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LTE Signals for Device-Free Crowd Density Estimation Through CSI Secant Set and SVD

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ABSTRACT The rising need of crowd monitoring in public spaces, especially for safety purposes, pushes the research community to propose and experiment novel methods of crowd density estimation. This paper focuses on device-free RF sensing, which does not require the monitored people to carry any electronic device. In particular, the paper proposes and assesses the performance of a crowd density estimation system based on the analysis of the variations of Channel State Information (CSI) computed from unencrypted synchronization signals transmitted by a eNodeB and reflected/scattered by people located in the monitored area. The proposed method uses features extracted from the list of singular values of the CSI secant set. This approach allows to reduce the impact of CSI variations due to noise or HW instability, improving the sensitivity to CSI variations caused by human presence. The average accuracy achieved by the proposed approach is 84%, which is comparable with the accuracy achieved with WiFi based crowd density estimation systems.

INDEX TERMS Crowd counting, LTE, passive device-free crowd density estimation, CSI, RF sensing, human sensing, singular value decomposition.

I. INTRODUCTION

Crowd counting systems are highly beneficial tools in several emerging applications such as: shopper analytics, where the information on how people move around in a shop can be used both for optimizing the layout of the shop and for optimizing the staff management and/or the goods organization; public safety and security, where crowd counting is fundamental for early detection of dangerous over-crowded situations; intelligent transportation systems (ITS), where bus and train schedules or boarding and payment processes may be adjusted according to the number of people waiting for the service. Several approaches for automatic crowd-counting have been proposed in literature. In this paper, we focus on device-free approaches where people do not need to carry any device (such as smartphones, RFID tags or sensors). Traditional device-free approaches are based on video-cameras and image processing [1], which have several limitations related to the light conditions and deployment costs in complex environments. Furthermore, the use of cameras poses privacy concerns. An alternative approach, which is gaining more and more interest, is based on the use of opportunistic RF signals [2]–[6]. The idea is to process the received RF signals of wireless networks to extract the changes of the propagation channel induced by the presence of different number of people. As a matter of fact, all mentioned works use WiFi signals. Recent works have started to consider also Long Term Evolution (LTE) signals for radio analytics applications [7]. LTE signals are excellent candidates as signals of opportunity thanks to their ubiquitous availability and penetration in indoor environments. They could be available in areas where the WiFi coverage is not present, such as remote and small railways stations or large open spaces, as city squares or stadiums. Most of the works are based on the use of LTE signals with a passive radar approach [8], [9], and not specifically for crowd counting, but for other applications such as localization and target tracking [10]–[12].

Authors of [13] have proved the feasibility of a crowd density estimation system based on LTE. In [13], the use of features extracted from the Reference Signal Received Power (RSRP) provides an accuracy of around 80% for a number of people up to 5 and by collecting data from LTE signals of 1.4 MHz of bandwidth. This paper aims to provide a significant step forward with respect to [13] in terms of

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performance. First of all, LTE signals with a bandwidth of one order of magnitude wider are considered (15 MHz instead of 1.4 MHz). Moreover, to fully take advantage of this wider bandwidth, novel features are extracted from the Channel State Information (CSI) vectors. In particular, the key contribution of this paper is the proposal to use features extracted from the SVD of CSI difference vectors (secant set). It is worth outlining that the use of data dimensionality reduction approaches such as Singular Value Decomposition (SVD) and Principal Component Analysis (PCA) have been proposed in several RF sensing systems (crowd counting, activity/gesture recognition, signal fingerprinting) to reduce the instability of the collected data due to noise and hardware impairments [14]–[17]. Usually, the idea is to extract features from a transformed dataset reconstructed using the components (singular values for the SVD or principal components for the PCA) that are considered to better represent the useful information contained in the original dataset.

The proposed approach is different as it uses all components (i.e. all the singular values) of the decomposition applied to the CSI secant set matrix. Then, a set of features is extracted from the overall list of singular values sorted in descending order. The experimental results reported in this paper confirmed that, as expected, there is a strong correlation between the number of people in the monitored room and the shape of the curve representing the sorted list of singular values of the CSI secant set. Therefore, the authors propose the use of features that characterize the above mentioned descending curve (its slope, center of gravity, etc.). Such approach also allows to reduce the impact on the performance of the power fluctuations resulting in an additive scaling constant, due to noise and other hardware instability. Experimental results carried out with a number of people up to 17, show that this novel approach, combined with the use of a larger bandwidth (15 MHz instead of 1.4 MHz), can provide performance comparable with the ones of a system based on WiFi signals.

The paper is organized as follows: Section II discusses the related works on RF-based crowd counting; Section III presents the CSI computation method and pre-processing; Section IV introduces the novel approach to feature extraction based on SVD; Section V shows the classification method and the experimental results; Section VI draws the conclusions.

II. RELATED WORKS

Currently, crowd counting and people monitoring through RF signals is a hot topic of research. In this framework, different approaches have been proposed in literature which can be divided at first instance in two main categories: device-aided or device-free. Device-aided solutions rely on the sniffing of up-link signals transmitted by user devices to capture the unique Medium Access Control (MAC) address. In this framework, different radio technologies can be used, such as Bluetooth (BT) sensors [18], WiFi access points [2], or integrated WiFi-BT technologies [19]. Some innovative passive systems using LTE have been recently proposed to identify the number of users served by an LTE base station through sniffing the down-link control information in physical layer protocol [20]. Such approaches, which depend on devices that are carried by the monitored people, could not be suitable for some security applications. RF device-free approaches are based on the analysis of the propagation channel variations of wireless signals (e.g. WiFi or LTE), which are induced by the monitored people. The impact of the monitored people on the RF signal can be assessed either using traditional radar methodologies (range and Doppler analysis) or by analyzing features extracted by channel quality measurements such as Received Signal Strength Indicator (RSSI) and CSI. WiFi passive radar approaches have been mainly proposed for indoor and outdoor moving target detection and localization; the system configuration is in general bi-static or multi-static, obtaining a range resolution of about 25 m, while the equivalent velocity resolution is less than 1 m/s (integrating Doppler analysis over less than one second) [21]. WiFi passive radar has been also used for through-the-wall sensing of personnel [22]. Also LTE signals have been recently applied with a passive radar approach to perimeter surveillance, monitoring pedestrians, vehicles and small drones and obtaining good performance in terms of probability of detection/false alarms (90% and 10^{-5}, respectively) and reaching a range of few kilometers [23]. Additional examples of the possibility to use a LTE passive radar approach for outdoor tracking of multiple targets can be found in [24]. It has to be outlined that, to the best of the authors knowledge, no specific application of passive radar for crowd counting, either with WiFi and LTE signals, has been proposed in literature.

The approaches based on channel quality measurements rely on predictive features that are extracted from RSSI, RSRP or CSI measurements. In general the performance obtained through RSSI analysis are good only for small environment monitoring, where the propagation channel variation is largely dominated by the attenuation caused by the monitored people; on the other hand, in a rich scattering environment the analysis based on CSI provides a more reliable understanding on the human activity in the room [25]. Most of the works in this field are based on features extracted from WiFi signals in different domains as time correlation and statistics, probability density function, Doppler spectrum, frequency analysis, etc [26]. As a matter of fact, very few scientific works have been focused on features extraction from LTE signals; in [13] the authors have demonstrated for the first time the use of features extracted from LTE signals for density estimation, obtaining very promising results. However, this feasibility study only considers signals with a bandwidth of 1.4 MHz and few people in the room (up to 5). The limited bandwidth that is considered in [13] does not motivate the use of features directly related to the CSI and to the frequency selectivity of the channel. As a matter of fact, in [13] the used features are related to the RSRP.

Therefore, the present paper represents a significant step forward in terms of performance, which is achieved by using a wider bandwidth and novel features extracted from the SVD of the CSI secant. It is worth outlining that the use of SVD has been proposed in several RF sensing systems. However, it is used either to reduce the instability of the collected data due to noise [17] or to reduce the impact of some component of the data that is common to all collected vectors, for instance related to the background environment [27]. This paper proposes a different use of the SVD. In particular, the paper shows a strong correlation between the number of the people and the shape of the curve achieved by the sorted list of singular values of the CSI secant set, motivating the extraction of novel features for crowd density classification.

III. COLLECTION AND PREPROCESSING OF CSI VECTORS

In OFDM systems, CSI represents an estimation of the Channel Frequency Response (CFR) and consists in a vector of complex channel gains per subcarrier, which are estimated by the receiver and used for channel equalization. In the following, we consider only the LTE Frequency Division Duplexing (FDD) mode, in which uplink and downlink channels are separated in frequency. In LTE, data are transmitted over a time-frequency grid, which is organized as follows: a *radio frame* has a duration of 10 ms and is the largest unit of time in the LTE resource grid. Each radio frame is divided into 10 *subframes* having a duration of 1 ms, each of which is split into 2 *slots* of duration 0.5 ms. Each slot consists of 6 or 7 OFDM symbols (depending on the cyclic prefix length). In the frequency domain, the finest granularity is provided by OFDM subcarriers which are spaced by 15 kHz from each other. The minimum resource unit is called Resource Element (RE) and consists of one OFDM subcarrier in the frequency domain and one OFDM symbol in the time domain. The smallest unit of resource that can be allocated to a User Equipment (UE) is called Resource Block (RB), which is a group of 12 contiguous OFDM subcarriers (180 kHz) in a time slot of 7 (or 6) OFDM symbols.

In the LTE standard, the concept of antenna port has been introduced. An antenna port is a generic term used for signal transmission under identical channel conditions and is defined for each independent channel in the downlink direction. A UE must perform a separate channel estimation for each antenna port through separate reference symbols. In order to exploit spatial diversity, an eNodeB can map logical antenna ports to different physical transmitting antennas.

The channel frequency response is a complex-valued vector of N_{sub} elements providing the base-band channel gain and can be estimated for each pair of transmitting antenna port and receiving antenna. Let us denote with $\mathbf{h^{i,j}} = [h_1^{i,j}, h_2^{i,j}, \dots, h_{N_{sub}}^{i,j}]$ the CFR for the i-th antenna port, $i = 1, \dots, N_{tx}$, and for the j-th receiving antenna, $j = 1, \dots, N_{rx}$. The received signal after the N-point Discrete Fourier Transform (DFT), at the j-th receiving antenna, and for the k-th subcarrier, $k = 1, \dots, N_{sub}$, can be computed as:

$$y_k^j = \sum_{i=1}^{N_{tx}} h_k^{i,j} x_k^i + n_k^j \tag{1}$$

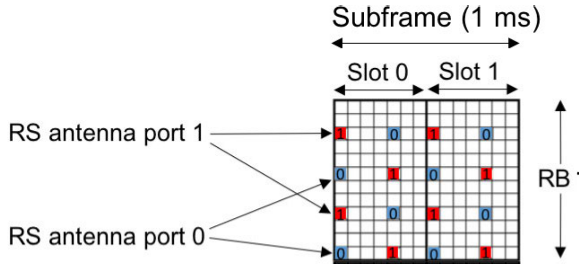

FIGURE 1. Cell-specific reference signals in one RB of the LTE resource grid.

where x_k^i is the transmitted symbol and n_k^j is the complex white Gaussian random process representing the noise and the inter-cell interference. The CSI is computed by the receiver using the Cell specific Reference Signal (CRS) inserted in specific OFDM symbols within every slot. Fig. 1 shows the CRSs in a RB, where CRSs represented by different colors correspond to reference symbols transmitted over different antenna ports (2 antennas are assumed). A single slot includes a total of 4 CRSs per antenna, located over different subcarriers and OFDM symbols.

In this work, we propose to extract the CSI from the LTE signal of bandwidth of 15 MHz. We assume that the channel stays rather stationary over a slot (0.5 ms), i.e. the coherence time is equal or greater than the time slot duration (this choice is consistent with crowd density estimation scenario). Under this assumption, the CRSs in different positions in the same slot can be aligned at the same instant of time for each antenna, doubling the size of the CSI resulting vector. The 15 MHz signal bandwidth consists of 75 RBs, which are employed to transmit both data and pilot symbols. This number of RBs carries $N_{sub} = 75 \cdot 2 \cdot 2 = 300$ (75 RBs $\times$ 2 CRSs $\times$ 2 positions) subcarriers that are used to estimate the complex channel gains. The complex vector that represents the channel estimation is the CSI vector. In our experimental setup we have used a single antenna LTE receiver and extracted the CSI from an eNodeB transmitting CRSs over 2 antenna ports. Let us denote the collected CSI with $\hat{\mathbf{h}}^i$, which can be expressed as:

$$\hat{\mathbf{h}}^i = [\hat{h}_1^i, \dots, \hat{h}_{N_{sub}}^i], \quad i = 1, 2 \tag{2}$$

where the index j of the receiving antenna was omitted, since in our setup just one receiver antenna is used.

CSI measurements are very noisy due to multiple sources of noise. Fig. 2 shows the amplitude of thousands of consecutive CSI overlapped to each other, collected for one of the antenna port and with a bandwidth 15 MHz. It can be clearly observed the noisiness of the estimated channel frequency response, which rapidly fluctuates both between adjacent subcarriers and between consecutive instants of time.

To minimize the effects of noise on the CSI, the least square estimates were averaged using an averaging window both in frequency and time domain. In particular, we have used

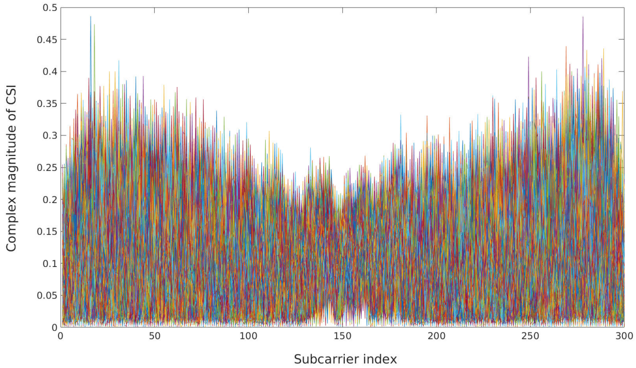

FIGURE 2. Complex magnitude of raw CSI vectors collected in an empty room.

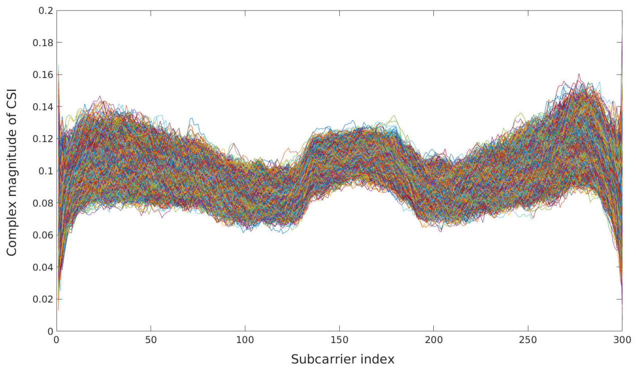

FIGURE 3. Complex magnitude of filtered CSI vectors collected in an empty room.

the filtering method described in [28] (Annex F.3.4), which consists of the following steps:

1) Time averaging is performed across each subcarrier for $W_t = 3$ consecutive OFDM symbols that carry pilot symbols, resulting in a column vector containing an average amplitude for each subcarrier that is carrying a reference signal.
2) Frequency averaging is performed by computing the moving average in the frequency domain of the time-averaged reference signal subcarriers. The sliding window size is $W_f = 19$, but for subcarriers at or near the edge of the channel the window size is properly reduced.
3) Decimation is performed to reduce the amount of data to process and is chosen such that system performance do not degrade. The decimation factor used in our processing is $D_f = 40$.

Fig. 3 shows the filtered CSI amplitude for the same series depicted in Fig. 2; it can be noted how the filtered CSI is much less noisy than the raw CSI, and the series of CSI vectors tend to follow a common "shape". As discussed in the next Section, the filtered CSI vectors are then processed to extract the features that are used by the classifier to count the number of people in a given environment.

IV. FEATURE EXTRACTION FROM CSI VECTOR DIFFERENCES AND SVD

First of all, the proposed crowd density estimation system is based on the observation that the higher is the number of people, the more significant is the variation on CSI vectors that is induced. However, there are three types of CSI vector variations: 1) CSI variations caused by human movements; 2) CSI variations caused by random noise and 3) CSI variations caused by unpredictable power fluctuations at the transmitter and/or at the receiver [29]. The first type of variation is the one that we aim to quantify. The second type of variation is partially filtered out through the CSI preprocessing step which was described in the previous Section. The third type of variation is counteracted in our approach as we extract features from the matrix of CSI vector differences which are not sensitive to the relative level of the CSI and hence to the power fluctuations, but are sensitive to their shape variations.

Let us denote with $\hat{\mathbf{h}}_k^i$ the CSI vector collected at time index k and let us compute the vector $\hat{\mathbf{a}}_k^i$ taking only the complex magnitude of the elements of $\hat{\mathbf{h}}_k^i$. Now, consider the set $\mathscr{A}$ of $W = 500$ consecutive CSI amplitude vectors – which are equivalent to 10 seconds –: $\mathscr{A} = \{\hat{\mathbf{a}}_{l+1}^i, \hat{\mathbf{a}}_{l+2}^i, \ldots, \hat{\mathbf{a}}_{l+W}^i\}$. A matrix D of CSI amplitude vector differences is extracted from $\mathscr{A}$ taking all vector differences of pair of vectors in $\mathscr{A}$. As a consequence, D is a $\frac{W(W-1)}{2} \times N_{sub}$ matrix representing the secant set of $\mathscr{A}$.

We then apply the SVD to the matrix D of CSI amplitude vector differences. The SVD of the matrix D is the factorization of D into the product of three matrices as follows:

$$D = U\Sigma V^T \tag{3}$$

where the columns of U are eigenvectors of DD^T, and the columns of V are eigenvectors of $D^T D$. Σ is a pseudo-diagonal matrix and the r singular values $s_n, n = 1, 2, \ldots, r$ on the diagonal of Σ are the square roots of the nonzero eigenvalues of both DD^T and $D^T D$.

We recall that the number of nonzero singular values is equal to the number of linearly independent rows or columns of D. As per convention, the singular values are sorted in descending order.

Smaller singular values are expected to be related to the noise or random instability on the collected data while higher singular values are related to independent patterns that can be identified in the collected data. Therefore, assuming that variations of the CSI amplitude induced by different persons are independent, we expect that the value of the largest singular values increases as the number of people increases. Therefore, considering the curve achieved by linearly interpolating the singular values, ordered in descending order, we expect that this curve decays less rapidly as long as the number of people increases. Moreover, this trend of singular values is independent from any additive scaling factor applied to the rows of D. In this framework, it can be expected that a method based on the characterization of this curve built on the singular values of the CSI secant set matrix D, is not sensitive to the power fluctuation of CSI amplitude vectors. Fig. 4

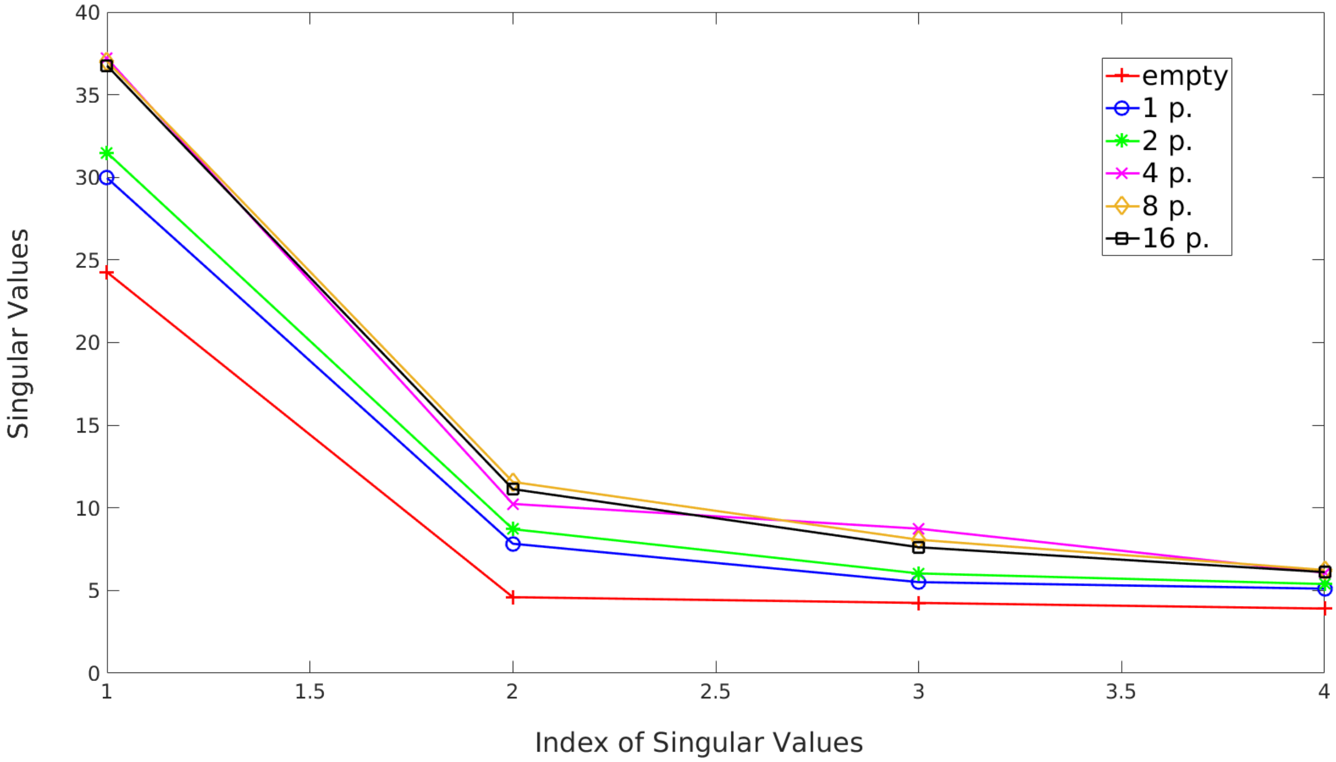

FIGURE 4. **List of singular values for different number of people.**

confirms this intuition. In Fig. 4, the curve of sorted singular values is shown for data collected in a room with different number of people; the ordinate reports the singular values while the abscissa reports the related index. It is evident that when the number of people is low (e.g. 1-2), the curve is less steep, while when it is high (e.g., 4-16), the curve is steeper. Therefore, we propose to use as features metrics characterizing the trend of this curve.

In particular, with reference to Fig. 4, let us denote with $y(x)$ the monotonically not increasing curve that linearly interpolates the singular value sequence, $y_n = y(x_n)$, where $x_n = \{x_1, x_2, \ldots, x_r\}$ are the singular value indexes. The following set of features can be defined for this type of function.

The m-th slope of $y(x)$ can be defined as:

$$f_s^m = \frac{y_m - y_{m+1}}{x_m - x_{m+1}} \tag{4}$$

which is a negative number if the curve is decreasing at the m-th point. Specifically, we restricted our analysis to the 1st and 2nd slope.

The average slope of $y(x)$ can be defined as:

$$f_s = \frac{1}{r}\sum_{m=1}^{r} f_s^m \tag{5}$$

where r is the number of points of the curve (the number of singular values).

The center of gravity of $y(x)$ can be defined as:

$$f_c = \frac{\sum_{i=1}^{r} y_i x_i}{\sum_{i=1}^{r} y_i} \tag{6}$$

The area under the curve $y(x)$ can be defined as:

$$f_a = \sum_{i=1}^{r-1} y_i \cdot (x_{i+1} - x_i) \tag{7}$$

It is worth noting that, for the particular case of singular values indexed by x_i, $\Delta x = x_{i+1} - x_i = 1, \forall i$, hence, $f_s^m = y_m - y_{m+1}, f_s = \frac{\max y - \min y}{r}, f_a = \sum_{i=1}^{r-1} y_i$.

V. PERFORMANCE ASSESSMENT

In the following, the performance of the proposed method is experimentally assessed, assuming a number of people up to 17. Moreover, the proposed method is compared with a method based on features extracted from the RSRP, as previously proposed for LTE crowd density estimation [13].

A. EXPERIMENTAL SETUP

The collection of CSI and RSRP measurements of our experiment has been carried out using the OpenLTE software and a USRP N210 SDR platform located in the monitored room of size 5 m × 9 m. The eNodeB is located at a distance of 550 m from the SDR platform. A total number of 17 volunteers took part to the experiment by moving in the considered room. CSI and RSRP measurements have been collected for at least two minutes and for each group of people present

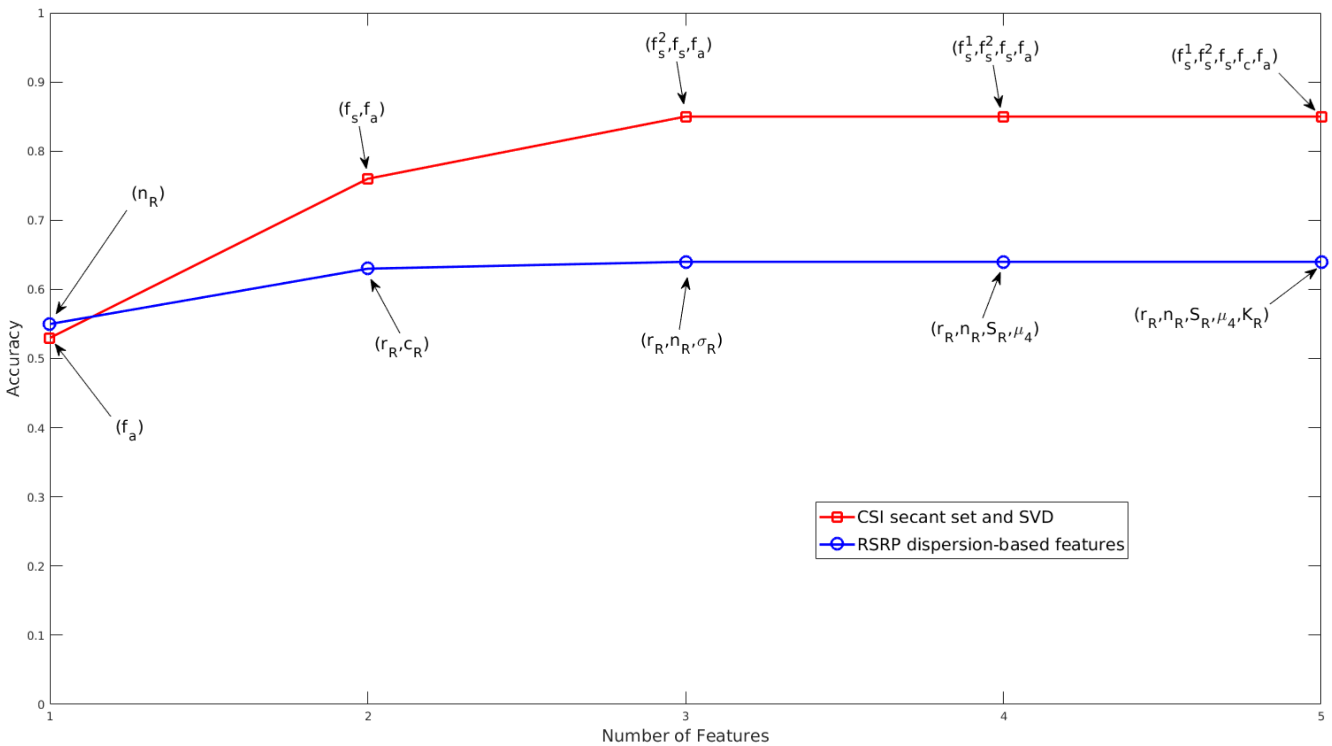

FIGURE 5. Accuracy of CSI secant set method and RSRP dispersion features method versus the number of features. The best set of features is also reported for each point of the curves.

in the room, ranging from 0 to 17 people. People were free to move or stand still during the experiments. The LTE receiver was placed on a desk near a wall at 1 meter height. It is worth noting that, volunteers were free to carry their own smartphones/LTE-device as this has no impact on the counting method. In fact, we only use synchronization signals transmitted by the eNodeB and these signals are orthogonal to any other signal transmitted by smartphones/LTE-devices, hence, we do not experience any interference. As outlined in Section IV, sensitivity of the proposed crowd density estimation technique decreases with the increase of the number of people in the room (see Fig. 4).

It has to be underlined that the crowds classes have been selected in order to demonstrate how the proposed approach based on CSI SVD could provide a performance improving with respect to RF crowd density estimation techniques found in literature. As a matter of fact, many works rely on the estimation of few crowds classes without the distinction between empty room class, one person class and the other classes, [6], [30], [31], in our work we pushed the system performance including these classes.

B. EXPERIMENTAL RESULTS

The overall set of features that are considered from the CSI secant set includes: 1st slope (f_s^1), 2nd slope (f_s^2), average slope (f_s), center of gravity (f_c), area under the curve (f_a). For what concerns the dispersion-based RSRP method, the overall set of features, defined in [13], consists of: standard

TABLE 1. Confusion matrix as a result of the classification process for CSI secant set and SVD method using the best set of 3 features (i.e. 2nd slope, center of gravity and area under curve).

Truth \ Prediction	Empty	1 p.	2-4 p.	5-12 p.	13-17 p.	
Empty	1	0	0	0	0	
1 p.	0.34	0.66	0	0	0	
2-4 p.	0	0.08	0.79	0	0.13	
5-12 p.	0	0	0.04	0.86	0.1	
13-17 p.	0	0	0	0.13	0.87	
						0.84

deviation (σ_R), coefficient of variation (c_R), Fano factor (F_R), range (r_R), normalized range (n_R), third central moment (μ_3), fourth central moment (μ_4), skewness (S_R), kurtosis (K_R).

After the computation of features for each different number of people and the separation of the overall dataset into a training set (50%) and a test set (50%), the naïve Bayes classifier is applied to every possible combination of 1, 2, 3, 4, 5 features from the overall set of features previously defined for both CSI secant set method and RSRP dispersion features method. Then, an exhaustive search was carried out to find the best set of features that maximizes the average accuracy of the classification.

Fig. 5 shows the average accuracy for CSI and RSRP methods, assuming a varying number of features. From Fig. 5 it is possible to conclude that: 1) the average accuracy reaches its maximum when the number of features is set to 3 (and

TABLE 2. Comparison of device-free crowd counting methods.

Ref	Environments	Max # of People	Standards	Source Data	# TXs	# RXs	Estimation Delay (window size W)	Crowd Counting Accuracy	Crowd Density Accuracy
[5]	2 (indoor 33 m^2, outdoor 70 m^2)	9	WiFi	RSSI	1	1	300 s	P(e≤ 2) = 96%(outdoor) P(e≤ 2) = 63%(indoor)	-
[32]	2 (indoor 150 m^2, indoor 400 m^2)	4	ISM 909.1 MHz	RSSI	12/13	8/9	1 s	84%	-
[30]	1 (indoor 324 m^2)	>10	ISM 2.4 GHz	RSSI	16	16	-	-	86% (0p-3p, 4p-10p, >10p)
[32]	2 (indoor 150 m^2, indoor 400 m^2)	4	ISM 909.1 MHz	RSSI	12/13	8/9	1 s	84%	-
[30]	1 (indoor 324 m^2)	>10	ISM 2.4 GHz	RSSI	16	16	-	-	86% (0p-3p, 4p-10p, >10p)
[6]	1 (indoor 100 m^2)	15	ZigBee 2.4 GHz	RSSI	1	3	-	-	73% (5p, 10p, 15p)
[31]	1 (indoor)	7	WiFi	RSSI	1	10	300 s	77%	94% (0p, 1p-3p, 4p-7p)
[33]	1 (indoor corridor ≈ 10 m^2)	5	HBE-Zigbex	RSSI	1	2	4.5 s	77%	-
[4]	2 (indoor, outdoor)	30	WiFi	CSI	1	3/4	-	P(e≤ 2) = 70% (outdoor) P(e≤ 2) = 98% (indoor)	-
[2]	3 (indoor 30 m^2, indoor 45 m^2, indoor 70 m^2)	7	WiFi	CSI	1	1	10 s	P(e≤2) = 99% (room A) P(e≤2) = 92%(room C)	73% (room A) 63% (room C) (0p, 1p, 2p, 3p-4p, 5p-7p)
[13]	1 (indoor 45 m^2)	5	LTE	RSRP	1	2	10 s	-	82% (0p, 1p, 2p-3p, 4p-5p)

then, it saturates; 2) the proposed method clearly outperforms the method based on RSRP. Table 1 shows the confusion matrix for the method based on the SVD of the CSI difference matrix, assuming that the best set of three features is computed on the sorted list the singular values (i.e. 2nd slope, center of gravity and area under curve). The accuracy, averaged on all considered classes, is of 84%. It is worth outlining that at the best of author's knowledge, the proposed work is among the first ones in literature that exploits the LTE signal for counting people in indoor environments. In Table 2 relevant works on crowd counting are reported. It can be noted how most of the works are based on the use of the WiFi signal or other 2.4 GHz signals. Being the type of signal used for sensing different, it is not possible to directly compare the results shown in this work with the results achieved by other passive device-free RF-based crowd counting methods. Moreover, systems performance are influenced by several aspects of the experimental setup: signal bandwidth, carrier frequency, distance between transmitter and receiver, number of transmitters and receivers, maximum number of people, room size, etc. Anyway, it is worth noting that our system has been tested over a maximum number of people higher than other works and the achieved recognition accuracy is comparable or higher with respect to the reported works. This is an important result as it proves the feasibility and goodness of the proposed approach for crowd density estimation, paving the way to further research.

VI. CONCLUSION

This paper proposes a novel approach for passive device-free crowd density estimation, based on CSI extracted from the LTE synchronization signals transmitted by an eNodeB. The novel approach proposed in this paper exploits the SVD of the CSI secant set. SVD has been extensively used in RF sensing systems to reduce the un-stability of the collected data due to noise or HW imperfections. On the other hand, the proposed method uses all components of the SVD. In particular, features are extracted from the sorted list of singular values, which has been demonstrated to be strongly correlated to the number of people in the monitored room. The performance of the proposed approach has been assessed assuming a number of people ranging from 0 to 17, achieving an average accuracy of 84%. This is a very promising result, which confirms the feasibility of the proposed crowd density estimation through LTE signals, whose performance is comparable with the ones of more extensively studied WiFi based system. The use of LTE for crowd density estimation widens the possibility to use passive RF-sensing also in indoor or outdoor scenarios where WiFi is not available, such as small train stations or city squares. Moreover, it could be also interesting to apply the proposed method based on the SVD and CSI secant set to WiFi based systems.

REFERENCES

[1] M. Li, Z. Zhang, K. Huang, and T. Tan, "Estimating the number of people in crowded scenes by MID based foreground segmentation and head-shoulder detection," in *Proc. ICPR*, Dec. 2008, pp. 1–4.

[2] S. Di Domenico, G. Pecoraro, E. Cianca, and M. De Sanctis, "Trained-once device-free crowd counting and occupancy estimation using WiFi: A Doppler spectrum based approach," in *Proc. IEEE 12th Int. Conf. Wireless Mobile Comput., Netw. Commun. (WiMob)*, Oct. 2016, pp. 1–8.

[3] S. Di Domenico, M. De Sanctis, E. Cianca, and G. Bianchi, "A trained-once crowd counting method using differential WiFi channel state information," in *Proc. 3rd Int. Workshop Phys. Anal.*, 2016, pp. 37–42.

[4] W. Xi, J. Zhao, X.-Y. Li, K. Zhao, S. Tang, X. Liu, and Z. Jiang, "Electronic frog eye: Counting crowd using WiFi," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Toronto, ON, Canada, Apr./May 2014, pp. 361–369.

[5] S. Depatla, A. Muralidharan, and Y. Mostofi, "Occupancy estimation using only WiFi power measurements," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 7, pp. 1381–1393, Jul. 2015.

[6] S. Y. Fadhlullah and W. Ismail, "A statistical approach in designing an RF-based human crowd density estimation system," *Int. J. Distrib. Sensor Netw.*, vol. 12, no. 2, pp. 8351017:1–8351017:9, 2016.

[7] S. Kumar, E. Hamed, D. Katabi, and L. E. Li, "LTE radio analytics made easy and accessible," *SIGCOMM Comput. Commun. Rev.*, vol. 44, no. 4, pp. 211–222, Oct. 2014. doi: 10.1145/2740070.2626320.

[8] A. A. Salah, R. S. A. Raja Abdullah, A. Ismail, F. Hashim, and N. H. Abdul Aziz, "Experimental study of LTE signals as illuminators of opportunity for passive bistatic radar applications," *Electron. Lett.*, vol. 50, no. 7, pp. 545–547, Mar. 2014.

[9] A. Evers and J. A. Jackson, "Cross-ambiguity characterization of communication waveform features for passive radar," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 51, no. 4, pp. 3440–3455, Oct. 2015.

[10] G. Pecoraro, S. Di Domenico, E. Cianca, and M. De Sanctis, "LTE signal fingerprinting localization based on CSI," in *Proc. IEEE 13th Int. Conf. Wireless Mobile Comput., Netw. Commun. (WiMob)*, Oct. 2017, pp. 1–8.

[11] S. Bartoletti, A. Conti, and M. Z. Win, "Passive radar via LTE signals of opportunity," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC)*, Jun. 2014, pp. 181–185.

[12] G. Pecoraro, S. Di Domenico, E. Cianca, and M. De Sanctis, "CSI-based fingerprinting for indoor localization using LTE signals," *EURASIP J. Adv. Signal Process.*, vol. 2018, no. 1, p. 49, 2018. doi: 10.1186/s13634-018-0563-7.

[13] S. Di Domenico, M. De Sanctis, E. Cianca, P. Colucci, and G. Bianchi, "LTE-based passive device-free crowd density estimation," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jul. 2017, pp. 1–6.

[14] S. Liu, Y. Zhao, F. Xue, B. Chen, and X. Chen, "DeepCount: Crowd counting with WiFi via deep learning," 2019, *arXiv:1903.05316*. [Online]. Available: http://arxiv.org/abs/1903.05316

[15] H. Li, X. Chen, H. Du, X. He, J. Qian, P.-J. Wan, and P. Yang, "Wi-motion: A robust human activity recognition using WiFi signals," Oct. 2018, *arXiv:1810.11705*. [Online]. Available: https://arxiv.org/abs/1810.11705

[16] S. Tan and J. Yang, "WiFinger: Leveraging commodity WiFi for fine-grained finger gesture recognition," in *Proc. 17th ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*, 2016, pp. 201–210.

[17] X. Dang, Y. Huang, Z. Hao, and X. Si, "PCA-Kalman: Device-free indoor human behavior detection with commodity Wi-Fi," *EURASIP J. Wireless Commun. Netw.*, vol. 2018, no. 1, p. 214, 2018. doi: 10.1186/s13638-018-1230-2.

[18] J. Weppner, P. Lukowicz, U. Blanke, and G. Tröster, "Participatory Bluetooth scans serving as urban crowd probes," *IEEE Sensors J.*, vol. 14, no. 12, pp. 4196–4206, Dec. 2014.

[19] A. Lesani and L. Miranda-Moreno, "Development and testing of a real-time WiFi-Bluetooth system for pedestrian network monitoring, classification, and data extrapolation," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 4, pp. 1484–1496, Apr. 2019.

[20] M. M. Olama, T. Kuruganti, M. Bobrek, S. Killough, J. J. Nutaro, and G. S. Thakur, "Real-time cellular activity monitoring using LTE radio measurements," in *Proc. IEEE 28th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Oct. 2017, pp. 1–5.

[21] F. Colone, K. Woodbridge, H. Guo, D. Mason, and C. J. Baker, "Ambiguity function analysis of wireless LAN transmissions for passive radar," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 47, no. 1, pp. 240–264, Jan. 2011.

[22] K. Chetty, G. E. Smith, and K. Woodbridge, "Through-the-wall sensing of personnel using passive bistatic WiFi radar at standoff distances," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 4, pp. 1218–1226, Apr. 2012.

[23] R. Blázquez-García, J. Casamayón-Antón, and M. Burgos-García, "LTE-R based passive multistatic radar for high-speed railway network surveillance," in *Proc. 15th Eur. Radar Conf. (EuRAD)*, Sep. 2018, pp. 6–9.

[24] R. S. A. R. Abdullah, A. A. Salah, A. Ismail, F. H. Hashim, N. E. A. Rashid, and N. H. A. Aziz, "Experimental investigation on target detection and tracking in passive radar using long-term evolution signal," *IET Radar, Sonar Navigat.*, vol. 10, no. 3, pp. 577–585, Mar. 2016.

[25] E. Cianca, M. De Sanctis, and S. Di Domenico, "Radios as sensors," *IEEE Internet Things J.*, vol. 4, no. 2, pp. 363–373, Apr. 2017.

[26] I. Sobron, J. Del Ser, I. Eizmendi, and M. Vélez, "Device-free people counting in IoT environments: New insights, results, and open challenges," *IEEE Internet Things J.*, vol. 5, no. 6, pp. 4396–4408, Dec. 2018.

[27] J.-Y. Chang, K.-Y. Lee, Y.-L. Wei, K. C.-J. Lin, and W. Hsu, "Location-independent WiFi action recognition via vision-based methods," in *Proc. 24th ACM Int. Conf. Multimedia*, New York, NY, USA, 2016, pp. 162–166. doi: 10.1145/2964284.2967203.

[28] *LTE; Evolved Universal Terrestrial Radio Access (E-UTRA); Base Station (BS) Conformance Testing*, document 3GPP TS 36.141, 2011.

[29] G. Bianchi, S. Di Domenico, M. De Sanctis, L. Liberati, V. Perrotta, and E. Cianca, "Unveiling access point signal instability in WiFi-based passive sensing," in *Proc. 26th Int. Conf. Comput. Commun. Netw. (ICCCN)*, Jul./Aug. 2017, pp. 1–9.

[30] Y. Yuan, J. Zhao, C. Qiu, and W. Xi, "Estimating crowd density in an RF-based dynamic environment," *IEEE Sensors J.*, vol. 13, no. 10, pp. 3837–3845, Oct. 2013.

[31] T. Yoshida and Y. Taniguchi, "Estimating the number of people using existing WiFi access point in indoor environment," in *Proc. 6th Eur. Conf. Comput. Sci. (ECCS)*, Nov. 2015, pp. 46–53.

[32] C. Xu, B. Firner, R. S. Moore, Y. Zhang, W. Trappe, R. Howard, F. Zhang, and N. An, "SCPL: Indoor device-free multi-subject counting and localization using radio signal strength," in *Proc. 12th Int. Conf. Inf. Process. Sensor Netw.*, New York, NY, USA, 2013, pp. 79–90.

[33] S. H. Doong, "Spectral human flow counting with RSSI in wireless sensor networks," in *Proc. Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, May 2016, pp. 110–112.

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