A Model-Based Approach for WLAN Localization in Indoor Parking Areas

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Abstract—Wireless location of a User Equipment (UE) has received growing attention in recent years. The first step for the design of a wireless location system consists in choosing the system architecture and the localization algorithm that match the requirements of the working scenario. In this paper the area of interest is represented by an indoor parking lot, in which the variable occupancy of motor vehicles alters the electromagnetic propagation and causes large errors in vehicle location estimation. The proposed strategy to deal with this problem is the use of a server-based architecture, that ensures security and scalability and accounts for the system state in terms of number and positions of already present vehicles. This concept of state is shown to be useful to design suitable algorithms, based on simplified electromagnetic models, to improve the localization performance.

I. INTRODUCTION

Wireless location of a User Equipment (UE) is intimately connected to the development of context-aware applications [1], [2] that benefit of the knowledge of the user position to process more specific information. The location based service of interested here is the automatic pricing of the vehicles in a parking lot, based on the occupied position. In particular we face the two main application requirements: the design of the system architecture and the choice of the localization algorithm that match the constraints of the working scenario.

The former is conditioned by the actual tendencies for the forthcoming data transmission infrastructures. The convenience of using the same end terminal to obtain seamless services across heterogeneous networks drives the development of fourth generation or beyond third generation (4G/B3G) networks. The main feature of the B3G network infrastructure, in addition to being based on an all-IP architecture, is the total independence between the various access technologies (both mobile and fixed) on one side and session control and the service provisioning platforms on the other.

For its convenience, cost efficiency, and ease of integration with other networks, easily conceivable that WLAN is such access technology. IEEE802.11 networks’ topological simplicity and technological evolution have fostered the development of such services and applications, as for example e-banking and automatic payments, requiring greater attention to security.

3GPP (3rd Generation Partnership Project), the main organization investigating B3G (Beyond-3G) research issues and producing the relative standardization proposals, has defined a scenario for WLAN-3G interworking called “WLAN Direct IP Access”. IEEE802.11i 2004 standard (WPA2) proposes a 802.1x/EAP based authentication to grant an adequate level of security.

This paper shows a possible location system based on a WLAN Access Network (AN) architecture with the addition of a Location Server (LS). To ensure a suitable level of security, UE access to WLAN is subject to authentication through an Home Network. After the UE performs a WLAN Direct IP Access to a 3GPP Core Network, the messages exchange between UE and LS is ruled by a novel Location Information Protocol (LIP).

The adoption of a server-based philosophy is advantageous not only to deal with architectural issues, but also to access the existing information about the environment state to improve the localization performance. The main idea is to use a standard technique, properly modified to take into account the environment state.

In the challenging scenario of the parking lot, the main difficulties arise from the extreme variability of the propagation channel due to moving obstacles and reflection surfaces: even a single vehicle, depending on its position, can obstruct the Line-Of-Sight toward an Access Point, as well as it can introduce a new path by reflecting the electromagnetic field.

Accordingly, the purpose of this paper is to model the effect of the vehicles inside the parking lot and to propose a localization algorithm that, after an offline construction of the propagation model of the empty parking area, continuously corrects it by the current vehicle localizations. To this aim we investigate the possibility to employ two commonly used localization algorithm, the RADAR [3] and the Bayesian grid-based filtering [4].

II. SERVER-BASED LOCALIZATION ARCHITECTURE

A. WLAN architecture

All components in a WLAN connected with a wireless medium are named stations and can be divided in two categories: access points (APs), and clients. Access points are base stations for the wireless network, that transmit and receive at fixed radio frequencies to communicate with wireless enabled devices. More than being used for the access to other network,
a WLAN AN can provide services by itself, and to do this, it’s necessary to add other nodes, known as Application Servers (AS) to the network. Among others, one task often assigned to AS’s is to improve the overall security to a level appropriate for the requested service.

One of the main scenarios proposed by 3GPP is just about the provision of services by the AN itself. This involves Authentication, Authorization, Accounting (AAA) procedures, for subscribers requiring connection through a WLAN AN, to be based on the same mechanisms employed for AAA in 3G networks. In this case, the AN will authenticate a user on the basis of the credentials contained in his USIM/ISIM (UMTS/IMS SIM), as it typically happens within a 3G environment.

According to IEEE802.11 standard, APs periodically emit a management frame, known as beacon frame, which provides information about the parameters and capabilities of a cell. This information is known as Basic Service Set (BSS) and is very important because UEs use it to decide which particular AP to associate with. Implicitly these beacons also carry information about the link quality, which can be derived from the signal strength and the background noise. Among other information, beacon frames report about the network name and the Basic Service Set IDentifier (BSSID), i.e. the unique identifier of an access point. IEEE802.11 specifies two scanning mode, but the amount of information that can be retrieved is essentially the same in both. The first mode is a passive scanning: UE performs it regularly to determine the access point with the best link quality; this is possible thanks to a sweep from channel to channel and a record of information received from any beacon. In this manner the cell identifiers and signal strengths of all visible access points can be determined. In the second mode, known as active scanning, UE actively probes for the available BSS.

B. Localization System

There are two main metrics that can be used to locate an UE: Cell IDentifier (CID) and Radio Signal Strength (RSS). Nearly all Wireless LAN location systems described in literature make use of these quantities for proximity detection or pattern recognition techniques. CID and RSS certainly do not achieve the best location performances. Using CIDs is straightforward, but this approach only provides a limited accuracy on the position estimate. Using RSS is feasible only if a wireless data connection is available between the UE and the remote side. In fact the measures are collected by the mobile equipment and sent to the network that provides the position estimate. In this architecture the UE plays an almost passive role and thus, as for the remote positioning systems, the number of users that can be localized is limited only by the computational capability at the remote side.

4) Indirect self-positioning system: Also in this case a wireless connection is required for sending the measurements that are collected at the remote side. Measures are used by the mobile to infer its own position, so in this latter alternative the limits are again due to terminals computation ability.

C. Architecture choice

We require a system with a high positioning accuracy, a good level of security in dealing position information based on the use of the beacon frame that gives continuous measures of the received signal intensity. In order to improve the performances by using global knowledge, we must exclude self-positioning systems. Finally since in IEEE802.11 network beacon frames are transmitted from APs to UE, we choose the remote indirect positioning system as indicated in Fig. 1.

Fig. 2 depicts the procedures taking place before starting location:

1) IEEE 802.11 association process takes place when UE enters in AP radio coverage. UE starts sending Association Request to the AP. After the AP receives the Association Request successfully, it will reply with Association Reply. When UE receives the Association Reply message, it changes its status from a new station to a registered station.

2) The second step is WLAN Direct IP Access procedure. In this case, the AN will authenticate a user on the basis of the credentials contained in his USIM/ISIM.
(UMTS/IMS SIM). Furthermore, authorization and accounting are provided by the 3G network itself, based on subscription data. Interworking architecture for the non-roaming case can be straightforwardly derived if the 3G AAA Server is directly connected to the WLAN. 3GPP proposes that the WLAN UE and the AAA server shall support both the EAP AKA and EAP SIM methods.

The solution we propose is founded on a localization protocol, named LIP, for the exchange of signaling data between UE and LS. LIP is an application layer protocol based on UDP, employing 3 types of messages:

- **LIP Init Message**;
- **LIP Info Message**;
- **LIP Update Message**.

The detailed description of these messages and their function will be illustrated in the next paragraph.

### D. Location message exchange

Let us see how the location process takes place in our design (Fig. 3). After a successfully completed WLAN Direct IP Access procedure between UE and AAA server, the Authenticator sends a **LIP Init message** to LS, containing the new user ID. LS first checks if UE is registered to parking service, then it retrieves information about the associated vehicle, such as its shape and size. Finally, in order to start the vehicle tracking, LS sends to UE a **LIP Info message** containing an APs list that indicates the Mac Addresses of the involved APs and the number of measures $N_m$ to collect for each AP. If this number is set to zero, no measure is collected and the tracking phase is skipped, otherwise UE starts collecting RSS samples. Then it sends $N_m$ measures for each AP to LS through **LIP Update messages** and the latter elaborates received data in order to estimate UE location.

When the vehicle stops, on the basis of the chosen algorithm, LS can perform another algorithm (or the same algorithm with another setup) in order to identify with a greater degree of precision the parking stall in which the vehicle is located. This new phase is started by UE that informs LS that the vehicle engine is turned off via a **LIP Info message**. Then LS sends another LIP Info message to the UE, containing the APs list and, above all, the new $N_m$ value. Finally, when LS supposes to have reached the desired precision in estimating the vehicle position, it sends a **LIP Info message** to UE in order to stop the RSS measures dispatching.

### III. Knowledge-based Localization Algorithm

The second part of the problem faced in this study concerns the design of the localization method. Our purpose is to exploit the network-based approach in localizing a mobile user in a parking area. The latter turns out to be a very challenging environment, being characterized by the presence of many obstructing and reflecting obstacles for the electromagnetic propagation. Moreover the mobility of some obstacles, like vehicles, further worsens the situation.

Accordingly, the proposed localization method consists of a preliminary offline characterization of the signals available in the empty parking and an online phase in which the expected signals are updated by using proper electromagnetic models for the diffraction or reflection effects.

$^1$It is supposed that there exists a strict integration between the vehicle and the UE.
In the following we illustrate the used electromagnetic model, together with the details of the positioning algorithms. They have been selected among the plethora of existing methods, according to their suitability for the proposed approach. In particular two different algorithms, basing on two completely different methodology, have been chosen for comparison. The former was presented in [3] and represents the most cited fingerprinting method in which a memoryless estimation algorithm, detailed in paragraph III-B1, is employed. The latter, on the contrary, belongs to the class of Bayesian estimation algorithms and thus takes into account the whole trajectory of the mobile user. Both have been properly modified to show adaptive features aimed to compensate the nonstationarity of the working scenario; the performances achieved are reported in paragraph IV.

A. Electromagnetic model

In this study the availability of a precise electromagnetic model plays a fundamental role. As anticipated, the characterization of the mobile propagation channel is a very hard task that is faced in several references (see for example [5]).

A very common approach consists in modeling the power of the received signals as a random process whose distribution depends on the peculiar characteristics of the working environment. In the cited reference [5] the suitability of several statistical models (Rayleigh, Rice, Nakagami, Lognormal) have been justified. Some of them turn out to be very fruitful in the practice because of their analytical tractability; for example the lognormal model corresponds, by measuring the received powers in logarithmic scale, to data described by a Gaussian distribution. A widely employed statistical model for signal amplitudes in indoor environments is the Rician distribution [6]

\[ p(r) = \frac{r}{\sigma^2} \exp \left( -\frac{(r^2 + V^2)}{2\sigma^2} \right) I_0 \left( \frac{rV}{\sigma^2} \right), \quad r \geq 0, \]

in which \( V \) is the amplitude of the Line-of-Sight component, \( \sigma^2 \) the variance of the scattered contribution and \( I_0 (\cdot) \) is the modified Bessel function of zeroth order. An alternative expression is in terms of the mean square value \( E[r^2] = V^2 + 2\sigma^2 \) and of the Rice factor \( K_f \triangleq V^2/2\sigma^2 \) that quantifies the ratio among the power of the two components:

\[ p(r) = \frac{2(1 + K_f)}{E[r^2]} \exp \left( -K_f - \frac{(K_f + 1)r^2}{E[r^2]} \right) \times I_0 \left( 2r \sqrt{\frac{K_f}{E[r^2]} (K_f + 1)} \right), \quad r \geq 0. \]

Anyway, a commonly used model for the path-loss, i.e. for the attenuation of the mean radiated power at a distance \( d \) from the transmitter, is given by the log-distance law

\[ P(d) = P_0 - 10\alpha \log \left( \frac{d}{d_0} \right), \quad (1) \]

where the power \( P(d) \) (in dB), available at a distance \( d \) from the AP, is function of the power \( P_0 \) at a reference point \( d_0 \) and of the decaying rate \( \alpha \).

This model, whose formal derivation follows from the free path propagation analysis, is successfully employed also for the indoor propagation, after a proper setting of the parameters. The latter have to be experimentally determined, since they greatly differ with the working scenario.

In this paper we propose to exploit this approach based on propagation model (1) by including other different effects, as for example those due to the interposition, possibly partial, of diffracting objects. In the same direction, the presence of a new reflecting surface can give a significant contribution to the received powers in the adjacent positions, but in a first approximation we neglect such effect.

Quantifying the contribution due to diffracting objects is in general a very difficult task, since the effect is extremely varying with the shape and the position of the obstacles. In this work we use a simplified setup that has turned to be very useful in communication theory, namely the knife-edge diffraction model [7]. It consists in treating the obstacle as a diffracting knife edge so allowing an easy solution evaluation of the Fresnel integral. In that case the diffraction gain \( G(\nu) \) is function only of the Fresnel Diffraction Parameter \( \nu \). The latter is defined, in terms of the quantities illustrated in Fig. 4, as

\[ \nu = h \sqrt{\frac{2(d_1 + d_2)}{\lambda d_1 d_2}}, \]

where \( \lambda \) is the signal wavelength and \( d_1, d_2 \) are, respectively, the distances between transmitter and obstacle and between receiver and obstacle and \( h \) is the effective height. The relation between the knife-edge diffraction gain and the Fresnel Diffraction Parameter \( \nu \) can be achieved by numerical methods; however a widely employed approximation, expressed in dB and valid for \( \nu > -0.7 \) is the following [8]

\[ G(\nu) = 6.9 + 20 \log \left( \sqrt{(\nu - 0.1)^2 + 1} + \nu - 0.1 \right) \text{dB. (2)} \]

An important consideration concerns the presence of multiple obstacles between transmitter and receiver. In this case the exact solution in very hardly affordable, but a useful approximation, whose accuracy decreases with the number of interposed obstacles, can be achieved with the Bullington’s construction of equivalent knife edge [7]. For example, when all the vehicles share the same height, this method consists in considering, for each position, only the closest one.
B. Localization algorithms

Two position algorithms have been chosen for the project and are described next. The former is one of the first proposed in literature and, despite of its simplicity, is often used as a benchmark for the other methods. In fact many effective practical realizations of positioning devices are today based on the RADAR method, that benefits of its wide applicability, mainly due to the intrinsic nonparametric approach. This permits to avoid the acquisition of information about the statistical distributions of data. On the contrary the other selected method relies upon a purely probabilistic approach and thus assumes that the functional form of the data model is perfectly specified. In the latter case superior performances can be achieved, as illustrated in the simulations.

1) Radar: The RADAR systems has been proposed in [3] as an alternative to triangulation methods, that, despite being successfully applied to the estimation of the position of a mobile user in outdoor scenarios, do not achieve satisfying performances indoor. This, is due, as described earlier, to the presence of obstacles and reflection surfaces that does not allow to relate in a straightforward manner, the received power to the distance from the transmitter.

To overcome this difficulty RADAR uses a fingerprinting (or scene analysis) approach that consists in composing a database, hereafter Radio Map, containing the means of the signal powers relative to a finite number of reference positions. The localization algorithm compares the powers received in the unknown position with those contained in the Radio Map and chooses the closest one.

In order to fully exploit the functioning of RADAR, several details have to be given. In particular the construction of the Radio Map can be performed by using the empirical method, i.e. by recording the signals in each reference point in a phase, that precedes the working moment. This approach turns out to be very time consuming as soon the number of such points grows. The alternative consists in using the radio propagation model described in par. III-A; however this second method always achieve unsatisfying performances, as fully illustrated in the cited reference.

As described until now, the RADAR approach consists in a pattern recognition methods to classify the unknown position. In particular the classification is achieved by simply finding the closest point (or nearest neighbor) in the signal space, according to the Euclidean distance. An improvement, aimed to limit the necessary discretization of the possible positions, consists in using multiple nearest neighbors; given the number \( k \) of neighbors (whose optimal value turns out to be comprised in the interval \([2, 4]\)), the position is achieved by averaging the \( k \) positions.

The main difficulty of the method consists in the impossibility to take into account the nonstationarity of the working scenario; at each variation the Radio Map has to be completely renewed and, especially in the fully working empirical approach, this procedure is very expensive. In a subsequent paper [9] the authors proposed the use of several Radio Map, corresponding to different situations for the working environment. In the localization phase the algorithm chooses the Radio Map that best represents the environment at the moment and thus estimates the position of the mobile user. In the parking application this approach is very hardly applicable, being the contributions of each vehicle very significant. This means that many different Radio Map should be constructed, corresponding to the different permutations of the vehicles layout. Therefore we propose to modify the Radio Map by means of the electromagnetic model described in paragraph III-A, thus leading to the following algorithm

- a) the usual training phase is performed when the parking lot is empty, in order to build a Radio Map;
- b) when the first vehicle stops into a parking stall, it is localized in the standard way, by collecting \( N_d \) RSS samples;
- c) on the basis of the estimated vehicle position and by means of the diffraction model of the vehicle, the variations in the electromagnetic environment are predicted and the Radio Map is consequently corrected;
- d) when another vehicle stops into another parking stall, it is localized by using the modified Radio Map;
- e) The steps c) and d) are performed for each vehicle that occupies (new correction) or leaves (remove the correction) a parking stall.

2) Grid-based: The other approach exploited in this study is a particular instance of the Bayesian filtering method [4]. It is a state-space approach in which the kinematic quantities (for example, position and velocity) compose the state \( \{x_t\}_{t=0,1,...} \) that evolves according to the equation

\[
x_t = f_t(x_{t-1}, v_t),
\]  

where \( f_t \) is a (possibly nonstationary and nonlinear) function of the previous state \( x_{t-1} \) and of the process noise sequence \( v_t \). The estimation of the position is performed by using the observations \( \{y_t\}_{t=0,1,...} \) (in this case the powers of signals received at the mobile device from the available APs) that depend, through a possibly nonstationary nonlinear function \( g_t \), on the state and on the measurement noise \( n_t \)

\[
y_t = g_t(x_t, n_t).  
\]  

A typical assumption is the Markov property of the state and measurement process, that permits to achieve a simplified expression for the transition conditional probability \( p(x_t|x_{t-1}, \ldots, x_0) \) and for the likelihood \( p(y_t|x_t, y_{t-1}, \ldots, y_0) \).

In particular we consider a model given by the equations

\[
x_t = A_t(x_t) x_{t-1} + v_t, \\
y_t = h_t(x_t) + n_t,  
\]  

where \( A_t \) is the motion matrix (possibly depending on the position to consider the presence of motion obstacles), \( h_t \) is the nonlinear function taking into account the WAF model relationship, \( v_t \) and \( n_t \) are zero mean processes with covariance matrix \( Q_t \) and \( R_t \), respectively.
When the state space is finite, the sequence \( \{x_t\}_{t=0,1,...} \) is a Markov Chain and the formalization is called Hidden Markov Model (HMM) since only the data \( \{y_t\}_{t=0,1,...} \) are accessible [10]. Then, if complete information regarding the involved statistical distributions are available, the path of the mobile user can be estimated by direct maximization of the pdf

\[
p(x_1, \ldots, x_0 | y_1, \ldots, y_0),
\]

and a very efficient approach, the Viterbi algorithm [11] can be exploited to limit the computational burden.

For the Viterbi algorithm the proposed localization system consists in the following steps:

a) the statistical model corresponding to an empty parking lot is calculated by employing the log distance (1) path loss;

b) the first vehicle is localized by maximizing the likelihood relative to both the tracking phase (from the gate to the stall) and \( N_d \) RSS samples acquired after the vehicle stops;

c) on the basis of the estimated position and by means of the diffraction model of the vehicle, the variations in the electromagnetic environment are predicted and the statistical model is consequently corrected;

d) when another vehicle enters the parking lot, it is localized as in b) but using the model computed in c);

e) The steps c) and d) are performed for each vehicle that enters (new correction) or leaves (remove the correction) the parking lot.

### IV. Experimental results

Firstly we validate the described electromagnetic model by statistical analysis of signal samples collected in an underground car park of the University of Salerno, sized about \( 45 \times 40 \) m and in which a 802.11 (WiFi) network with 5 APs 3COM 7760 operates (see Fig. 5). Next we report the results of the Monte Carlo simulations for comparing the performances of the two chosen algorithms without and with the diffraction correction.

#### A. Electromagnetic model

The adequateness of the log-distance path loss model has been confirmed by the validation campaign carried out in the cited parking lot. In particular, the box-plot corresponding to the 6 positions with no obstacles between transmitter and receiver, as depicted in Fig. 6, is shown in Fig. 7. It indicates that the central tendency indicator of measured data follows the regression line achieved by Least-squares method. The value of parameters of the regression line corresponding to a confidence interval of 0.95 are the following

\[
E[|P0| db] = -28.6 \pm 0.2
\]

\[
\alpha = 1.98 \pm 0.02
\]

In Fig. 8(b) we report the time series of the power of the signal transmitted by AP 1 and received by vehicle \( V_3 \) with the successive interposition of the two vehicles \( V_1 \) and \( V_2 \), positioned according to the layout shown in Fig. 8(a). Regarding the first vehicle \( V_1 \), the heights of AP \( h_{AP} = 2.55m \),
that of vehicle $h_v = 1.45$m and the distances $D_1 = 22.5$m and $D_2 = 14.5$m (see Fig. 4) yield, by simple geometrical calculations and by using the formula (2), an expected loss of 1.4 dB, very close to the actual value 1.2dB. For vehicle $V_2$ the analogous values amount to $h_{AP} = 2.55$m, $h_v = 1.45$m, $D_1 = 28$m and $D_2 = 9$m; the consequent expected loss is 2.7dB, while the measured value is 2.6dB.

The data used in the simulations have been generated according to a Rice distribution. In fact a comparison of the cumulative distribution function (cdf) of the collected data indicates that the Rician distribution achieve the best fit on the empirical distribution (see Fig. 9).

The analysis of the performances of the localization algorithms has been carried out by generating datasets of signals that simulate the real working scenario of the park under investigation. The arrivals and the departures have been modeled by a random birth and death process. The measurements are the power levels of the signals transmitted by the APs, that are typically acquired with sampling frequency of about 2 measurements per second. With reference to the power of signal transmitted by a single AP, the attenuation (2) due to the presence of vehicles is graphically exemplified in Fig. 10. We will not explicitly take into account the typical quantization introduced by the acquisition devices. In order to avoid side-effects in the vehicle contribution characterization, no wall have been considered in the working area. Therefore received signals have been generated according to a Rice distribution that adequately models Line-Of-Sight (LOS) propagation.

To single out the effect of the diffraction factor correction, both algorithms have been first tested on a simplified setup.
Fig. 11: RADAR localization algorithm without and with diffraction factor correction: RMS error VS. number of samples in the test set $N_d$: (a) exact position of parked vehicles; (b) estimated position of parked vehicles. Number of samples in the training set $N_t = 200$, Rice factor $K_f = 2$, number of APs $N_{AP} = 3$.

wherein exact knowledge of the state (number and position of already parked vehicles) is assumed, thus avoiding the influence of the occupancy estimation phase. Thereafter the tests have been extended to the complete setup, i.e. including the effects of the park state estimation.

As to the RADAR algorithm, we tested its most widely employed version, in which the Radio Map is constructed by in-situ measurements of the signal received in the reference points. The spatial distribution of the latter is graphically illustrated by Fig. 5. The training phase is simulated by employing 200 samples for each point. Since each possible parking position coincides with a training point, the algorithm does not perform any averaging of neighbors (i.e. $k = 1$), which would worsen, in this case, the performances. The results relative to Rice factors $K_f = 2, 10$ and 3 APS are shown in Fig. 11 as a function of $N_d$, the number of samples used in the localization phase. The arrival of vehicles is simulated by means of a Bernoulli birth and death process whose probabilities, respectively, decays and grows linearly with the parking lot occupancy. In particular the expected occupancy of the parking lot is $1/2$. In the top plot we show the performances when the system knows the actual distribution of the parked vehicles. The necessity of the diffraction loss correction is highlighted by the accuracy degradation, from about 1 meter to 9 meters. The effective capability of the proposed method is clarified in Fig. 11(b), where the realistic decision-directed framework is examined. The algorithm, besides preserving the stability (one of the main problems of such working mode), achieves a very significant precision enhancement. This behavior is always more evident with the growth of Rice factor $K_f$; in fact a greater value of the latter means a more significant presence of the Line-Of-Sight propagation path, that is mainly affected by diffraction loss.

The correlation between the modification of the received power due to interposition of obstacles is illustrated in greater detail in Fig. 12 that reports a toy example corresponding to the presence of a row of vehicles. In Fig. 12(a) the maximum variation of the collected power due to diffraction loss is depicted. In Fig. 12(b) the RMSE for each reference point shows how the positions closer to the row of cars are mainly liable to performance degradation. Finally Fig. 12(c) illustrates how, after correction, the RMSE error more uniformly distributes in the whole parking area.

Analogous considerations can be made concerning the Viterbi localization algorithm. It commonly achieves performances significantly better than the RADAR algorithm, since it exploits a larger amount of information. In fact to make the results comparable, $N_d$ refers again to the number of samples acquired in the parking stall; however, depending on the trajectory followed by the vehicle, several previous measurements are collected, from the parking access until the final position. Fig. 13(a) shows upper bounds on the accuracy achievable, while Fig. 13(b) shows the results concerning the more real scenario of estimated vehicles positions. The Viterbi algorithm benefits of a reduced improvement respect to RADAR. Indeed the diffraction loss correction only impacts the mean value of the collected power, that is the only quantity used by the latter method.

Interestingly, this method is able to face this kind of nonstationarity, better than other existing Bayesian sequential methods, developed for indoor localization in time-varying environments. In fact previous methods are able to estimate some of the propagation parameters and follow their variation with time when modifications affect the whole investigated area [12], but fail when, as illustrated in Fig. 12(a) for our case, the power variations are also spatially inhomogeneous.

V. CONCLUSION

We studied the possibility to implement a network-based solution to the problem of automatic localization of vehicles in a parking lot equipped by a WLAN transmission infrastructure. We propose a novel protocol, named LIP, to manage the communication of the mobile with the location server that estimates the position of the arriving vehicles. Furthermore we deal with the main problem that degrades the performances of
Fig. 12: Effect of obstacle interposition on the RMSE: (a) maximum diffraction loss; (b) RMSE without correction; (c) RMSE with correction. Number of samples in the training set $N_t = 200$, Rice factor $K = 2$, number of APs $N_{AP} = 4$.

Fig. 13: Viterbi localization algorithm without and with diffraction factor correction: RMS error VS. number of samples in the test set $N_e$: (a) exact position of parked vehicles; (b) estimated position of parked vehicles. Rice factor $K = 2$, number of APs $N_{AP} = 3$.

Each positioning algorithm in such scenarios, namely the non-stationarity of the electromagnetic environment. We approach this problem by introducing a diffraction loss model to correct the expected received signal strenghts, according to the current parking occupancy. Both the ideal capability of such path loss correction and the practical consequences of replacing the true occupancy with an estimate thereof are considered. Future studies concern the enhancement of correction loss evaluation by more accurate modeling of the training field and an experimental validation of the proposed architecture.

REFERENCES


