Please Stand By: TV-based Indoor Localization

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***Abstract*—Despite the decades of efforts, indoor positioning remains an open research challenge. While existing solutions already demonstrate high accuracy, their in-building infrastructure — such as Wi-Fi access points or Bluetooth beacons — provides only a limited coverage.**

This paper investigates feasibility of accurate indoor positioning using broadcast digital TV signals, readily available in populated areas worldwide. We experiment with the classic received signal strength (RSS) fingerprinting, and introduce a novel approach based on channel state information (CSI), which leverages frequency-selective multipath fading of wideband TV signals. The proposed methods are experimentally evaluated on an extensive dataset of DVB-T signals, systematically collected in two large buildings over the course of 8 months. The results show that the proposed approach consistently outperforms RSS fingerprinting and achieves 92–98% localization accuracy.

While this study is based on the European DVB-T signals, the proposed method is directly generalizable to other TV standards (such as ATSC, ISDB, DTMB and DMB) and wide-area TV white space (TVWS) networks.

I. Introduction

The lack of a globally available indoor positioning system is one of the key factors that limit the development of ubiquitous mobile services. The best candidates for large-scale indoor positioning — Wi-Fi based systems — have made a remarkable progress over the last decade, achieving sub-meter accuracies [1], [2] and minimizing the installation efforts with inertial navigation and crowdsourcing [3], [4]. In turn, dedicated solutions based on ultrasound [5], [6], ultrawideband radio [7], [8], visible light [9], [10] and Bluetooth beacons [6], [11] provide even higher performance.

However, all these systems require dedicated indoor infrastructure which limits their availability to specific rooms and buildings. Inertial tracking, in turn, relies on absolute positioning to reset the accumulating integration error [3], [4], [12]. Overall, there is a need for a globally available absolute indoor positioning system.

Ambient indoor localization — or infrastructure-free indoor localization using ambient radio sources — addresses this gap. Indeed, broadcast radio signals are specifically intended for indoor reception, are usually transmitted with high power and cover most populated regions across the globe. The approach has already been demonstrated with FM radio [13]–[17], cellular networks [18]–[20] and television signals [21]–[23].

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TV broadcasts play an important role in the modern communication landscape [24]. Despite the increasing popularity of online video streaming, over-the-air TV provides news and entertainment at a zero cost for viewers. Moreover, TV and radio are the key channels for public safety announcements and emergency updates [25]. As a critical national security resource, TV broadcasts are remarkably reliable: transmitters are centralized, have local power backup, are protected from unauthorized access, and operate in congestion-free licensed frequency bands.

In this paper, we investigate feasibility of indoor positioning using digital TV signals. In contrast to the previous ranging-based TV localization systems with poor indoor performance [26], [27], we employ signal fingerprinting approach which *leverages* multipath propagation instead of suffering from it. Besides the classical received signal strength (RSS) fingerprinting, we introduce a novel method based on lightweight statistical channel estimation. As a result, channel state information (CSI) fingerprints provide rich information about radio propagation environment and receiver position, and thus enable higher localization performance.

The contribution of this paper is three-fold. First, we demonstrate feasibility of accurate *indoor* positioning using broadcast TV signals. To our knowledge, this is the first TV-based localization study specifically focused on indoor scenarios. Second, we introduce an advanced CSI-based TV positioning approach, which outperforms RSS fingerprinting and achieves 92–98% localization accuracy in large-scale testbeds. Finally, we present a long-term experimental evaluation of the proposed methods, using real-world DVB-T signals collected in two large multi-floor buildings over an 8-month period.

II. Related work

Although ambient indoor positioning is mainly inspired by the extensive research on Wi-Fi based localization [28], there are a number of fundamental differences between Wi-Fi and ambient radio broadcasts.

Firstly, before arriving into a building, ambient radio signals mainly propagate outdoors where they are exposed to external interference, both static (terrain and buildings) and dynamic: climatic (humidity, precipitation), social (road traffic), and even seasonal changes (foliage, snow cover). Wi-Fi signals, in contrast, propagate for only tens and hundreds of meters, typically indoors, and are less susceptible to external dynamics.

Secondly, ambient radio broadcasts use substantially lower frequencies than Wi-Fi's 2.4 and 5 GHz (with wavelengths of 0.12 m and 0.06 m, respectively). For example, European DVB-T broadcasts range from 174 to 862 MHz (1.7 to 0.35 m). The difference in wavelengths leads to different wave interaction with indoor objects and building materials [29]. As a result, performance of a TV-based indoor positioning system cannot be directly predicted from that of Wi-Fi based solutions.

A number of studies have investigated the feasibility of indoor localization based on ambient radio signals.

In particular, TV-based positioning systems used signal propagation time and multilateration approaches. For instance, Eggert [30] evaluated the time-difference of arrival (TDOA) method on analogue TV signals, and reported errors of up to 300 m. A number of studies used ranging methods based on synchronization subcarriers in digital TV signals [21], [23], [27], [31]. For Rosum [22], [23] — one of the first such systems based on the ATSC standard — the authors reported a "30–50m indoor accuracy" [26]. A similar performance has also been demonstrated with DVB-T signals, both in simulations [27], [31] and in outdoor experiments [21]. Overall, due to the multiple reflections and non-line-of-sight radio propagation in buildings, the indoor performance of these TV-based positioning systems was rather poor.

While TV-based systems focused on outdoor scenarios, a number of studies specifically explored indoor localization, using RSS fingerprinting of narrowband GSM and FM radio channels. In particular, several authors reported meter-scale localization accuracies [14], [15], [20]. A common observation in both GSM and FM based studies was the significant benefit of additional signal features, be it advanced physical-level FM properties [15], or additional GSM carriers [18]–[20].

While additional carriers are beneficial for system performance, the number of ambient radio channels and their features is limited: installing another public TV station would be considerably more difficult than adding a Wi-Fi access point. However, wideband TV signals with OFDM (orthogonal frequency-division multiplexing) modulation already include a large number of carriers. For Wi-Fi based systems, information about OFDM carriers (available from some Wi-Fi modules) resulted in a breakthrough in localization performance [32]: CSI-based Wi-Fi positioning systems now achieve sub-meter accuracies [1], [2], [33]–[36].

In this paper, we combine the rich CSI data from ambient TV signals and the fingerprinting approach, well-tailored for multipath scenarios. To the best of author's knowledge, this is the first study of TV-based localization in indoor environments.

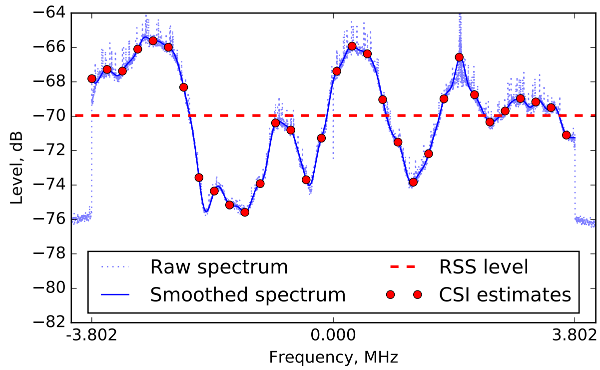


Fig. 1. Spectrum of a real DVB-T signal received indoors, with frequency-selective fading and narrow-band interference.

III. Our Approach

A. Frequency-selective fading

Our approach is based on the location-sensitive specifics of radio wave propagation in buildings [29].

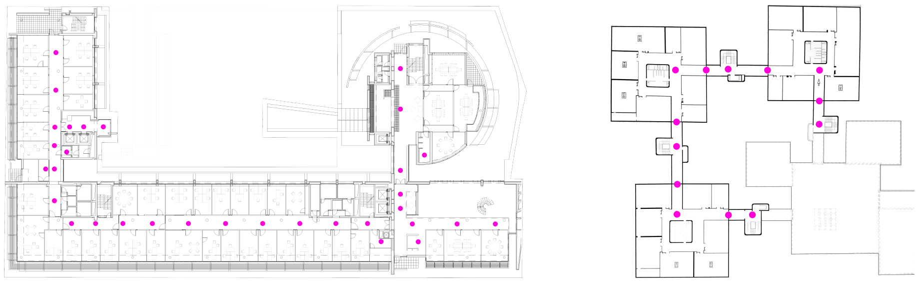
During their travel through the environment, radio waves are reflected and scattered by the surrounding objects. These reflections — randomly attenuated, delayed and arriving from various directions — interfere with the original wave. This, in turn, creates areas of constructive and destructive interference. The locations of these areas are defined by the relative positions of the obstacles and the transmitter, their properties (such as dimensions, conductivity, permeability), as well as the wave frequency.

Frequency dependence of multipath fading is particularly important for wideband signals, as they experience constructive and destructive interference simultaneously in different parts of their spectrum (*frequency-selective fading*) [37]. For instance, OFDM signals are transmitted with a flat-top spectrum; however, due to the multipath fading the received signal's spectrum is far from flat (Fig. 1). Moreover, in static environments the spectrum shape depends mainly on receiver location, as the fading becomes "a purely spatial phenomenon" [37].

B. CSI estimation

Multipath fading can be described by the CSI vector, which contains estimated attenuation and phase shift of the OFDM carriers (the phase shift is not utilized in this study).

Although CSI estimation is performed internally by all OFDM receivers for channel equalization purposes, the resulting CSI values are not exposed to the application layer. To overcome this limitation, we used a software-defined radio (SDR) receiver to collect raw radio frequency (RF) samples of DVB-T signals, and then estimated CSI vectors from the power spectra of the acquired signals.



(a) Office Building (b) Campus Building

Fig. 2. Testbed floorplans and test point locations. (Different floors of each building have similar layouts.)

For this study, we employed a statistical approach for CSI estimation — a computationally lightweight alternative to pilot-based channel estimation methods [38]. In the first step, we average several consecutive OFDM blocks over a 0.1 s window (similarly to the Bartlett's method for estimation of smooth power spectra [39].) This provides a relatively stable spectral envelope, with peaks of the continual DVB-T pilots and narrow-band interference (see Fig. 1); these peaks are removed by a low-pass filter. Finally, the CSI is estimated by sampling the smooth spectral curve at 32 uniformly spaced locations.

While dedicated pilot-based methods could provide more frequent CSI updates [38], [40], our statistical approach is more robust to narrowband noise and does not require synchronization. More importantly, our method directly generalizes to other DTV standards — such as North American ATSC, South American ISDB, and Chinese DMB-T — as well as other OFDM signals, including IEEE 802.22 TVWS regional area networks [41].

C. Localization method

To leverage the location dependence of the CSI, we use signal fingerprinting — one of the most widely used indoor localization methods. This technique includes two phases. In the initial calibration (training) phase, the environment is surveyed to build an empirical spatial model of signal fingerprint distribution. Here, a *fingerprint* is a vector of CSI or RSS values received from the stationary TV transmitters. Then, in the localization phase, the system uses the created empirical model and machine learning methods to identify locations by their signal fingerprints.

Before localization, we preprocess the fingerprints in a two-step procedure. Firstly, CSI vectors of different channels are merged into one wide fingerprint. Secondly, fingerprints are standardized by independently centering and scaling CSI values of each carrier to zero-mean unit-variance sequences:

$$x_i' = \frac{x_i - \langle x_i \rangle}{\sigma[x_i]}$$

where x_i is a sequence of CSI values in carrier i, while $\langle x_i \rangle$ and $\sigma[x_i]$ are its mean and standard deviation. In contrast to simple min/max normalization, statistical standardization is more robust to occasional outliers. RSS fingerprints undergo the same preprocessing.

Finally, for learning the signal distribution maps and recognizing locations by signal fingerprints, we tested three classifiers from Scikit-learn library [42]: k-nearest neighbor (kNN), random forest and support vector machine (SVM). The latter provided the highest localization accuracy (percentage of correctly recognized fingerprints) and is used for the rest of the paper.

D. CSI vs. RSS

While RSS is a single-number estimate of the received signal power, CSI vector provides substantially more detailed information about signal propagation paths. As will be shown later, this information proves beneficial for the localization accuracy.

Moreover, our CSI estimation method exploits only the *shape* of the channel profile regardless of its absolute bias (while the RSS describes the bias, but not the shape). As a result, CSI vectors are invariant to transmitted signal power and receiver sensitivity (as long as the signal is above the noise floor). In contrast, RSS values directly depend on both of these factors and RSS fingerprinting may require additional device-specific calibration.

Finally, it should be noted that CSI estimation does not require decoding of the received DVB-T signals. As a result, even weak and noisy signals that are unsuitable for TV-watching purposes can still be used for CSI estimation and localization.

IV. Experiment setup

To ensure comprehensive evaluation of the proposed approach, the experimental evaluation was conducted in two large buildings over several months (see Fig. 2). One testbed ("Offices") hosted university administration and research offices, while the other one ("Campus") featured mainly lecture halls and research labs. In each testbed, we have defined a number of test locations (test points), aiming at wider coverage of different parts

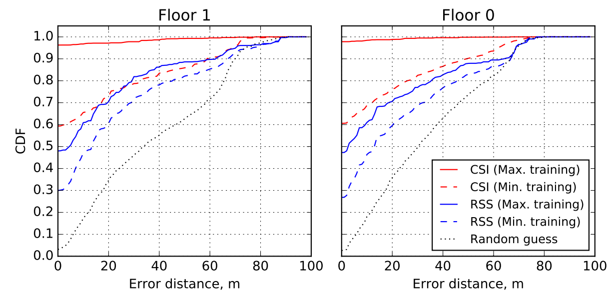
TABLE I
EXPERIMENTAL TESTBEDS AND SAMPLING CHARACTERISTICS.

Testbed	Dimensions	Number of test points	Sampling period	Number of sessions	Samples collected
Office Building	100×50 m	$33 + 36$ (floors 1 and 0)	9 months (Apr–Dec 2016)	17	1173
Campus Building	80×80 m	$13 + 13$ (floors 1 and 0)	8 months (May–Dec 2016)	14	364

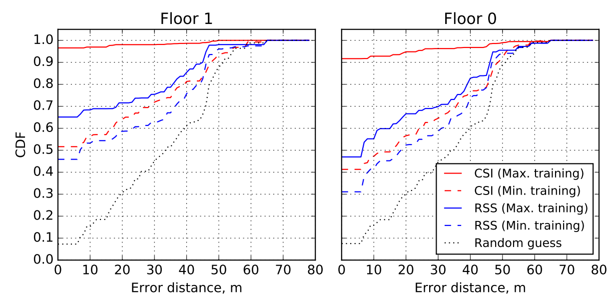
of the buildings. To ensure consistent ground truth throughout the study (and thus accurate performance evaluation [43]), the test points were defined with about 2 cm precision, using laser rangefinders. Further testbed details are summarized in Table I.

Acquisition of TV signal samples has been performed within the scope of a multi-radio ambient localization project [44], [45], using a dedicated data collection platform based on a USRP B210 software-defined receiver. While our setup employs a relatively expensive and bulky SDR hardware, the CSI estimation method is hardware-independent and can as well be used with low-cost consumer SDR receivers (such as RTL-SDR devices).

At each test point, we recorded 2-second long samples of raw radio frequency (RF) signals from several radio bands, including six DVB-T channels. Due to the tuning and storage delays of multi-band sampling, the dwell time at each point was about 70 s. The acquired samples were preprocessed offline using the CSI estimation method described in Section III-B. This provided twenty 192-element wide CSI fingerprints (6 channels $\times$ 32 CSI elements per channel) for each RF sample. Overall, this study is based on 31 measurement sessions (1537 point-samples) from both testbeds.



(a) Offices



(b) Campus

Fig. 3. Indoor localization performance with TV-based CSI and RSS fingerprints.

V. EXPERIMENTAL RESULTS

A. *General performance evaluation*

In this section we evaluate the general performance of the system in two extreme cases. In the first scenario, the system is trained on all but one sessions, and tested on the remaining single session ("*maximal training*"); this provides an optimistic upper-bound performance estimate of a well-trained system. In turn, in the "*minimal training*" scenario the system is trained on a single session and tested on the rest of data; this provides a lower-bound estimate of the localization performance.

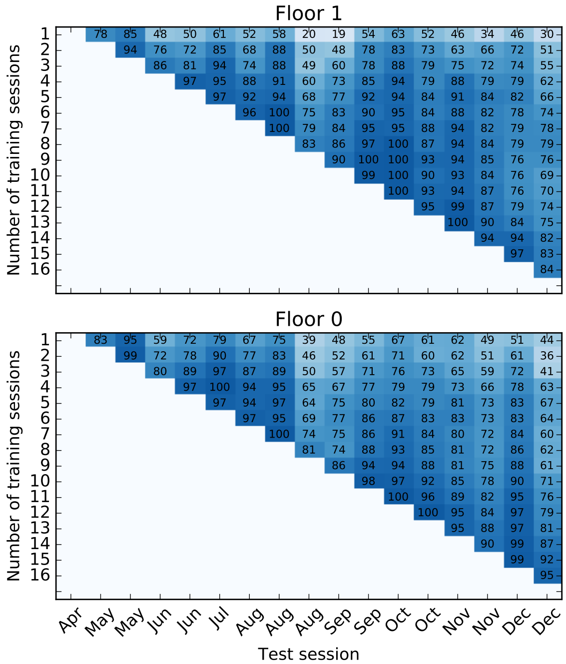
Since the experiment involves multiple data sessions, their results are combined as follows. The evaluation procedure iterates through all the sessions, picking them one-by-one as a training (testing) session; at each step, we calculate error distances for every test fingerprint. Once evaluation of all the N session combinations is complete, we merge the N sets of error distances into a single vector. Finally, the cumulative distribution function (CDF) of all the error distances represents the localization performance of the system.

The results are shown in Fig. 3. Both RSS and CSI fingerprints provided localization performance well above the random-guess baseline. In the minimal training scenario, where the system was calibrated only once, the average RSS-based accuracies were between 27% and 49% on different floors of the testbeds. In contrast, CSI fingerprints outperformed RSS-based localization and provided accuracies of 41% to 61%.

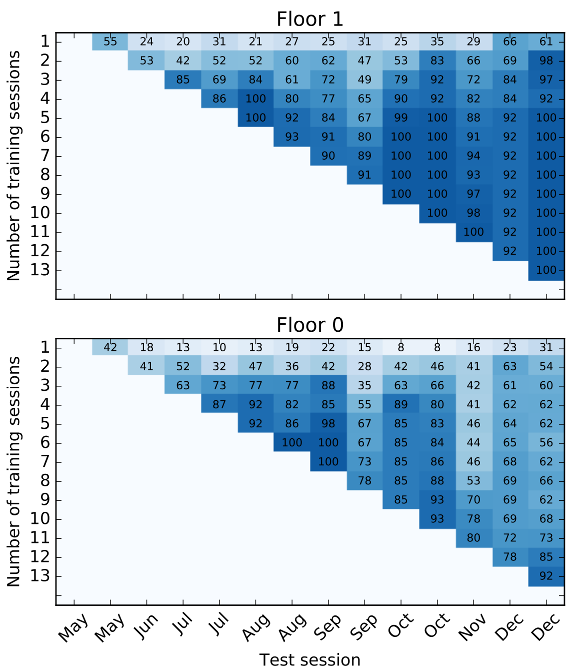
The performance further improved with the additional calibration in the maximal training scenario: both RSS- and CSI-based accuracy increased, achieving 47–65% and 92–98%, respectively. As before, CSI outperformed RSS-based positioning by a factor of 1.5–2.0 (Campus) and 2.0–2.1 (Offices). The results demonstrate the high potential of TV CSI-based localization in comparison to the classical RSS fingerprinting approach.

B. *Performance over time*

Since TV signals propagate mainly outdoors, they are subject to temporal variability caused by external interference, such as road traffic and weather changes. To address this, in this section we model a realistic scenario of *incremental training*, where the system is calibrated



(a) Offices

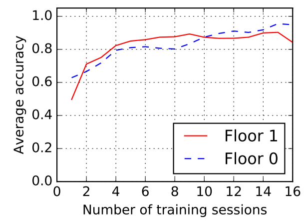


(b) Campus

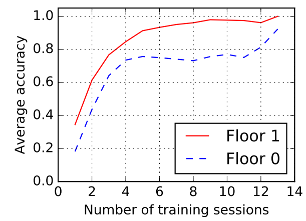
Fig. 4. CSI-based localization performance over time, with incremental training. Numbers in the cells are percents of correctly recognized fingerprints. Random-guess levels are 3% (Offices) and 8% (Campus).

on several consecutive sessions, and then evaluated over the following months.

The detailed outcomes of incremental training are shown in Fig. 4. There, each row represents an evaluation history of the system trained on several first sessions



(a) Offices



(b) Campus

Fig. 5. Impact of incremental training.

and tested on the remaining ones. Towards the bottom rows, the system has more and more calibration data, which reduce the number of low-accuracy test sessions and ensure stable localization performance over time.

Fig. 5 summarizes the impact of incremental training, showing the average localization accuracy of the system trained on several data sessions. While the results vary across the testbeds, the common trend shows a quick increase of the localization accuracy over the first few sessions. After about four training sessions (corresponding to a two-month period), the system typically achieved its highest performance.

Overall, given that the experiments were conducted in real-world conditions in live buildings, the results demonstrate the high accuracy and robustness of the proposed TV CSI-based indoor localization method.

VI. Conclusion

The paper presented a novel indoor positioning approach based on ambient TV signals. The proposed method leverages frequency-selective multipath fading of radio signals — a physical phenomenon sensitive to receiver's location. We exploit this effect in wideband digital TV signals using statistical CSI estimation.

The proposed approach has been experimentally evaluated on the massive AmbiLoc dataset [44] of real-world DVB-T signals. The results suggest that TV-based indoor positioning can provide high accuracy over the long term. With abundant calibration data, RSS fingerprinting achieved 47–65% localization accuracy (depending on testbed), while the proposed CSI-based method improved the accuracy to 92–98%.

Admittedly, the immediate adoption of the proposed approach might be somewhat constrained by the current lack of TV-enabled mobile devices. However, TV-capable smartphones are widely popular in Asian countries, while add-on USB receivers are available for all major mobile platforms worldwide. Furthermore, the upcoming ATSC 3.0 standard [46] is specifically designed for mobile TV reception, and is likely to increase the global availability of TV-capable mobile devices. In combinations with the high achievable accuracy and zero infrastructure costs, this makes TV-based indoor localization a promising direction for further research.

Acknowledgments

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