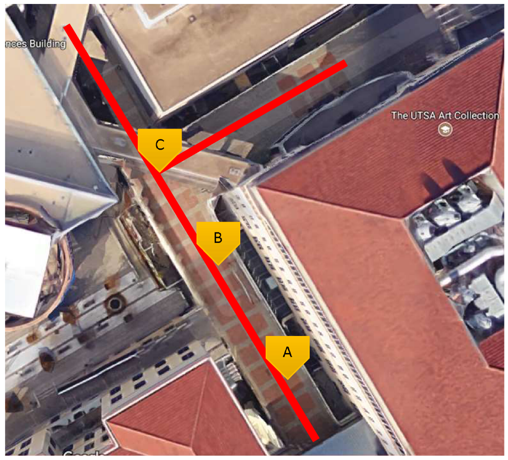


Fig.5- The actual picture of the experimental area. Red lines show the experimented area.

$$\underbrace{\begin{pmatrix} 0 \\ \vdots \\ 1_{l+1} \\ \vdots \\ 0 \end{pmatrix}}_{\mathbf{x}_{l+1}} = \mathbf{F}_l \underbrace{\begin{pmatrix} 0 \\ \vdots \\ 1_l \\ \vdots \\ 0 \end{pmatrix}}_{\mathbf{x}_l} + \underbrace{\begin{pmatrix} w_b[l] \\ w_b[l] \end{pmatrix}}_{\mathbf{w}_l} \qquad \mathbf{y}_l = \boldsymbol{\Psi} \underbrace{\begin{pmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix}}_{\mathbf{x}_l} + \mathbf{v}_l \tag{11}$$

where $\mathbf{F}_l$ is the state transition matrix, and $\boldsymbol{\Psi}$ is the radio map of the selected region. The coarse localization enables the model to invoke part of the radio map of the selected region and hence, reduces the high memory requirement to fetch the radio map for the whole environment. The solution to (11) so that sparsity is imposed on the state can be obtained through solving the following minimization problem:

$$\hat{\mathbf{x}}_{l+1} = \underset{\mathbf{x}_{l+1}}{\operatorname{argmin}} \left\{ \|\mathbf{y}_l - \boldsymbol{\Psi}\mathbf{x}_l\|^2_{\mathbf{R}_l^{-1}} + \|\mathbf{x}_{l+1} - \mathbf{x}_l\|^2_{\mathbf{P}_l^{-1}} + 2\lambda_l \|\mathbf{x}_{l+1}\|_1 \right\} \tag{12}$$

where $\mathbf{R}_l$ is the covariance of the measurement errors, $\mathbf{P}_l$ is the state covariance matrix, and λ is a tuning parameter. The first term minimizes the difference between the measurements and columns of radio map selected by the state vector. The second term minimizes the difference between the current state and the next state (confines the state in the uncertainty region), and the last term renders a sparse solution of the state vector.

This solution provides continuous localization in the sense that in the areas where GPS is not available, WiFi provides the solution. The system can automatically detect the number of satellites and switch to WiFi if there is not minimum number of satellites to solve the WLS for GPS.

EXPERIMENTAL RESULTS

To evaluate the performance of the proposed method, an experiment in a real environment has been conducted with the Google Nexus 9 tablet. WiFi data are recorded on narrow pathways at the campus of the University of Texas at San Antonio (UTSA). Fig.5 depicts these pathways which are surrounded with tall buildings and have narrow LOS sky views. The area has been divided into 25 RPs A set of WiFi measurements have been recorded for a static receiver.

In the online phase, the device receives the GPS and WiFi signals. The implemented structure of the proposed method is illustrated in Fig. 6. The device receives the raw GPS measurements in Android API from which the GPS parameters and corresponding uncertainties are computed. These measurements along with the WLAN radio map and the AP indices are

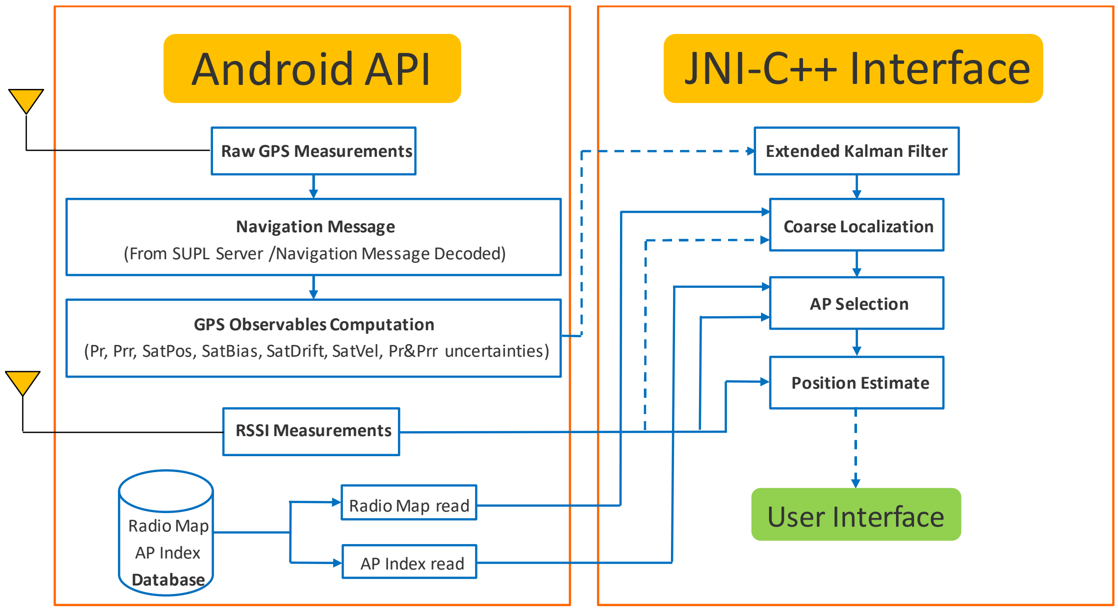


Fig. 6 – Structure of the implemented approach.

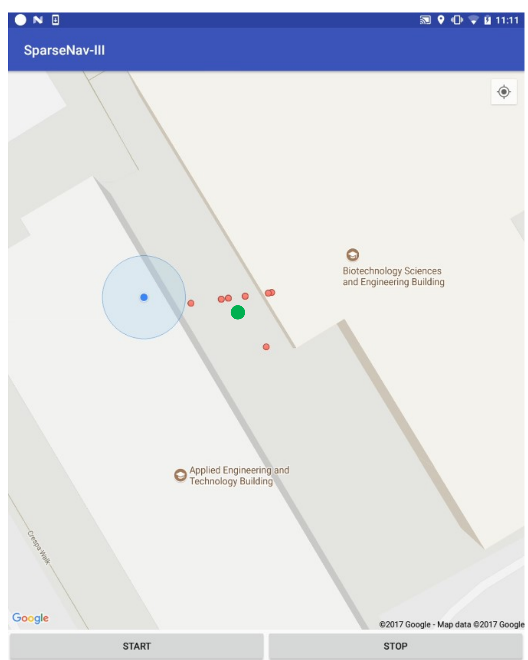
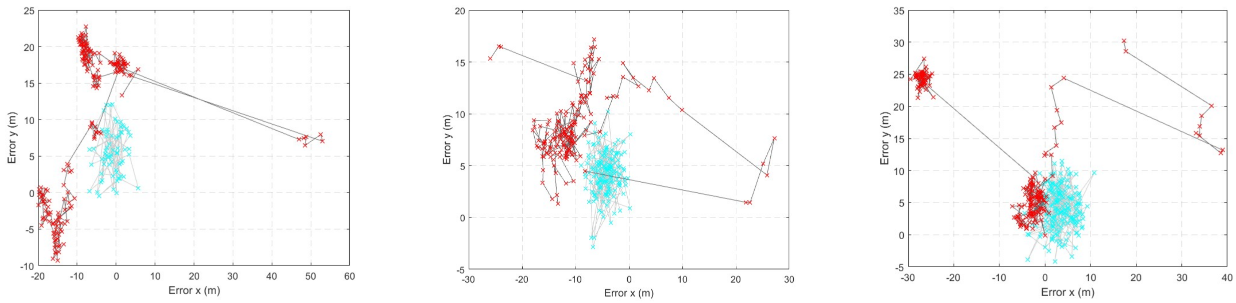


Fig. 7- View of developed Android application. GPS-WiFi Application: Green dot is the true location and red dots indicate the estimated locations by the proposed technique. Blue dot is the estimated location of Android fused location provider.

passed to JNI-C++ interface. The GPS measurements are evaluated and if more than four satellites are visible to the user, an EKF is used for coarse localization. If the number of satellites are less than four, the coarse localization is performed through WiFi RSSI



(a) Point A (b) Point B (c) Point C

Fig.8 – Estimated solution of the proposed approach (cyan) compared with the solutions of the Google fused location provider (red).

measurements. Once the coarse localization is completed, a region around this estimate is selected as the coarse location of the user. A screenshot of the developed application is shown in Fig. 7.

Then, for fine localization, the SKF is applied on the WiFi RSS measurements. Fig. 8 shows the localization error of our scheme in the environment with different characteristics. The estimated locations of our technique are compared with the Google fused location provider solutions. At point A, GPS signals are not available and the whole localization procedure is performed through WLAN. The solutions of fused location provider converge to two different areas, which shows the bias in the estimated location. Regarding the estimated location at point B, the area is open from the left of the figure and GPS signals are available. The estimated locations of the fused location provider are more stable than the ones of Point A; however they render larger errors. Point C is in a region where GPS signals are available some times and the solution switched between GPS and WLAN coarse localization. In this area, the estimated locations by the fused location provider is also trapped in two distinct and distant regions. The proposed solution in all areas shows consistent performance. The experiment shows that the estimated location of the user by GPS has been greatly enhanced with a localization error mean of 5.2 meters.

CONCLUSION

This paper addressed the problem of GPS localization in urban canyon environments. We showed that enhancements of GPS measurements based on Doppler smoothing do not provide satisfactory localization performance. Hence, we integrated GPS measurements with WiFi fingerprints using sparse Kalman filtering. The WiFi is ubiquitous as is densely deployed in campus environments. The results showed considerable improvement in localization accuracy.

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