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Indoor detection of passive targets recast as an inverse scattering problem

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Abstract. The wireless local area networks represent an alternative to custom sensors and dedicated surveillance systems for target indoor detection. The availability of the channel state information has opened the exploitation of the spatial and frequency diversity given by the orthogonal frequency division multiplexing. Such a fine-grained information can be used to solve the detection problem as an inverse scattering problem. The goal of the detection is to reconstruct the properties of the investigation domain, namely to estimate if the domain is empty or occupied by targets, starting from the measurement of the electromagnetic perturbation of the wireless channel. An innovative inversion strategy exploiting both the frequency and the spatial diversity of the channel state information is proposed. The target-dependent features are identified combining the Kruskal-Wallis test and the principal component analysis. The experimental validation points out the detection performance of the proposed method when applied to an existing wireless link of a WiFi architecture deployed in a real indoor scenario. False detection rates lower than 2 [%] have been obtained.

1. Introduction

Many application fields related to security, smart home services [1], healthcare [2], benefit from the detection and localization of device-free targets. Several detection technologies have been investigated including wireless sensor networks (WSNs) [3]-[7], ultra-wideband (UWB) [8], radio frequency identification (RFID) [8], and wireless local area networks (WLANs) [10].

Recently, the channel state information (CSI) used by WLANs in the framework of orthogonal frequency division multiplexing (OFDM) has been exploited to enable location-based services. The CSI is a fine-grained feature of the channel frequency response (CFR) providing both magnitude and phase information at multiple frequencies [11]. This indicator is highly sensitive to the environmental changes and its information content can be exploited to characterize the target signature on the electromagnetic field. The multiple-input multiple output (MIMO) architecture has been introduced by the current WLAN standards to further improve the quality of the data transmission. The intrinsic spatial diversity of a MIMO system has been also exploited to enhance the performance of the wireless localization problem.

Many techniques exploiting the prominent features of the CSI exist in the state of the art, but the indoor scenario and the system setups are often dedicated to the localization itself. On the contrary, the proposed technique aims to introduce the detection capability on top of an existing wireless architecture already used for communication.

The goal of the proposed method is to provide a robust target detection only using a single pair of transmitter-receiver, which is the minimum set of hardware required to enable a wireless communication. The main contributions of the proposed solution include the definition of a target-dependent feature of the CSI, which is robust across the whole frequency spectrum, and the improvement of the detection performance respect to the state of the art (false detection rates lower than 2 [%] with a single pair of devices).
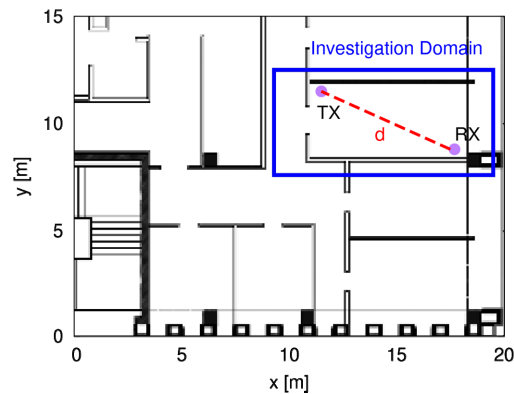
(*a*)

(*b*)

Figure 1. Investigation domain located in a standard office-area (*a*), and commodity WiFi receiver with *L=3* antennas (*b*).

2. Target Detection Strategy

The wireless channel measurement at multiple and orthogonal frequency sub-carriers is enabled by the OFDM technique adopted by the IEEE 802.11a/b/n wireless standard. The channel properties are represented in the form of the CSI. More in detail, the received signal can be defined as [12]

$$\underline{Q}(t) = \underline{\underline{H}}(t)\underline{P}(t) + \underline{\beta}(t) \tag{1}$$

where $\underline{Q}(t) = [q_k(t); k=1,...,K]$ and $\underline{P}(t) = [p_k(t); k=1,...,K]$ are the time-domain representation of the received and the transmitted complex-valued signals, respectively, K is the number of frequency sub-carriers, $\underline{\beta}(t) = [\beta_k(t); k=1,...,K]$ is the noise vector, and t is the measurement time. Moreover, $\underline{\underline{H}}(t)$ is the multi-frequency channel matrix represented as

$$\underline{\underline{H}}(t) = \left[\underline{\underline{H}}_1(t), \underline{\underline{H}}_2(t), ..., \underline{\underline{H}}_K(t) \right]^T \tag{2}$$

where $\underline{\underline{H}}_k(t)$ is a complex matrix with elements $h_{il}^{(k)}(t) = \left| h_{il}^{(k)}(t) \right| e^{j\angle h_{il}^{(k)}(t)}$, $i = 1,...,I$ and $l = 1,...,L$ being the transmitting and the receiving antennas, respectively, and T is the transpose symbol. The magnitude $\left| h_{il}^{(k)}(t) \right|$ [dB] and the phase $\angle h_{il}^{(k)}(t)$ [deg] are inferred from the knowledge of the transmitted and the received signals when the i-th antenna is transmitting and the l-th antenna is receiving. The fine-grained channel frequency response given by the matrix $\underline{\underline{H}}(t)$ includes both frequency and spatial diversity information, since $W = I \times L$ wireless links exist between the transmitter and the receiver.

Only the CSI amplitude has been exploited for detection purposes. The phase information is fundamental but the calibration procedure has been avoided in this work to reduce as much as possible the computational complexity of the method. The processing of the phase is under study to make the such information stable and usable for detection purposes. Up to now, the CSI phase has introduced a very high sensitivity that is less compatible with the robustness objective addressed in the proposed detection method. The attention has been focused on the exploitation of the spatial and frequency diversity to maximize the robustness of the target detection even in complex and real-world scenarios, as opposite to several solutions in the state of the art that apply data fusion strategies to combine the multiple links and carriers in a single aggregated data stream.

In order to solve the inverse problem, the time evolution of the CSI has been analyzed to recognize the presence of patterns in the received signal due to the target presence in the domain. The probability density function (PDF) of the CSI correlations $C_{k,w}^{(void)}$ (i.e., the correlation between two CSI streams acquired without targets) and $C_{k,w}^{(full)}$ (i.e., the correlation between one CSI stream without targets and one CSI stream with targets) has been considered for all the carriers $k = 1,...,K$ and the links $w = 1,...,W$ to detect the pattern changes in the data acquired in absence and in presence of the targets. The *absence* data set has been acquired when the detection domain is empty, while the *presence* data set has been collected when targets are within the area of interest. The comparison between the PDFs of the correlations has been performed using the non-parametric Kruskal-Wallis (KW) test to statistically quantify the similarity of the distributions. The KW test has been adopted since the strong assumption that the PDFs of the correlations are normally distributed is not required. The p-values $\rho_{k,w}$, $k = 1,...,K$, $w = 1,...,W$ returned by the KW test is a measure of statistical similarity. High p-values stand for distributions of the same population, whereas lower p-values are obtained when at least one sample of the distribution is significantly different from the others. The computed p-values are the set of features sensitive to the target presence, and rapidly decrease in presence of targets.

### 2.1. Target-dependent features selection

The positions of the multiple transmitting and receiving antennas of the MIMO link determine different propagation paths and consequently the mutual correlation among the W wireless links can be leveraged for the solution of the detection problem. The perturbations due to the presence of a human body introduce noisy but highly correlated changes of amplitudes across the W wireless links. The main challenge is to identify the components of the perturbations that are target-dependent. Toward this end, the PCA method [12] has been adopted to select the orthogonal components of the p-values not belonging to the noise subspace. The computed principal components $\underline{\gamma}_{\hat{k}} = \left[\gamma_{\hat{k},w} ; w = 1,...,W \right] = \Omega \left[\rho_{\hat{k},w} ; w = 1,...,W \right]$, $\hat{k} = 1,...,K$, where $\Omega[\cdot]$ computes the PCA of the p-values, are ordered so that the first ones account for most of the data variability. The goal is to identify the PCA components more related to the target absence/presence. Accordingly, it has been verified in

[13] that the first components (i.e., the ones with the higher eigenvalues) can be discarded in order to remove the intrinsic noise of the input data and to isolate the smaller variations.

The binary status of target absence/presence has been inferred applying the following thresholding strategy

$$\chi_w = \begin{cases} 1 & if \quad \dfrac{1}{K}\sum_{k=1}^{K}\gamma_{k,w} < \gamma_{th} \\ 0 & otherwise \end{cases} \quad ; \quad w = 1,...,W \tag{3}$$

to the set of principal components of each wireless link. The components more related to the actual target absence/presence are selected as the target-dependent features.
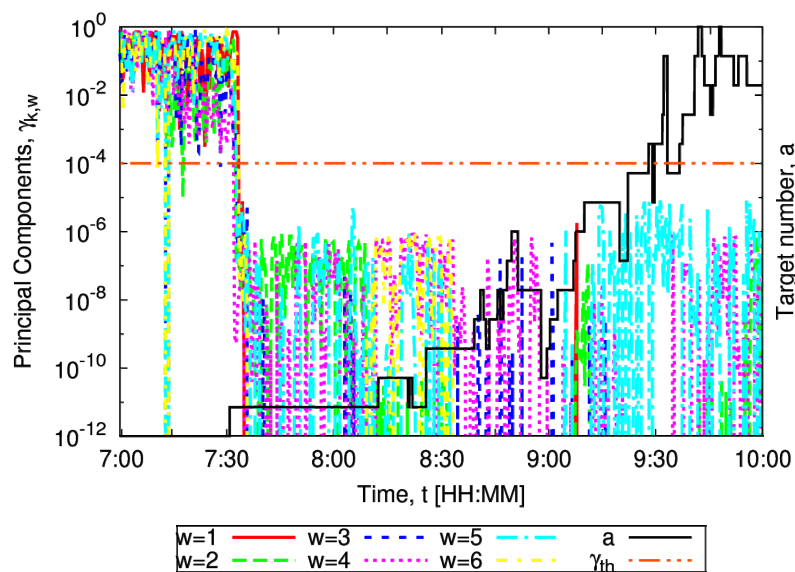
Figure 2. Temporal trend of the principal components of the CSI computed in absence and in presence of targets in the investigation domain.

3. Experimental Validation

The experiments have been carried out using commodity WiFi devices deployed in indoor areas. The WiFi access point TP-Link AC1750 compliant to the IEEE 802.11n standard has been adopted as transmitter operating at frequency $f = 2.4$ [GHz], and the Intel 5300 NIC has been used for the acquisition of the CSI at the receiver [Fig. 1(*b*)].

Multiple wireless links ($W = 6$) have been considered, since $I = 2$ transmitting and $L = 3$ receiving antennas have been assumed. The sampling rate of the receiver is $t = 0.5$ [s], which is the default rate of the ping command adopted to detect network devices, so that the CSI acquisition is transparent in terms of network overhead). The data sets have been collected from 2:00 AM to 5:00 AM for the *absence* status, and during the daytime for the periods of target *presence*. The actual number of targets $a = 0, ...,A$ is inferred from the recordings taken by a video surveillance system installed ad-hoc to acquire the ground truth during the experiments.

The false positive rate $\omega_w^{(FP)}$ and the false negative rate $\omega_w^{(FN)}$ have been computed for each wireless link $w = 1,...,W$ starting from the comparison of the estimated target absence/presence in (3) and the actual conditions of the scenario at hand. Such performance indicators are representative of the detection robustness, defined as the stability and reliability of the estimations respect to the actual target absence and presence.

The detection has been performed in a classroom of size 40 [m^2] shown in Fig. 1(*a*). The wireless link between the transmitter and the receiver graphically represented in the map has a length of *d = 8* [m].

The CSI data set is composed by an *absence* period from 7:00 AM to 7:30 AM, and successively by a *presence* period when one target entered the area until 8:10 AM. After that, a variable number of targets up to *A = 14* occupied the classroom until 10:00 AM.

For the sake of conciseness, the principal components have been computed choosing the center subcarrier *k = 15*. Figure 2 shows the temporal trends of the obtained principal components $\gamma_{\hat{k},w}$; $w = 1,...,W$ of each wireless link *w=1,...,W* , *W=6*, together with the number of targets *a = 0, ...,A, A = 14*. The trends point out a rapid decrease of all the principal components when the first target occupies the area at 7:30 AM. The decrease is the result of an evident change between the PDFs regardless the wireless links *w = 1, ...,W*.

The false positive and false negative rates have been averaged over the wireless links pointing out detection performance of $\omega_w^{(FP)} = 1.17$ [%] and $\omega_w^{(FP)} = 0.16$ [%] with the threshold $\gamma_{th} = 10^{-4}$. Such a threshold has been calibrated computing the lower boundary $\bar{\gamma} - 3\sigma$, where $\bar{\gamma}$ is the average value of the principal components measured during the experimental acquisition in absence of targets, and σ is the variance. The obtained performance outperform other state of the art methods, like PADS [14] and FIMD [15], which show higher false rates (ROC curves point out false positive rates higher than 5 [%] with detection rates of 80 [%]).

4. Conclusions

In this paper, the robust detection of device-free targets using commodity WiFi devices has been addressed. The detection problem has been recast as an inverse problem since the properties of the investigation domain (i.e., the absence/presence of at least one target) have been reconstructed starting from the electromagnetic perturbation measured by one wireless link. The CSI data have been processed exploiting both the frequency and the spatial diversity of the MIMO wireless architecture and the proposed PCA-based method pointed out reliable detection performance with failure rates lower than 2 [%].

References

[1]   Viani F, Polo A, Garofalo P, Anselmi N, Salucci M, and Giarola E 2017 Evolutionary optimization applied to wireless smart lighting in energy-efficient museums *IEEE Sensors Journal* **17** 1213-1214

[2]   Viani F, Robol F, Polo A, Rocca P, Oliveri G, and Massa A 2013 Wireless architectures for heterogeneous sensing in smart home applications – concepts and real implementations *IEEE Proc. IEEE* **101** 2381-2396

[3]   Patwari N and Wilson J 2010 RF sensor networks for device-free localization: Measurements, models, and algorithms *Proc. IEEE* **98** 1961-1973

[4]   Viani F, Lizzi L, Rocca P, Benedetti M, Donelli M, and Massa A 2008 Object tracking through RSSI measurements in wireless sensor networks *Electron. Lett.* **44** 653-654

[5]   Viani F, Rocca P, Benedetti M, Oliveri G, and Massa A 2010 Electromagnetic passive localization and tracking of moving targets in a WSN-infrastructured environment *Inverse Problems* **26** 1-15

[6]   Viani F, Rocca P, Oliveri G, Trinchero D, and Massa A 2011 Localization, tracking, and imaging of targets in wireless sensor networks: An invited review *Radio Science* **46**

[7]   Viani F 2015 Opportunistic occupancy estimation in museums through wireless sensor networks *Microw. Opt. Techn. Lett.* **57** 1975-1977

[8]   McCracken M and Patwari N 2014 Indoor localization with range-based measurements and little prior information *IEEE Trans. Mobile Comput.* **13** 1509-1521

[9]   Ni L M, Zhang D, and Souryal M R 2011 RFID-based localization and tracking technologies *IEEE Wireless Comm.* **18** 45-51

[10]   Ahmadi H, Polo A, Moriyama T, Salucci M, and Viani F 2016 Semantic wireless localization of WiFi terminals in smart buildings *Radio Science* **51** 876-892

[11]   Chapre Y, Ignjatovic A, Seneviratne A, and Jha S 2015 CSI-MIMO: an efficient Wi-Fi fingerprinting using channel state information with MIMO *Pervasive Mob. Comput.* **23** 89-103

[12]   Wu K, Xiao J, Yi Y, Chen D, Luo X, Ni L 2013 CSI-based indoor localization *IEEE Trans. Parallel Distrib. Syst.* **24** 1300-1309

[13]   Jolliffe I T 2002 Principal Component Analysis *Springer-Verlag, New York, 2nd Ed.*

[14]   Qian K, Wu C, Yang Z, Liu Z, Zhou Z 2014 PADS: Passive detection of moving targets with dynamic speed using PHY layer information *20th IEEE Int. Conf. on Parallel and Distributed Systems* (ICPADS 2014), Hsinchu, Taiwan, 16-19 December.

[15]   Xiao J, Wu K, Yi Y, Wang L, Ni L M 2012 FIMD: Fine-grained device-free motion detection *18th IEEE Int. Conf. on Parallel and Distributed Systems* (ICPADS 2012), Nanyang, Singapore, 17-19 December