An Indoor Localization Algorithm in a Small-Cell LED-based Lighting System

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***Abstract*—Nowadays, the use of Visible Light Communications is growing towards several applications, due to the many benefits of this technology. By efficiently modulating visible light, it is possible to reach very high data rates, while at the same time providing illumination. As a result, traditional indoor systems, like open offices and homes, become smarter, providing high efficient services *i.e.*, localization, positioning and navigation.**

In this paper, we propose a simple method for indoor localization service provided by infrared LED devices. The positioning estimation can be calculated by exploiting the uniform deployment of LED-based transmitters, and the information of the impulse responses. The comparison to the impulse responses time samples of a room map, opportunely built according to the transmitters' deployment, allows to estimate the position of a mobile device inside the room. The estimation error can be then reduced on the basis of the number of LED devices used.

I. INTRODUCTION

Localization techniques for indoor environments are increasing as a new class of services, called as Location Based Services, and providing positioning information to track and navigate users in a location-aided environment [1]. Different technologies and products are available for indoor positioning and navigation, such as infrared, computer vision, ultrasound, laser, radio frequency, cellular communication, and so on. Traditionally, the use of wireless technology, like IEEE $802.11x$ [2] and RFID [3], has acted as the main solution for indoor localization services. WiFi localization systems have been validated [4], [5], also via experimental results [6], to arise as the most challenging and promising choices thanks to their quickly growing degree of the coverage in most of indoor buildings (*i.e.*, offices, malls, hospitals, etc.).

As an alternative, the rapid development of new "white" LED materials in the visible spectrum has been given for consideration of Visible Light as novel Communication medium (VLC), in addition to traditional illumination [7]. This represents the "dual-paradigm" of VLC *i.e.*, comprising of high-speed medium access—and then also localization and positioning services—, as well as illumination.

Compared to wireless optical communications in the IR and UV wavelengths, VLC results safer to human eyes, due to the intense visible light triggering the blinking reflex, and then preventing a prolonged exposure. This allows to increase the transmission powers, providing ubiquity, high illumination levels, coverage and link robustness at high receive powers, even in Non Line-Of-Sight (NLOS) scenarios.

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As a consequence, the use of the visible spectrum to provide service in densities exceeding femtocells (*i.e.*, < 10 m) for wireless access is a viable alternative that can achieve high data rates (*i.e.*, $800+$ Mb/s has been demonstrated for a VLC link [8]), while also providing illumination. This configuration minimizes packet collisions due to Line-Of-Sight (LOS) property of light and also alleviates the wireless bottleneck that exists when there is a high density of rich-media devices seeking to receive data from the wired network. Finally, LED-based lighting systems offer considerable advantages in energy savings and controllability, as well as opportunities for advanced home/building management and connection to smart grid applications.

In this paper, we propose a simple, while effective, method for *indoor localization* service provided by infrared LEDs. The estimation of the mobile device's position inside a grid (*e.g.*, a conference room) is provided through a set of four LED-based transmitters uniformly deployed in the room. The proposed technique exploits the information of the impulse responses to determine the estimations of a mobile terminal's position. This approach has been tested via simulation results, carried out via Candles software [9], by assuming a mostly realistic scenario, comprised of a room as a grid of uniformly displaced receivers, and four transmitters.

The localization procedure is based on a *fingerprinting* approach, and can be performed according to real-time measures by cross checking them with already available statistics present in a geographical database. This is a map that collects power samples of the transmitters in the room, and the time samples for the impulse responses. By comparing the impulse response peaks in the map, it is possible to estimate the mobile terminal's positions. We simulated the mobile terminal's path, known a priori, inside the room, and obtained the impulse responses from each transmitter; then compared to the values in the power map.

The algorithm is a cyclic process, returning a number of available receivers, which approximate the mobile node's positions. For a number of receivers greater than two, the algorithm calculates the sums of the differences between impulse responses' peaks at the receiver sides, and those in the map. The mobile terminal's position is estimated in the middle between two receivers with lowest sum.

The remainder of this paper is as follows. In Section II a description of related works dealing with indoor localization through VLC is provided. In Section III the main contribution of this paper is introduced, by means of a VLC model for indoor localization, aiming to avoid the ambiguity issues. A solution is then presented, which exploits the deployment of multiple LEDs so that the error of estimated position can be minimized. Section IV describes the proposed indoor localization algorithm based on the infrared LEDs impulse responses. In Section V simulation results have been carried out in order to validate the proposed method in real indoor environment. Finally, conclusions are drawn at the end of the paper.

II. Related Work

Several techniques have been proposed for indoor positioning and navigation through the use of VLC system and LED-based devices. This is mostly due to the "dual-use" paradigm of VLC technology, since it can provide both illumination, as well as wireless connectivity for wide-band services. This represents a valid solution also taking into account the availability of a simple hardware installation. All these features have been largely exploited by the research community, and several approaches for indoor localization services have been presented.

In [10], Cossu *et al.* consider a localization algorithm based on VLC, and exploiting adaptive OFDM model. Through experimental results they have demonstrated that the localization accuracy obtained is fully compatible with the angle tolerance required by focalized LoS VLC system. The localization error is low enough to guarantee a data-rate between 300 and 410 Mb/s using only one transmitting RGB LED, and covering an illumination angle of $90°$ and at 90 cm link length. Other excellent results have been obtained by Jung *et al.* in [11], and although the performance of the proposed localization method have been evaluated by computer simulation, the indoor location accuracy is less than 1 cm in the space of 5 m $\times 5$ m $\times 3$ m. This approach considers the phase difference, and a Time Difference of Arrival (TDOA) localization algorithm. However, as one of the main drawback in—*mostly general*—localization systems, is the requirement of a perfect synchronization among the transmitters, and between the transmitters and the receivers. In [12], Zhang and Kavehrad have adopted a framed slotted ALOHA protocol working in indoor VLC system, so that the need for total synchronization can be eliminated. By measuring the transmitted and received powers and using triangulation, the proposed method can locates a target in a room to within centimeter.

Different solutions consider hybrid approaches, based on VLC and other technologies. In [13], in order to improve position accuracy, the VLC method is merged with the conventional received signal strength indication based positioning methods into a hybrid positioning method for indoor wireless sensor network. This solution results very effective in order to get more accuracy position messages with lower power consumption. The use of LED devices is exploited to decide the possible position area of the receiver. As expected, the high the number of multiple LED bulbs, the small the possible position area of the receiver, and thus a relatively accurate position decision of the receiver can be made.

Another approach is presented by Sertthin *et al.* in [14] which propose a Switching Estimated Receiver Position (SERP) scheme for the VLC-ID and 6-axes sensor based positioning system. Such approach improves the positioning accuracy by optimizing estimated error distance, which is varied in proportion to the receiver's tilt angle. Moreover, in [15] the proposed technique considers an algorithm for high precision indoor positioning using lighting LEDs, and image sensors. At least three LEDs transmit their three dimensional coordinate information which are received and demodulated by two image sensors at the unknown position. The unknown position is then calculated from the geometrical relations of the LED images created on the image sensor. The system is able to estimate the unknown position within the accuracy of about 10 cm. Positioning accuracy can be increased by using high resolution image sensors.

In [16], Kim *et al.* present a technique for estimating the position of mobile station, relying on the comparison of the received light intensity at the receiver with a pre-calculated light intensity at a given position. Simulation results have verified that the proposed estimation algorithm can provide good position accuracy. A LED Access Point (AP) traces the changing pattern in received light intensity. Then, it compares intensity difference and in the comparison process, selects the position that provides the closest match between the measured at the precalculated at a specific location.

Finally, in [17] Rust and Asada present a VLC system for communication and localization for robots in underwater networks. The localization is carried out using an Extended Kalman Filter algorithm in order to gain an estimate of the orientation and position of the vehicle in space

III. Model for VLC-based Indoor Localization

We assume a geographical DataBase (DB) that collects several—power and time—measurements, which can be compared to real-time acquisitions. Let us assume the case with a single LED in an area (*e.g.*, a room), designed as a $N_x \times N_y$ [m] grid, where

$$N_x = \frac{d_x}{\Delta x}, \quad \text{and} \quad N_y = \frac{d_y}{\Delta y}, \tag{1}$$

where $d_{x,y}$ are the lengths on two orthogonal directions $\{x, y\}$, and $\Delta\{x, y\}$ are the paces, assumed identical, along $\{x, y\}$, respectively.

In this environment, ambiguity issues can occur, for instance when in different positions *i.e.*, (x_i, y_i) and (x_j, y_j), with $x_i \neq x_j$ and/or $y_i \neq y_j$, the energy measurements are almost the same, such as

$$E_{(x_i,y_i)} \simeq E_{(x_j,y_j)}. \tag{2}$$

One solution to fix this ambiguity issue is to use several LED devices, accordingly displaced in order to provide an statistical independence of measurements w.r.t the LEDs. As an instance, if we considers M LED devices deployed in the room, in the (x_i, y_i) position, we can have M measurements.

For deterministic measurements *i.e.*, not dependent on noise and propagation losses, the ambiguity issues can be fixed through $M \times N_x \times N_y$ measurements. Basically, we can state that for N measurements for each (x_i, y_i) position, we obtain a d.d.p., whose mean value for the k-th LED, with $k = \{1, 2, \cdots, N\}$, is

$$\bar{E}_{x_i,y_i}(k) = \mathbb{E}\left\{E_{x_i,y_i}(k)\right\} = \sum_{l=1}^{N} E^{(l)}_{x_i,y_i}(k)\, p\left(E_{x_i,y_i}\right), \quad (3)$$

where $p\left(E_{x_i,y_i}\right)$ can be calculated through a histogram.

In order to fix the ambiguity issues, we can consider the Maximum Likelihood (ML) criteria, so that

$$(\hat{x}_i, \hat{y}_i) = \arg\max_{x_i,y_i} p\left(\mathbf{r}|\mathbf{m}\right), \quad (4)$$

where $\mathbf{r}$ is the measurements vector w.r.t the LEDs, while $\mathbf{m}$ is the vector of mean values of measurements, so that $\mathbf{r}|\mathbf{m}$ means the measurements conditioned to the average value. Moreover, under Gaussian hypothesis of $p\left(E_{x_i,y_i}\right)$, we can consider that

$$(\hat{x}_i, \hat{y}_i) = \arg\min_{x_i,y_i} \left\|(\mathbf{r} - \mathbf{m})\right\|^2. \quad (5)$$

This approach is very effective although we have to opportunely consider the deployment of LEDs in the room. As a matter, for two LEDs deployed far away from each other, the difference in (5) can still provide ambiguity issues.

As a drawback, the proposed approach needs the acquisition of multiple measurements. In fact, it is well known from several works in the literature that a single measurement can only provide an estimation of the distance, which however does not fix ambiguity issues. As a solution, we need to implement a multiple ranging procedure by *mixing* different measurements since the simple distance estimation induces a localization ambiguity.

Adding only one more LED, unfortunately, does not solve this problem: ambiguity is still possible, since in some positions in an indoor environment, it is possible to have the same distances from the above LEDs. This implicitly tells us that we need *at least* three LEDs—non-aligned each other along the same line—to reduce considerably the effect of ambiguity. This can be well justified in two different ways. First, if we dispose three LEDs on a line there are still two points presenting the same measurements *i.e.*, the two points on the ground at the vertex of an isosceles triangle. Second, the displacement in terms of distance between LEDs is useful in order to guarantee spatial diversity. In fact, in the case of the very close LEDs, it is possible that there measures the same energy level from two different points and this does not help to solve the ambiguity problem. As a consequence, it appears clear that we need at least 3 LEDs and a proper displacement of them.

A typical VLC link can be modeled according to the following expression, which identifies the k-th output signal of the k-th LED transmitting device:

$$Y_k(t, \vartheta, \varphi) = rA_e(\vartheta, \varphi)X(t, \vartheta', \varphi') * h_k(t) + N(t), \quad (6)$$

where r [A/W] is the responsivity of the photodiode, A_e [m^2] is the effective receiver area, $X(t, \vartheta', \varphi')$ is the emitted signal, depending on time t and space (ϑ', φ'), and $N(t)$ is shot noise due to ambient light.

Under the *optimistically* assumption that the k-th channel impulse response $h_k(t)$ is ideal *i.e.*, $h_k(t) = a_k\delta(t)$, with $a_k \neq 0$ as a constant, we have

$$Y_k(t, \vartheta, \varphi) = rA_e(\vartheta, \varphi)a_kX(t, \vartheta', \varphi') + N(t), \quad (7)$$

and for $N(t) \to 0$, (7) becomes

$$Y_k(t, \vartheta, \varphi) = rA_e(\vartheta, \varphi)a_kX(t, \vartheta', \varphi'), \quad (8)$$

where the term a_k and $X(t, \vartheta', \varphi')$ consider respectively the distance from the receiver to the transmitter, and the intensity emission, while $A_e(\vartheta, \varphi)$ refers to the angle of emission of the signal.

Let us assume $k = \{1, 2, \cdots, M\}$ LEDs deployed in the room. Under the assumption of knowledge of $A_e(\vartheta, \varphi)$, we can solve the following system comprising of M output signals, such as

$$\begin{cases} Y_1(T_c, \vartheta, \varphi) = \xi_1 \\ Y_2(T_c, \vartheta, \varphi) = \xi_2 \\ \vdots \\ Y_M(T_c, \vartheta, \varphi) = \xi_M \end{cases} \quad (9)$$

which becomes

$$\begin{cases} a_1 rA_e\left(\vartheta, \varphi\right) X\left(T_c, \vartheta', \varphi'\right) + N_1\left(T_c\right) = \xi_1 \\ a_2 rA_e\left(\vartheta, \varphi\right) X\left(T_c, \vartheta', \varphi'\right) + N_2\left(T_c\right) = \xi_2 \\ \vdots \\ a_M rA_e\left(\vartheta, \varphi\right) X\left(T_c, \vartheta', \varphi'\right) + N_M\left(T_c\right) = \xi_M \end{cases} \quad (10)$$

Assuming the knowledge of a_k, it is then easy to obtain the estimated position. Notice that some considerations about possible practical implementation of average values obtained by a foregoing measurement campaign are required. Since we deal with infrared measurements, the temperature of the room influences the statistics with the exception of room that present artificial constant temperature. In order to reduce the real-time implementation and computational cost of the localization algorithm—in terms of statistics, measurements and probabilities processing—it is worth to store in a database seasonal measurements for the considered room, and then to compare the real-time sensed energy levels with those available in the database.

Finally, notice that the use of multiple LED devices recall the well know *Multiple Input Multiple Output* (MIMO) scheme, adopted in different wireless communication systems. Exploiting MIMO techniques also in VLC has been already introduced [18], considering multiple LEDs and photodiodes, working at the transmitter and the receiver, respectively. Among the main advantages, MIMO in VLC works easily, and network performances are strongly enhanced. In [18], by exploiting a MIMO-LEDs scheme, based on Pulse Position Modulation, we have highlighted the achievable benefit in *localization*, *access* and *transmission* for an indoor VLC system. However, in this paper do not address directly to the MIMO approach but focus on the localization goal, achieved through a simple, while effective, algorithm, as described in next Section IV.

IV. VLC Indoor Localization Algorithm

The VLC indoor localization algorithm considers the information from different LED transmitters (*i.e.*, power and time measurements), which is stored in an existing room map, also called as database.

The localization algorithm results as a cycle process, based on the following steps [1]:

1) In each—*unknown*—position $P = (x, y)$, it is possible to consider a vector $\mathbf{t}$, gathering the information on impulse response times from different—four—transmitters (*i.e.*, $t_{Tx_i}^{(P)}$ [ns], with $i = \{1, 2, 3, 4\}$), such as
$$\mathbf{t} = \left[t_{Tx_1}^{(P)}, t_{Tx_2}^{(P)}, t_{Tx_3}^{(P)}, t_{Tx_4}^{(P)}\right]. \tag{11}$$
By sorting the elements of $\mathbf{t}$ in a time ascending order, the algorithm compares the lowest impulse response time (*i.e.*, $t_l = \min \mathbf{t}$) to the time measurements collected in the database S (*i.e.*, $t_{Tx_i}^{(S)}$ [ns]), so that
$$-\Delta \leq t_{Tx_i}^{(S)} - t_l \leq \Delta, \tag{12}$$
where Δ represents a constant factor. As a result, the algorithm selects those receivers whose impulse response times verify (12). The database S will be updated to obtain a subset $S^{(1)} \subset S$, comprising of all the selected receivers. The value of t_l will be updated to the second lowest element of $\mathbf{t}$;
2) Among the elements in $S^{(1)}$, the algorithm will select those experiencing the following equation:
$$-2\Delta \leq t_{Tx_i}^{(S^{(1)})} - t_l \leq 2\Delta, \tag{13}$$
where $t_{Tx_i}^{(S^{(1)})}$ is the time measurements in $S^{(1)}$. Again, the algorithm selects those receivers whose impulse response times verify (13), and then the database $S^{(1)}$ will be updated to obtain a subset $S^{(2)} \subset S^{(1)}$. The value of t_l will be updated to the third lowest element of $\mathbf{t}$. This step is repeated till the following equation holds:
$$t_l = \max \mathbf{t}. \tag{14}$$
Again, the subset $S^{(2)}$ will be updated up to $S^{(3)} \subset S^{(2)}$, and then to $S^{(4)} \subset S^{(3)}$;
3) In the last step, the localization algorithm estimates the position of the receiver, according to the cardinality of $S^{(4)}$ *i.e.*, $\left|S^{(4)}\right|$:
   A. If $\left|S^{(4)}\right| = 1$, the estimated position of the unknown receiver (*i.e.*, $\hat{P}$) will be that of the receiver belonging to $S^{(4)}$ (*i.e.*, Rx_1), such as:
   $$\hat{P} = P_{Rx_1}. \tag{15}$$
   B. If $\left|S^{(4)}\right| = 2$, the estimated position of the receiver will be in the middle between the positions of two receivers in $S^{(4)}$ (*i.e.*, $Rx_{1,2}$), such as
   $$\begin{aligned}\hat{P} &= avg\{P_{Rx_1}, P_{Rx_2}\} = \\ &= \left[(x_{Rx_1} + x_{Rx_2})/2, (y_{Rx_1} + y_{Rx_2})/2\right].\end{aligned} \tag{16}$$
   C. If $\left|S^{(4)}\right| \geq 2$, the algorithm calculates several estimations $\hat{P}_j$, where j is the cardinality of $S^{(4)}$, as the sums of differences among the impulse response times of the receiver and those one in $S^{(4)}$:
   $$\hat{P}_j = \sum_i \left|\mathbf{t} - t_{Tx_i}^{(S^{(4)})}\right|. \tag{17}$$
   Considering the two lowest values of $\hat{P}_j$, we select the two associated receivers (*i.e.*, $Rx_{1,2}$). The algorithm estimates the position of the receiver as the middle between the positions of two selected receivers:
   $$\hat{P} = avg\{P_{Rx_1}, P_{Rx_2}\}. \tag{18}$$

[1]We assume 4 LED transmitters are uniformly deployed in the room.

TABLE I
Practical example of the localization algorithm. Selected receivers for the position estimate.

Rx ID	P [m]	t_{Tx_1} [ns]	t_{Tx_2} [ns]	t_{Tx_3} [ns]	t_{Tx_4} [ns]
17	$[5, 1]$	11.5	21	12	21
28	$[5, 2]$	11	18	11.5	18.5
39	$[5, 3]$	11.5	15.5	12.5	16

In order to understand the process, we provide a practical example, as follows.

Let us consider the vector $\mathbf{t} = [10.5, 19.5, 12.5, 20]$ [ns] in an unknown position P. TABLE I collects the receivers belonging to $S^{(4)}$ (*i.e.*, with ID numbers $17, 28, 39$), and the associated impulse response times from four different transmitters (*i.e.*, $t_{T_{x_i}}$ [ns], with $i = \{1, 2, 3, 4\}$). Since three receivers have been selected during the localization process, from (17) we obtain:
$$\begin{cases} \hat{P}_1 = |-0.5| + |1.5| + |1.5| + |1.5| = 4.5 \text{ [ns]} \\ \hat{P}_2 = |-1| + |4.5| + |0| + |4| = 9 \text{ [ns]} \\ \hat{P}_3 = |-1| + |-1.5| + |0.5| + |-1| = 4 \text{ [ns]} \end{cases} \tag{19}$$
where the lowest values are 4 and 4.5 ns, respectively for the receivers in $[5, 2]$ and $[5, 1]$ m. The estimated position will be then $[5, 1.5]$ m; since the true position is in $[4.8, 1.5]$ m, the positioning error is only 20 cm.

The localization process provides a *Positioning Service* for *Indoor* environment, namely IPS. The IPS architecture belongs to the mobile-executed and network-assisted class. A mobile device requiring IPS in an unknown environment can download the database collection, in order to start moving while being tracked. The IPS installed in the LED-based device calculates the positions, by checking real-time measurements with collected data. The network's control is provided directly by the LED transmitters by means of the database download.

V. Simulation Results

The effectiveness of the proposed technique has been proven in a mostly realistic scenario, depicting a room as shown in Fig. 1. The room represents an open office at the Department of Applied Electronics of Roma Tre University. This environment is comprised of 4 workspaces with several chairs. The wall reflectivity is 80% while for the workspaces it is 50%,

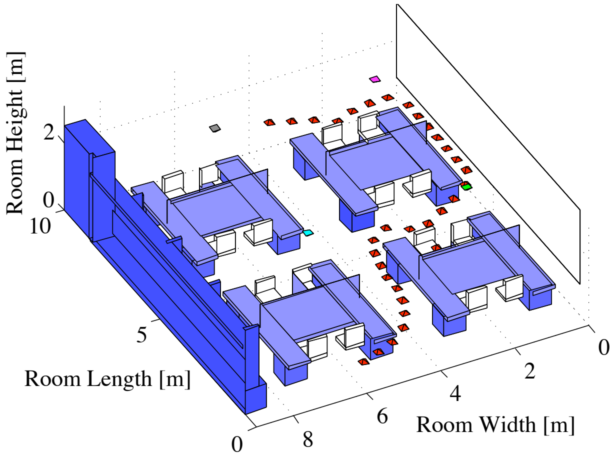


Fig. 1. Simulated 10m $\times$9m $\times$3.1m room in the Department of Applied Electronics at Roma Tre University. 4 LED transmitters are uniformly deployed in the ceiling (*i.e.*, *black*, *blue*, *green* and *pink* points), while a mobile terminal is moving according to a 32-steps path (*i.e.*, *red* points).

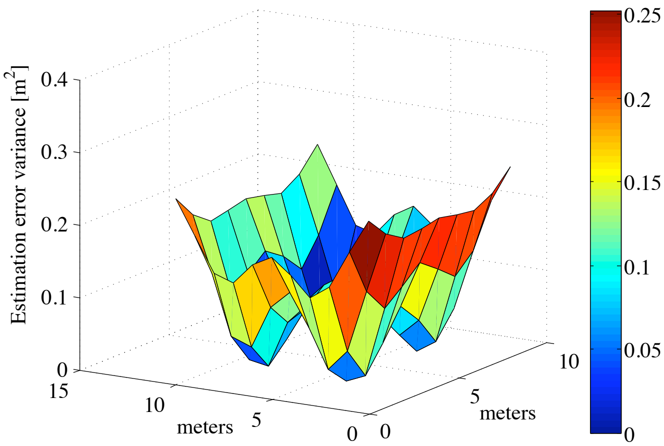


Fig. 2. Estimation error variance for different positions in the considered room.

typical for wooden tables. Under each workspace, there is a chest whose reflectivity has been assumed equal to 70%. No reflectivity factor has been assumed for the chairs.

Along the south wall, there is a huge window covering almost the room length, with a reflectivity factor of 0%; while along the north wall, we assume a bookcase with 80% of reflectivity. In the whole room, a noise level of 5.8 W/cm^2/nm has been considered, approximating typical daily hours.

In the ceiling, 4 LED-based transmitters have been uniformely deployed in the positions $P_1 = (2.7, 1.9, 3.1)$, $P_2 = (2.7, 6.2, 3.1)$, $P_3 = (7.5, 1.9, 3.1)$, and $P_4 = (7.5, 6.2, 3.1)$, each one emitting a 1500 lm of luminous flux, corresponding to a power level of 6.55 W.

In Fig. 2 the estimation error variance [m^2] is reported by mapping this quadratic difference in different positions inside the room. It is possible to appreciate how the higher values of the error—limited to 0.3 m^2—are in correspondence of the walls, far away from the LEDs' positions, while for an estimated position close to the LEDs, a low error value is not always assured since it also depends on the LEDs' emission profile.

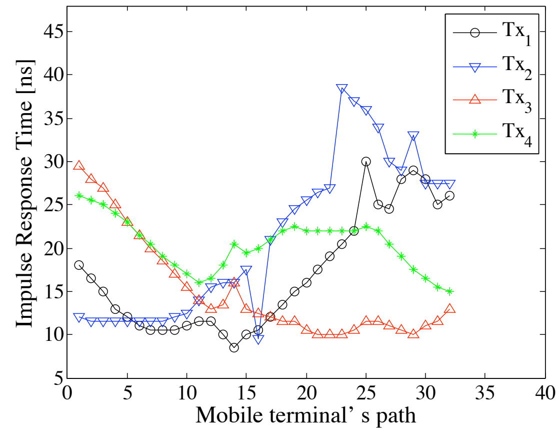


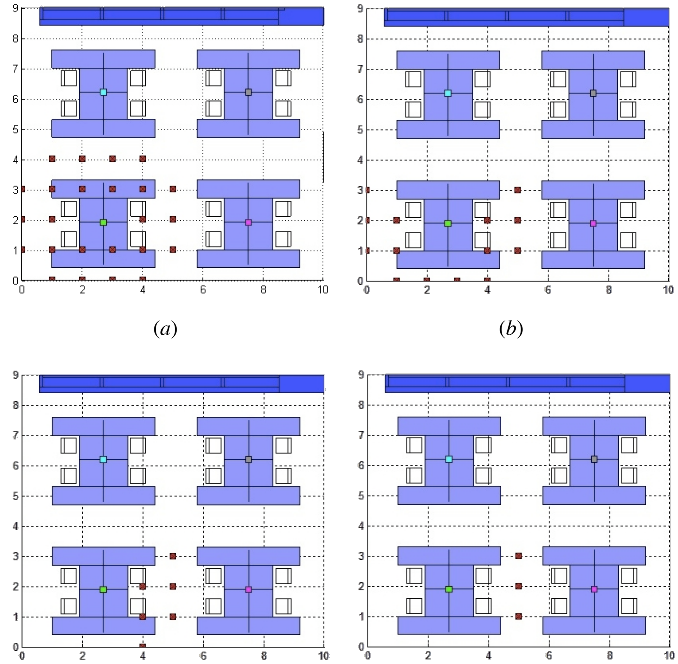
Fig. 3. Times of impulse responses at different positions in a path, for each transmitter in the room.

It is then worth to notice not only the behavior of the estimation error, but also the estimation error variance, especially when a position very close to one of the LEDs is considered. In this case, the error falls short but—mildly—increases when the position of the node is in the middle of the room. This leads to conclude that the coverage and positioning capability of the VLC indoor localization algorithm is strictly dependent from the number of LEDs and their relative and absolute positions, as well as from the room height.

Let us assume a user is moving inside the room with his own terminal, equipped with a VLC-based network interface card, according to the red path in Fig. 1. The simulation results have been run via Candles software, [9]. For each step of the path, we calculated the peaks of impulse responses times from different transmitters, as shown in Fig. 3. Basically, the lowest the value of the impulse response times from a given transmitter, the closest the receiver from such transmitter. As an instance, the red values decrease on average during the mobile terminal's path *e.g.*, in the position number 10, the time peak is 15 ns, while it is 10 ns in position number 20. The values from Fig. 3 have been used and compared to those in the measurements map, during the localization algorithm for $\Delta = 2$ ns.

Fig. 4 shows how the localization algorithm selects different receivers for position estimation of the mobile terminal when it moves near the third desk of the room (placed on bottom and left in Fig. 4). In Fig. 4 (a) the number of receivers, selected as potential mobile terminal's positions, is 24, which reduces to 14, 6 and then 3 at the end of the localization algorithm, as depicted in Fig. 4 (b), (c) and (d), respectively. The final step represents the case C of the localization algorithm, and in this situation the information of estimated position is provided with an high error of 20 cm.

The effectiveness of the proposed localization algorithm is due to the measurements map and the sampling frequency of such measurements. In the simulations, we considered a gap between two consequent measurements of 1 m; a reduction of this factor provides an reduction of the estimation error. For the given path, the comparison between the true positions



(*a*) (*b*)

(*c*) (*d*)

Fig. 4. Localization algorithm, case C. (*a*) Step 1, the number of (selected) receivers is 24; (*b*) step 2, the number of receivers is 14, and then (*c*) 6; (*d*) step 3, the number of receivers is 3.

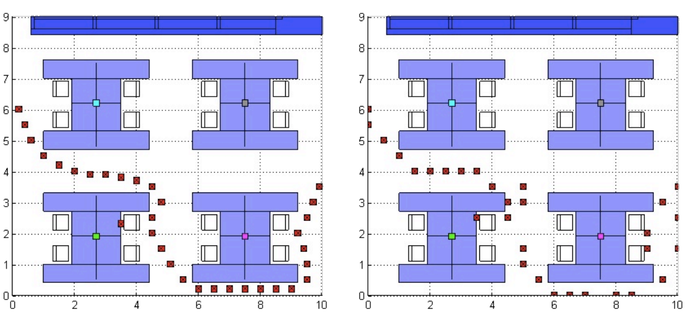


Fig. 5. Comparison between (*left*) the true mobile terminal's path, and (*right*) the estimated path via the localization algorithm.

and the estimated measurements is depicted in Fig. 5. We can notice that the positioning error is mostly limited except in some positions. Obviously, this result can be easily enhanced by increasing the number of transmitters in the ceiling, as well as the inter-measurements gap in the map.

More in detail, the positioning error vs. the mobile terminal's path is shown in Fig. 6. We can notice that the estimated error reduces when the mobile terminal approaches near the transmitters' positions. Lowest values are experienced in the center of the room *i.e.*, when all four transmitters are involved in the localization process, and the mobile terminal is near the desks. As expected, highest values of estimation error are when the mobile terminal is near the boundaries of the room *i.e.*, the mobile user is leaving the open office. Notice that the highest estimation error is 0.8 m, which is strictly depending on the measurement sampling gap (*i.e.*, assumed equals to 1 m in our simulations). Obviously, the higher errors are when the positioning estimation is done along the diagonal linking

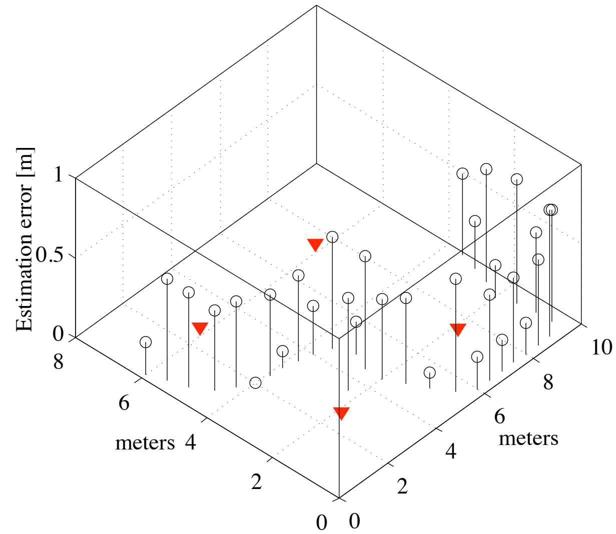


Fig. 6. Estimation error for the considered path. The red points indicate the positions of LEDs, while the black circles are the estimated user's positions.

two consecutive transmitters, while the lower errors are for estimations along the horizontal and vertical lines between two consequent transmitters.

At a first glance this may appear in contradiction with the 3D plot shown in Fig. 2 since the minimum error experienced is correspondent to the LEDs' positions. However it is important to stress that the path is not covered by the maximum intensity of the LEDs (*i.e.*, LEDs are displaced on the top w.r.t the 4 workspaces) and, also, in a central position w.r.t the room the diversity order is the highest possible.

VI. Conclusion

In this paper we have investigated the localization issue in indoor environment, through Visible Light Communication. The use of visible spectrum is increasing in popularity since it can provide high speed data communications, as well as illumination. As a consequence, exploiting the directionality of lighting signals can provide high accuracy indoor localization services.

The proposed technique allows an Indoor Positioning Service (IPS), by means of a fingerprinting approach *i.e.*, exploiting of the knowledge of impulse responses, and comparison to samples of a power and time measurements map of the environment. Ambiguity cases can be avoided by opportunely sampling the environment, as well as deploying the LEDs transmitters. Simulation results have shown the effectiveness of the proposed technique, in terms of number of detected receivers, and positioning error. Future works will address to a validation of the proposed technique in a real—more complex—environment.

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