Cognitive Indoor Positioning in TV White Spaces

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***Abstract*—Recent evolution in regulation of access to TV channels allocated in UHF frequencies (DVB-T) makes vacant channels (TV White Spaces - TVWS) available to wireless data services. While this opportunity is currently widely studied by the cognitive radio community for communications, the use of TVWS for indoor positioning is all but unexplored. Frequencies below 900 MHz are extremely appealing for positioning due to a more uniform signal propagation with respect to the ISM bands and a lower attenuation when passing through obstacles. This work focuses indeed on indoor positioning in the TVWS. A TVWS positioning system is proposed and compared against WiFi-based solutions, in terms of energy efficiency, operating range, and impact of network topology. Moreover, the formulation of a cognitive paradigm for optimal selection of the topology of Access Points and of network topology in a TVWS communication and positioning system is given. The proposed algorithm takes into account constraints related to positioning accuracy and communication performance. Results obtained analytically and by simulation show that favorable propagation conditions characterizing the TVWS frequencies, in conjunction with an optimized system organization and topology, lead to highly accurate positioning and improved energy efficiency over traditional schemes, thanks to lower transmit power levels. The proposed solution is therefore also appealing in light of recent trends towards *green* wireless communications.**

I. Introduction

Position information, obtained by means of wireless communication devices, is nowadays commonly adopted in a wide range of outdoor application scenarios such as logistics, geographic routing, security, navigation, and deployment of vehicles and workers. Research efforts are currently focusing on making position information available with similar accuracy and reliability in indoor environments.
Considering the increasing number of WiFi access points for communication purposes, WiFi-based Positioning Systems (WPSs) have been primarily studied and implemented. One of the main challenges in the efficient deployment of WPSs is the impact of limited coverage, due to relatively stringent transmit power regulatory levels and to high wall and floor penetration loss suffered by signals in the ISM bands. This work proposes to overcome the above limitations by moving the operation frequency of the positioning system from the the ISM bands to the so-called TV White Spaces (TVWS).

The availability of TVWS arises from the introduction of digital terrestrial broadcasting (DVB-T and T-DAB systems), which is underway in many parts of the world at different stages of completion, and is complementary to the well known concept of Digital Dividend. Generically, a white space is a frequency band, licensed for a broadcasting service but not used on designated geographical area. With the constraint of guaranteeing no interference to existing or future broadcasting services, those parts of spectrum could be reallocated, making them accessible to unlicensed devices. Systems that could benefit from operating in white spaces definitely include WiFi that, at TV frequencies, could guarantee a higher efficiency in broadband access, in particular in densely forested areas when line of sight is not guaranteed. By using more favorable spectrum bands than the ISM, the new WiFi will be able to support QoS, providing intensive multimedia services more easily than the current WiFi. This suggests the importance of investigating this opportunity for wireless networking: already in 2008, Google and Microsoft announced their interest in using TVWS for an enhanced type of WiFi, called WiFi 2.0, WiFi on steroids, or White-Fi.
This work investigates the use of such bands for WiFi-based localization and positioning applications, in order to determine the advantage in this specific case. In the following we first describe the considered fingerprinting localization technique and give a theoretical model for the localization estimation error in order to determine how effectively the use of TV bands can improve localization performance. Next, a comparison based on simulations is carried out between 802.11 (the traditional WiFi) and WiFi operating at TVWS frequency bands in terms of localization performance. Finally, the potential role of TVWS in lateration positioning system is evaluated as well.

The paper is organized as follows: Section II is divided in two subsections. The first subsection introduces the TVWS idea, providing basic definitions and concepts, a short overview of ongoing standards, regulations and technical considerations on the exploitation of these particular spectrum opportunities; the second subsection briefly recalls potential approaches and challenges for WiFi-based indoor positioning systems. Section III introduces the system model and the framework for the design of a positioning system working in TVWS: the proposed system is described, and a theoretical model for the evaluation of positioning error is introduced. Section IV presents and discusses simulation results: first a comparison between TVWS and WiFi fingerprinting solutions is presented, assuming random topologies of access points used for the localization. Next, a lateration solution is considered, and the analysis focuses on the impact of spatially constrained topologies, suggesting an algorithm for the selection of the optimal topology of APs in order to reduce the localization error. Finally, Section V concludes the paper.

II. Related Work

A. TV White Spaces and Cognitive Radio Networking

As mentioned in Section I, TV White Spaces spectrum arises following the beginning of UHF band reallocation for DVB-T services. Three reasons are crucial for the existence of this spectral opportunity [1]: 1) In the same licensed area and thanks to improved signal characteristics, DVB-T services need a reduced amount of guard intervals respect to analog TV adiacent transmissions; 2) Given different licensed areas, TV services broadcasting on the same channel need to be geographically separated; 3) In areas where there is a limited demand of broadcasting services, some TV channels are not allocated yet. The TVWS usage by the so-called White Space Devices (WSDs) requires, first of all, an adequate protection of licensed systems; for this reason, regulation activities are presently ongoing in US (by FCC [2]), UK (by Ofcom [3]) and Europe (by CEPT [4]).

In November 2008 the United States FCC issued a technical report on the unlicensed use of TV white space spectrum [2]. A number of the requirements to operate in TV white space are based on Cognitive Radio (CR) technology including location awareness and spectrum sensing. These requirements impose technical challenges for the design of devices operating in TV white space spectrum. According to [5] the devices operating according to these rules are referred to as TV band devices (TVBDs) by the FCC. There are two classes of TV band devices: fixed and portable (furtherly divided into Mode I and Mode II). Fixed Devices are permitted to transmit up to 30 dBm (1 watt) with up to 6 dBi antenna gain, while portable devices are permitted to transmit up to 20 dBm (100 mw) with no antenna gain. Fixed devices are permitted to use a higher gain antenna as long as the transmit power is decreased dB for dB for any antenna gain above 6 dBi. The TV channels include the very high frequency (VHF) channels 2-13 and the ultra high frequency (UHF) channels 14-51. However, there are restrictions on which channels are permissable for use by TVBDs. Television broadcast signals are protected with a protection contour. The FCC rules provide distances that a TVBD must be outside the protected contour for it to transmit. Within the protected contour there are special rules for operation on a TV channel adjacent to the TV broadcast channel.

In the United Kingdom, Office of Communications (Ofcom) is the independent telecommunications regulator and competition authority for the communication industries. On the 1st of July 2009, Ofcom published its statement report on TVWS usage [3]. OFCOM makes no distinction between devices, they are permitted to transmit from 4 dBm (adjacent channels) up to 17 dBm (in terms of effective isotropic radiated power (EIRP) into an 8 MHz bandwidth).

Following a 2007 European Commission (EC) mandate, in 2008 the Electronic Communications Committee (ECC), under the European Conference of Postal and Telecommunications Administrations (CEPT), issued a report acknowledging the need for further studies on 470-862 MHz band white space use by CR devices before deciding to proceed to a European recommendation on that matter [4]. According to this report, white spaces devices (WSD) should not be protected form interference among them. However, they must not interfere with licensed primary users, and move to other white spaces channels whenever necessary. At the 22nd ECC Meeting, held on March 2009, it was requested to form working group CEPT SE43 under WG-SE. This group should define technical and operational requirements for the operation of cognitive radio systems in the white spaces of the UHF broadcasting band (470-790 MHz) to ensure the protection of incumbent radio services/systems and investigate the consequential amount of spectrum potentially available as white space. The role of CEPT is crucial because Europe is fragmented by many country borders belonging to different regulation agencies, requiring careful harmonization across borders. One key concern is to evaluate the expected amount of spectrum available to secondary TVWS devices. Relatively little is known on the availability of white space in European countries. It is generally expected that capacity achieved through the use of white space will be much less in Europe than in the USA, but a solid quantitative foundation of such statements is still missing.

Cognitive Radio [6], in particular in the form known as dynamic spectrum access (DSA), is being intensively researched as the enabling technology for secondary access to the TVWS. Its aim is to achieve device-centric interference control and dynamic re-use of radio spectrum based on the frequency agility and intelligence offered by this technology, that allows the system to dynamically and autonomously adjust its operational parameters and protocols according to its obtained knowledge on the surrounding environment in order to achieve predefined objectives and to learn from the results obtained. In [7] the state-of-the-art in technology, regulation and standardisation of cognitive radio access to TVWS is reviewed: both the FCC and Ofcom have considered three methods for ensuring that cognitive devices do not cause harmful interference to incumbent:

- *Beacons* - With the beacon method, unlicensed devices only transmit if they receive a control signal (beacon) identifying vacant channels within their service areas. The signal can be received from a TV station, FM broadcast station, or TV band fixed unlicensed transmitter. Without reception of this control signal, no transmissions are permitted. One issue with the control signal method is that it requires a beacon infrastructure to be in place, which needs to be maintained and operated, either by the incumbent or a third party. Furthermore, beacon signals can be lost due to mechanisms similar to the hidden node problem;

- *Location Awareness* - This location awareness is coupled with Internet access capability for both fixed TVBDs and portable devices, and must be accurate to within 50 meters. This Internet access is utilized to obtain access to a database containing information about licensed transmission in the various TV channels. These licensed transmissions include ATSC (Digital TV) high-power broadcasts, ATSC and NTSC (Analog TV) low-power transmitter, and wireless microphones used by the broadcast industry;
- *Spectrum Sensing* - The device attempting to access the spectrum must observe the various TV channels and determine if these channels are occupied by any licensed transmission.

B. WiFi-based Indoor Positioning Systems

The term Indoor Positioning denotes the possibility to identify and recognize a mobile device within an indoor environment, in order to interact with it providing various kinds of services [8]. WiFi network infrastructure is an excellent support for indoor positioning because it is already strongly widespread, the equipment is cheap and this involves low time and development costs. Two of the most popular method for positioning are the so-called *Lateration* and *Fingerprinting* [9]. Lateration method involves two specific phases:

- *Ranging* - The purpose of this phase is to estimate the position of the targeting device to each reference node. A variety of modalities can be used to perform ranging such as Received Signal Strength (RSS), Time Of Arrival (ToA), Angle Of Arrival (AoA), Time Difference Of Arrival (TDoA) and so on. Given that wireless devices are carried by many people and objects, and almost all modern radio chipsets include the hardware necessary to measure the RSS of transmitted packets (WiFi devices provide a received signal strength indicator (RSSI) as a built-in function), RSS is by far the most used approach for localization. The advantage of using a RSS-based approach becomes noticeable by comparing it with one of the other geometric methods, in particular with ToA approach. WiFi positioning systems based on ToA, in particular, present several open issues [12], the main one related to the lack of accurate timestamping for IEEE 802.11 frame transmission and reception. A number of notable works were been proposed on this topic but a feasible and enough accurate solution is still missing [13] [14]. Scalability with the number of devices in the network is a second potential issues for ToA ranging in WiFi, due to the random access adopted in IEEE 802.11 MAC: higher delays can be expected at high traffic loads, resulting in a decrease of positioning accuracy in ToA based systems relying on Round Trip Time estimation, especially for high mobile devices [15]. On the other hand, RSS-based solutions do not need to access the MAC for the RSS evaluation, and are thus not subject to the same issue;
- *Lateration* - Moving from the distance information obtained in the ranging phase, its aim is to estimate the position of the target. Two well-known methods are mostly used: Nonlinear Least Squares (NLS) and Linear Least Squares (LLS).

The fingerprinting method relies on the creation of a database including the information obtained by using one of the methods introduced in the Ranging phase of the Lateration approach for a set of reference nodes. The position estimate is then obtained by comparing the database entries with the measurements obtained for the specific user/device, avoiding the conversion from RSS/ToA to distance required in the ranging phase. This allows to create and monitor the database without requiring accurate environmental and physical channel models, making the system implementation simpler than in the lateration case. Moreover, in this case, the use of access points already present in the area, but not specifically belonging to the positioning system, is allowed since no specific information about the access points positions are needed for the database creation.

In light of the above observations on the open issues of WPSs related to reduced coverage and difficult distance estimation for ranging, a positioning system based on a RSS-Fingerprinting approach appears one of the most suitable method within the WiFi scenario.

III. System Model

A. Positioning Error evaluation for RSS-based positioning systems

In this section we develop a model for uncertainty of an RSS-based localization system inspired by [16] and [17]. We develop this model in order to find a correspondence between the localization uncertainty (and so the error) and the limits of the RSS method, due to the fact that at any given location in a multi-path environment the received signal strength exhibits shadowing and so the signal strength fluctuates over time. In this way we can verify if there are other parameters which influence the localization error specifically due to signals behavior. Typically, in RSS approach, a signal strength vector $s(x, y) \in \mathcal{S}$, consisting of the received signal strengths from n different Access Points is associated with each location $(x, y) \in \mathcal{A}$, where $\mathcal{A}$ is the considered area. Using propagation models a mapping relationship $\mathcal{M} : \mathcal{A} \longrightarrow \mathcal{S}$ is generated: the location of the target is estimated by obtaining the signal strength vector at the target device and finding the closest matching vector from $\mathcal{M}$. Thanks to this mapping relationship we can map the uncertainty of the signal strength domain into the positioning plane one. The received signal strength vector at (x, y) is $s = (s_1, s_2, \ldots, s_n)$. The received signal strength s_i from the ith AP is a stochastic variable due

to the effect of multipath propagation, it can be modeled as a normal distribution around a mean value $\bar{s}_i$ with a variance σ_i^2, so we have: $s_i = \bar{s}_i + \Delta s_i$, where $\Delta s_i \sim \mathcal{N}(0, \sigma_i^2)$. By dividing the signal strength into this two components, we can consider the mapping from location to mean signal strength $\bar{\mathcal{M}} : \mathcal{A} \longrightarrow \bar{\mathcal{S}}$ and evaluate the effect of $\Delta \mathbf{s}$ on it.
Moreover we make other reasonable hypothesis:

- We assume that the mean signal strength $\bar{s}_i(x, y)$ at location (x, y) is a differentiable function over the region of interest and that the partial derivatives $\frac{\partial s_i}{\partial x}$ and $\frac{\partial s_i}{\partial y}$ are constant in the local neighborhood of (x, y). This means the signal is no subjected to strange propagation phenomena like distortions;
- The components of $\mathbf{s}$ are independent, so the covariance matrix of $\Delta \mathbf{s}$ is given by $\mathbf{C}_{\Delta s} = \mathsf{diag}(\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2)$.
- We consider a common exponential path loss model the propagation loss is thus a monotonic function of the distance from the transmitter. In this case the mapping $\bar{\mathcal{M}}$ is a one-to-one (injective) function.

Under these assumptions we can calculate the uncertainty in signal space and then map it in location. To do this we define the *uncertainty region* $\mathcal{A}_\alpha \subseteq \mathcal{A}$ for $\alpha \in [0, 1]$ (which can be named as *degree of confidence*), as follows:

$$\int_{\mathcal{A}_\alpha} \mathsf{p}\{\mathbf{s}|(x, y)\} dx dy = \alpha \tag{1}$$

$\mathcal{A}_\alpha$ is a set of locations in $\mathcal{A}$ such that the probability that the observed signal strength vector is due to an AP located into a generic $(x, y) \in \mathcal{A}_\alpha$ is α. p is a pdf with support over $\mathcal{A}$. Considering $\mathbf{s'} = \bar{\mathcal{M}}(x, y)$ and $\mathcal{S}_\alpha = \bar{\mathcal{M}}(\mathcal{A}_\alpha)$ and thanks to the properties 2 and 3 we can write:

$$\alpha = \int_{\mathcal{S}_\alpha} \mathsf{p}\{\mathbf{s}|\mathbf{s'}\} d\mathcal{S} \tag{2}$$

Due to signal variance, the signal strength vector at a given location (x, y) is distributed, with a certain pdf, in a region centered around the mean signal strength vector $\bar{\mathbf{s}}$ at that location. Given α we can compute the characteristics of the hypervolume in the n-dimensional signal strength vector space having probability mass α and center $\bar{\mathbf{s}}$. From Equation (2) and hypothesis 2, we can write:

$$\alpha = \frac{1}{\prod_1^n \sigma_i (\sqrt{2\pi})^n} \int \cdots \int_{\mathcal{H}_e} e^{-\sum_1^n \frac{x_i^2}{2\sigma_i^2}} dx_1 dx_2 \ldots dx_n \tag{3}$$

where, for simplicity of notation, only in this calculation, we write $\Delta \mathbf{s} = \mathbf{x}$ and $\mathcal{H}_e$ is the hyperellipsoid defined by the equation:

$$\sum_{i=1}^n \frac{x_i^2}{\sigma_i^2} \leq \mathcal{R}_n^2 \tag{4}$$

where $\mathcal{R}_n$ is the radius of a n-dimensional hypersphere containing the same probability mass. By perfoming the substitution $z_i = \frac{x_i}{\sigma_i}$ and moving to polar coordinates, one obtains,

$$\begin{aligned} \alpha &= \frac{1}{(\sqrt{2\pi})^n} \int_0^{\mathcal{R}_n} e^{-\frac{r^2}{2}} r^{n-1} dr \int_0^{2\pi} d\phi_1 \prod_{i=2}^{n-1} \int_0^\pi \sin^{i-1} \phi_i d\phi_i \\ &= \frac{2}{(\sqrt{\pi})^{n-2}} \mathcal{M}_{r,n} \prod_{i=2}^{n-1} \mathcal{N}_i \end{aligned} \tag{5}$$

Remembering the Gamma function $\Gamma(x)$, one can compute

$$\prod_{i=2}^{n-1} \mathcal{N}_i = (\sqrt{\pi})^{n-2} \frac{1}{\Gamma(\frac{n}{2})}. \tag{6}$$

Regarding $\mathcal{M}_{r,n}$, with the substitution $\nu = \frac{r^2}{2}$ and few mathematical steps, one can obtain

$$\mathcal{M}_{r,n} = \frac{1}{2} \Gamma\Big(\frac{\mathcal{R}_n^2}{2}, \frac{n}{2}\Big) \tag{7}$$

Substituting (6) and (7) in (5):

$$\alpha = \Gamma_{\mathsf{inc}}\Big(\frac{\mathcal{R}_n^2}{2}, \frac{n}{2}\Big) \tag{8}$$

where $\Gamma_{\mathsf{inc}}(., .)$ is the incomplete Gamma function. With this relationship we have characterized the uncertainty in the signal domain. To translate this uncertainty in the location domain we consider $\Delta p = (\Delta x \quad \Delta y)^T$, the vector of the change in location in the neighborhood of (x, y) and, similar, $\Delta s = (\Delta s_1 \Delta s_2 \ldots \Delta s_n)^T$ is the vector of signal strength variations around $\bar{\mathbf{s}}$. The relationship between these two vectors is given by:

$$\Delta \mathbf{s} = T \Delta \mathbf{p} \tag{9}$$

where $T = \{t_{ij}\}$, that is:

$$T = \begin{pmatrix} \frac{\partial \bar{s}_{11}}{\partial x} & \frac{\partial \bar{s}_{12}}{\partial y} \\ \frac{\partial \bar{s}_{21}}{\partial x} & \frac{\partial \bar{s}_{22}}{\partial y} \\ \vdots & \vdots \\ \frac{\partial \bar{s}_{n1}}{\partial x} & \frac{\partial \bar{s}_{n2}}{\partial y} \end{pmatrix}$$

is the Jacobian of the mapping $\bar{\mathcal{M}}$. From (9) and thanks to the hypothesis 1, one can write:

$$\Delta s_i = t_{i1} \Delta x + t_{i2} \Delta y, \qquad i = 1, 2, \ldots, n. \tag{10}$$

We have found that the uncertainty region for a point (x, y) in signal strength domain is the hyperellipsoid centered in $\bar{\mathbf{s}}$ defined by the equation:

$$\sum_{i=1}^n \frac{\Delta s_i^2}{\sigma_i^2} = \mathcal{R}_n^2 \tag{11}$$

By substituting (10) in (11):

$$\sum_{i=1}^n \frac{(t_{i1} \Delta x + t_{i2} \Delta y)^2}{\sigma_i^2} = \mathcal{R}_n^2. \tag{12}$$

Equation (12) can be written as a quadratic of the canonical form $\mathsf{a}x^2 + \mathsf{b}y^2 + \mathsf{c}xy + \mathsf{d} = 0$ in the (x, y)-plane, with, in this case:

$$\mathsf{a} = \sum_{i=1}^{n} \frac{t_{i1}^2}{\sigma_i^2}, \quad \mathsf{b} = \sum_{i=1}^{n} \frac{t_{i2}^2}{\sigma_i^2}, \quad \mathsf{c} = \sum_{i=1}^{n} \frac{2t_{i1}t_{i2}}{\sigma_i^2}, \quad \mathsf{d} = -\mathcal{R}_n^2 \tag{13}$$

In order to know the kind of curve, it is important to study the discriminant function $\mathsf{c}^2 - 4\mathsf{ab}$. Following few mathematical steps one obtains:

$$\mathsf{c}^2 - 4\mathsf{ab} = -4 \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{(t_{i1}t_{j2} - t_{i2}t_{j1})^2}{\sigma_i^2 \sigma_j^2} \leq 0 \tag{14}$$

Excluding the equality, $\mathsf{c}^2 - 4\mathsf{ab} < 0$ indicates that the quadratic form is an ellipse. Remembering the geometric properties of the ellipse, we have found that the uncertainty region in the location plane is an ellipse with semi-axis:

$$r_{\mathsf{max,min}} = \sqrt{\frac{-2\mathsf{d}}{(\mathsf{a}+\mathsf{b}) \pm \sqrt{(\mathsf{a}-\mathsf{b})^2 + \mathsf{c}^2}}} \tag{15}$$

So the location estimation accuracy ellipse is described by the equation:

$$\frac{x^2}{r_{\mathsf{max}}} + \frac{y^2}{r_{\mathsf{min}}} = 1 \tag{16}$$

The measure of the uncertainty needs to be related with the mean location error. A possible way is to use the Circular Error Probability (CEP). CEP is defined as the radius of a circle, centered about the mean, whose boundary is expected to include 50% of observations, as shown in Figure 1.

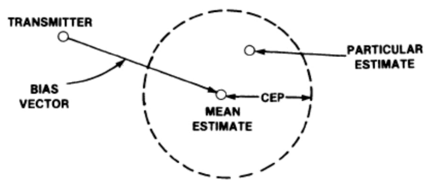


Fig. 1. Circular Error Probability (CEP).

Considering an unbiased estimation the center of this circle is the real position of the target, so we have that the CEP is an approximation for the positioning mean error. As shown in [18] the expression of the CEP is quite complex and depends on the ratio between the semi-axis of the ellipse $\beta \triangleq \frac{r_{\mathsf{min}}}{r_{\mathsf{max}}}$. It can be shown that a good approximation that is accurate to within approximately 10% for all values of β is:

$$\mathsf{CEP} \approx 0.75\sqrt{\mathsf{c}_1 + \mathsf{c}_2} \tag{17}$$

where $\mathsf{c}_1 = \frac{r_{\mathsf{max}}^2}{\kappa}$ and $\mathsf{c}_2 = \frac{r_{\mathsf{min}}^2}{\kappa}$ where κ depends on the confidence level α and under the Gaussian hypothesis is $\kappa = -2\ln(1-\alpha)$. In order to evaluate the CEP we first have to calculate the coefficients t_{i1} and t_{i2}. To do this we consider a log-distance radio propagation model, so the mean signal strength $\bar{s}$ at a location (x, y) at a distance d from a radio source is given by:

$$\bar{s} = \bar{s}_0 - 10\gamma \log \mathsf{d} \tag{18}$$

where $\bar{s_0}$ is the signal strength (measured in dBm) at the reference distance of 1 meter and γ is the path loss exponent. Assuming the same propagation constant for all the landmarks we have: $\bar{s}_i = \bar{s}_0 - 10\gamma \log \mathsf{d}_i, \quad i = 1, 2 \ldots, n$, with $\mathsf{d}_i = \sqrt{(x-x_i)^2 + (y-y_i)^2}$. From this we get:

$$t_{i1} = \frac{\partial \bar{s}_i}{\partial x} = \frac{-10\gamma(x - x_i)}{(x-x_i)^2 + (y-y_i)^2}, \tag{19}$$

$$t_{i2} = \frac{\partial \bar{s}_i}{\partial y} = \frac{-10\gamma(y - y_i)}{(x-x_i)^2 + (y-y_i)^2}. \tag{20}$$

Several interesting observations can be done about the CEP and its dependence on location estimation problem parameters. The confidence level α influences the CEP indirectly through its effect on the factor $\mathcal{R}_n$. For a given value of α, $\mathcal{R}_n$ increases with increasing n. However this effect is countered by the other factors in (15). Let us consider the case where $\sigma_i = \sigma, \quad i = 1, 2, \ldots, n$. In this case, by extracting the common factor σ^2 in the definitions 13, we can see that the CEP is proportional to σ by using the equation (15). As expected the error in estimation decreases by decreasing signal variance.

We investigate the dependence of CEP on the distance between APs by varying the considered area in which APs are distributed according to a uniform random distribution. Results are shown in Figure 2 and we note that for a given value of the number of landmarks, the value of CEP increases by increasing the distance between APs. If we consider more APs for a fixed area the CEP decreases, as we expected.

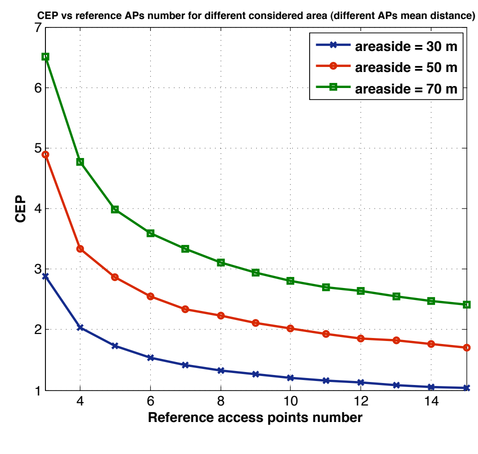


Fig. 2. CEP vs number of landmarks, varying the areaside.

The most important dependence which arises by analyzing this model is that on the propagation constant. Equations indicate that the accuracy increases with increasing γ, although the signal becomes weaker. This is explained by the fact that as γ increases, the signal level is more sensitive to location changes. That is: a large γ is given by a large propagation constant and this implies rapid change in signal strength over distance and hence a given variation in signal strength will correspond to a smaller distance than with a smaller propagation constant. This could be a problem in the evaluation of the possible advantages of using TV bands for positioning because in that case the operating frequencies (and so γ) are smaller than the WiFi ones and so we might expect a worse performance in term of localizetion error, despite the better propagation characteristics. Nevertheless, Figure 3 shows that the perfomance improvement obtained by increasing the number of APs overcomes the negative impact of having a smaller γ.

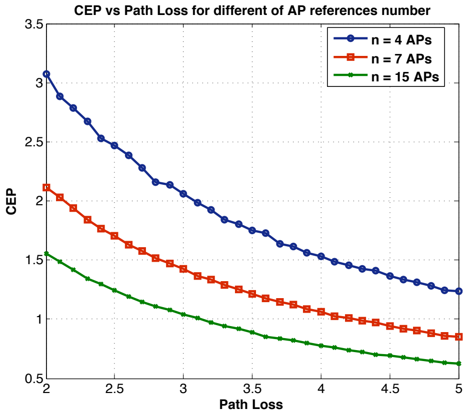


Fig. 3. CEP vs γ, variyng n.

B. Positioning in TVWS

The architecture of the hypothesized network is based on the use of geo-location database. Each access point is assumed to be connected to one, or multiple, databases which provide information on the unused TVWS channels that are available at the location of the access point and information on maximum transmit power levels that could be used in each channel. Furthermore, the use of master-slave technology means that the necessary functionalities for database lookup and channel selection need to be implemented only in the access points, so keeping the complexity and cost of end-user devices to a minimum. Users with a TVWS modem, or dongle, can connect from outside to home access points via a TVWS channel that is periodically advertised via beacons by each access point. In [19] the problem of coverage was addressed: it can be seen that coverage is very patchy when the system operates at 5 GHz and some improvement is gained by switching to 2.4 GHz. The most striking result is achieved when home access points switch operation to TVWS. From a TVWS-end user point of view this corresponds to an increase in range of transmission. In this way the device which is trying to establish its position by WPS can reach a greater number of access points. As shown in the previous subsection, the positioning error depends, among various parameters, on the available number of access points. In particular positioning error decreases when the number of APs increases [11].
The first step in order to compare TVWS vs WiFi for positioning is to choose an appropriate radio propagation model. A good compromise between simplicity and accuracy for an indoor-outdoor analysis is the widely used log-distance path loss model, that we already adopted in Section III-A and characterized by the following equation:

$$\mathsf{PL}_{\mathsf{dB}} = -27.55 + 20 \log f_{\mathsf{MHz}} + 10\gamma \log \mathsf{d} + \mathcal{X}_{\mathsf{g}} \qquad (21)$$

where f_{MHz} is the carrier frequency expressed in MHz; γ is the path loss exponent, usually taken between 2 (free space loss exponent) and 5 (dense urban); $\mathcal{X}_{\mathsf{g}}$ is a random variable $\sim \mathcal{N}(0, \sigma^2)$ that takes into account fading, cable and body losses. We consider an extended squared area, of area A, which represents for example an university campus, a factory and so on. In this area a certain number of access points (N_{ap}) are distributed according to a random uniform distribution. For the WiFi case we consider a classic 802.11/b system with 20 MHz channel bandwidth and data rate 11 Mb/s. For the TVWS, because of the lack of a standard, we assume to adopt an 802.11/af system, based on 802.11/n standard. We consider the worst case: only one available TV channel, so the channel bandwidth is 8 MHz, considering for example a 16 QAM modulation scheme and a convolutional code with code rate of $\frac{1}{2}$ we obtain approximately 11 Mb/s data rate. We suppose to use commercial Access Points with a receiver sensitivity (for f_b = 11 Mb/s) of -82 dBm.

IV. Results and Discussions

A. TVWS vs WiFi: Positioning

Matlab simulations were carried on for perfomance evaluation. In [11] it was already reported that for the same transmitted power, the average number of APs reached by a TVWS device (both 470 and 790 MHz) is by far much greater than the WiFi one and that this is reflected in localization performances where TVWS device strongly outperforms the WiFi one, obtaining a very small average error value. In the following we focus on the impact of operating the positioning system at TVWS frequencies on energy efficiency. The simulation parameters are listed in Table I and II.

TABLE I
Propagation Model and Network Setup Parameters

Parameters	Values
γ	3.2 (WiFi) - 3 (TVWS)
σ^2	6 dB
N_{ap}	15
A (Area)	200 m^2

Figure 4 presents the average localization error for TVWS and WiFi systems as a function of the transmitted power. Results show that the TVWS system, thanks to the capability to reach an higher number of APs compared to the WiFi

TABLE II
SYSTEMS TECHNICAL SETUP

Parameters	WiFi	TVWS
Radio Frequency	2.4 GHz	700 MHz
EIRP	14.77÷20 dBm	2÷14 dBm
Channel Bandwidth	20 MHz	8 MHz
Receiver Sensitivity	-82 dBm	-82 dBm

one, guarantees better perfomance at lower transmitted power levels, and this is a very attractive feature in modern communication systems, given the recent, increasing attention towards *green* communications.

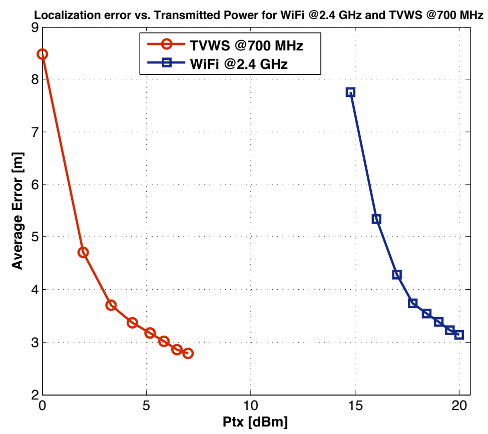


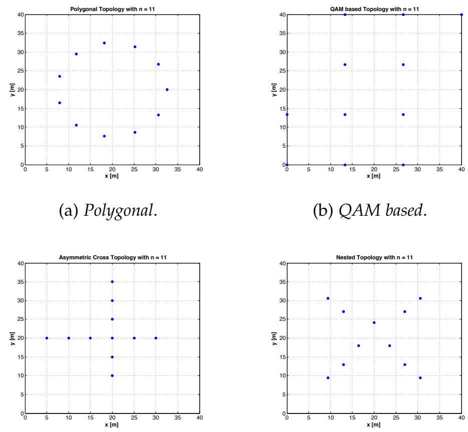
Fig. 4. Average position error and energy savings: TVWS vs WiFi.

B. Analysis on constrained topologies

The results presented in the previous section were obtained for a fingerprinting-based system operating on a *free* topology, that is a topology in which the reference nodes are deployed in a random way inside the considered area, in order to simulate real situations like a university, a campus or simply a residential quarter. In this subsection we consider a different case where a lateration-based system is deployed with constrained topologies, which follow fixed spatial structures. Together with Random topology for comparison, we consider four types of topology:

- *Polygonal*: n nodes are distributed on the vertexes of a polygon inscribed in a circumference of radius which depends on the number of nodes and the (fixed) distance (called s) among nodes;
- *QAM based* (Regular grid): n nodes are distributed on a QAM constellation which is limited by the entire considered area. If n is not a power of 2 we consider the next power of 2 (M) and we take away from the M-QAM constellation the M-n exceeding nodes;
- *Asymmetric cross*: n nodes are equally spatial (with distance s) distributed on an horizontal line and on a vertical one, similar to the shape of a cross;
- *Nested*: based on the number of nodes n, this topology is composed by nested squares, and/or triangles, and/or a single central point. The distances among nodes are proportional to the nesting degree.

In Figure 5 an example of these topologies for n = 11 is given.



(a) *Polygonal*. (b) *QAM based*.

(c) *Asymmetric Cross*. (d) *Nested*.

Fig. 5. Example of topologies with n = 11.

When talking about constrained topology we generally refer to real situations such as an indoor environment in which we can organize the nodes with a fixed structure (for example to allow the localization of products in a supermarket) or a big factory which has a plan about network deployment. However, another interesting case can be envisioned, where a constrained topology is generated by appropriately selecting a subset from a network of nodes with random topology, in case this is expected to lead to a possible performance improvement.
Rather than relying on the CEP model for localization error, introduced in Section III-A and well-fitting a fingerprinting-based system, in this section we adopt a simpler error estimate model, suitable for the lateration approach, that defines a positioning error upper bound, correlated to the smallest eigenvalue of the reference points coordinates matrix [20]. With the parameters in Table III we obtain the results presented in Figure 6.

TABLE III
PROPAGATION MODEL AND NETWORK SETUP PARAMETERS

Parameters	Values
N_{ap}	3:16
A (Area)	100 m^2
s	8 m

Figure 6 shows that the general trend is the higher the number of nodes the higher value of the eigenvalue, even if the trend is irregular for the nested topology and the QAM based one. We notice that only the QAM topology outperforms the random one for the most values of the reference nodes number while the nested and the polygonal have an higher eigenvalue only for high values of n (n $>$ 14). The asymmetric cross topology goes always worse. It is important to notice that the QAM based topology presents a very high value of the

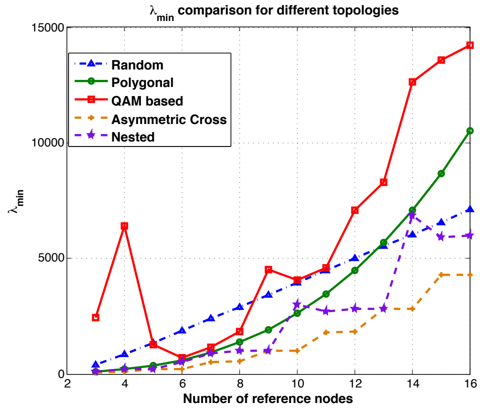


Fig. 6. Pattern of the smallest eigenvalue of the coordinates matrix for different topologies.

eigenvalue for n = 4. This depends on the fact that, even if the number of nodes is low, they have the maximum distance among them (equal to the areaside = $\sqrt{A}$). In this way the elements of the coordinates matrix are very spread. Regarding the global upper bound trend, Figure 7 confirms that the QAM based, the nested and the polygonal topologies outperform the random one while the asymmetric cross goes worse.

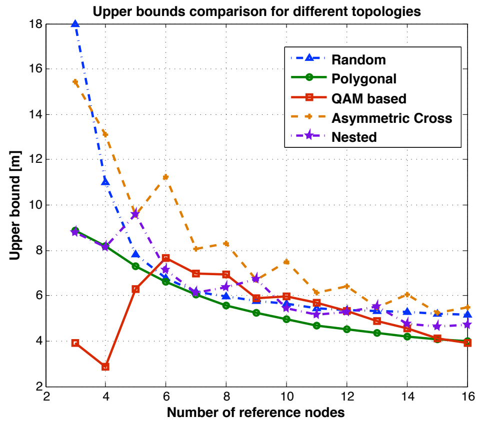


Fig. 7. Pattern of the positioning error upper bound for different topologies.

Results show that regular topologies, particularly the polygonal one, and, in some cases, the nested and the QAM-based ones, may lead to better performance compared to the random topology, even for a lower number of reference nodes. This justifies the idea of operating a selection procedure in order to obtain a subset of well-located reference nodes. Even in this scenario, working at TVWS frequencies can provide an advantage thanks to the larger coverage that will guarantee a larger set of nodes from which to perform the subset selection.

V. Conclusions

In this work the use of TV White Spaces for indoor positioning was proposed, relying on solutions currently being developed for communications in TVWS such as cognitive radio technology, and adopting a fingerprinting approach. A theoretical model for the positioning error and accuracy was introduced and analyzed, showing a strong relation with the number of access points available as reference nodes for the positioning algorithm. In particular, the greater the number of access points reached the lower the mean positioning error. Based on the proposed model, traditional solutions based on Wi-Fi are compared with a TVWS positioning system. Results show that a TVWS positioning system can guarantee higher accuracy than WiFi while operating at lower transmission power levels thus enabling significant energy savings. The performance analysis of positioning at TVWS frequencies was then extended to a lateration-based system where the access points are deployed according to predetermined topologies, and results show that positioning performance can be further improved if the system is capable of selecting, from a random topology, a subset of reference nodes that form a structure characterized by simple symmetric shapes like squares, triangles or polygons.

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References

[1] B. P. Freyens and M. Loney, *Digital switchover and regulatory design for competing white space usage rights,* IEEE Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN), pp. 32 40, 2011.

[2] FCC, *Second report and order and memorandum opinion and order the matter of unlicensed operation in the tv broadcast bands, additional spectrum for unlicensed devices below 900 mhz and in the 3 ghz band,* Federal Communication Commission, Document 08-260, Nov. 14 2008.

[3] Ofcom, *Digital dividend: cognitive access statement on licence exempting cognitive devices using interleaved spectrum,* Telecommunication Review, 2009.

[4] E. C. C. (ECC), *Technical considerations regarding harmonization options for the digital dividend,* CEPT techreport 24, June 2008.

[5] S. J. Shellhammer, A. K. Sadek, and W. Zhang, *[*Technical challenges for cognitive radio in the tv white space spectrum,] Information Theory and Application Workshop, pp. 323 333, 2009.

[6] J. Mitola and G. Q. Maguire, *Cognitive radio: Making software radios more personal,* IEEE Personal Communications, vol. 6, no. 4, pp. 1318, August 1999.

[7] M. Nekovee, *A survey of cognitive radio access to tv white spaces,* International Conference on Ultra Modern Telecommunications and Workshops, pp. 1 8, 2009.

[8] F. Lassabe, P. Canalda, P. Chatonnay, and F. Spies. *Indoor wi-fi positioning: techniques and systems,* Annals of Telecommunications, 64: 651664, 2009.

[9] K. Kaemarungsi and P. Krishnamurthy. *Properties of indoor received signal strength for wlan location fingerprinting,* In Mobile and Ubiquitous Systems: Networking and Services, 2004. MOBIQUITOUS 2004. The First Annual International Conference on, pages 14 23, 2004.

[10] P. Bahl and V. Padmanabhan. *Radar: an in-building rf-based user location and tracking system,* In INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE, 2000.

[11] M.-G. Di Benedetto, A. Ferrante and L. De Nardis, *Cognitive Radio and Networking for Cooperative Coexistence of Heterogeneous Wireless Networks*, First international IEEE-AESS conference in Europe about Space and Satellite Telecommunications (ESTEL 2012), October 2-5, 2012, Rome, Italy, pp. 1-6.

[12] S. Golden and S. Bateman. *Sensor measurements for wi-fi location with emphasis on time-of-arrival ranging,* Mobile Computing, IEEE Transactions on, 6(10):11851198, 2007.
[13] A. Gunther and C. Hoene. *Measuring round trip times to determine the distance between WLan nodes,* NETWORKING 2005, pages 768779, 2005.
[14] M. Ciurana, F. Barcel, and S. Cugno. *Indoor tracking in wlan location with ToA measurements,* In Proceedings of the 4th ACM international workshop on Mobility management and wireless access, Mobi-Wac 06, pages 121125, New York, NY, USA, 2006.
[15] M. Llombart, M. Ciurana, and F. Barcelo-Arroyo. *On the scalability of a novel WLan positioning system based on time of arrival measurements,* In Positioning, Navigation and Communication, 2008. WPNC 2008. 5th Workshop on, pages 15 21, 2008.
[16] C. D. Meyer, *Matrix Analysis and Applied Linear Algebra*. SIAM, 2000.
[17] S. Zekavat and R. Buehrer, *Handbook of Position Location*. Wiley, 2011.
[18] D. J. Torrieri, *Statistical theory of passive location systems,* IEEE Transaction on Aerospace and Electronic Systems, 1984.
[19] M. Fitch, M. Nekovee, S. Kawade, K. Briggs, and R. MacKenzie, *Wireless service provision in tv white space with cognitive radio technology: A telecom operators perspective and experience,* IEEE Communications Magazine, March 2011.
[20] G. Chandrasekaran, M. Ergin, J. Yang, S. Liu, Y. Chen, M. Gruteser, and R. Martin, *Empirical evaluation of the limits on localization using signal strength,* IEEE SECON proceedings, 2009.