Is Centimeter Accuracy Achievable for LTE-CSI Fingerprint-Based Indoor Positioning?

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ABSTRACT Channel state information (CSI) fingerprint based indoor positioning has been extensively studied. While centimeter-level positioning accuracy has been demonstrated for Wi-Fi systems, only meter-level accuracy was reported for Long-term Evolution (LTE) systems. To investigate whether the centimeter accuracy is achievable or not for LTE systems, we examine the factors that affect the positioning accuracy to guide the implementation of a LTE-CSI fingerprinting system, where a novel phase compensation method is proposed to improve the CSI quality. We demonstrate for the first time that the centimeter-level positioning accuracy is achievable for LTE systems through extensive experiments.

INDEX TERMS Indoor positioning, fingerprinting, channel state information (CSI), LTE.

I. INTRODUCTION

With the rapid development of wireless techniques and the wide proliferation of smart devices, wireless indoor positioning has received considerable attention [1]. Wireless indoor positioning suffers from complex multipath propagation environment, under which the traditional methods for outdoor positioning usually perform poorly [2]. Nevertheless, the rich multipath leads to a significant change of small-scale channel state information (CSI) over small distances on the order of a wavelength, which has been exploited to achieve high-accuracy indoor positioning by applying the fingerprint based positioning techniques [3], [4].

CSI fingerprint based indoor positioning (*CSI fingerprinting* for short in the sequel) is typically applied in wideband communication systems such as Wi-Fi and LTE. There have been numerous studies with respect to Wi-Fi systems in the literature, where various CSI fingerprinting methods have been proposed [1] and the centimeter-level positioning accuracy has been reported [4]. For LTE systems, there are only few works on fingerprint based indoor positioning, e.g., [5]–[7]. In [5] the fingerprints are generated based on reference signal received power (RSRP) and reference signal received quality (RSRQ) rather than CSI, and thus far [6] and

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[7] are the only two works studying the LTE-CSI fingerprinting. We conjecture that the very little attention paid to the LTE-CSI fingerprinting in the literature is mainly caused by the difficulty of acquiring the LTE CSI. For Wi-Fi systems the CSI can be easily extracted by, e.g., the Intel 5300 network interface card [4], [8]. For LTE systems, although the RSRP and RSRQ can be readily obtained, e.g., via the application program interface (API) of some mobile phones, off-the-shelf equipment for CSI acquisition is still unavailable. For example, the SDR platform is employed in [6] and [7] while we employ the ZedBoard, both of which require the implementation of LTE baseband processing via either software or hardware.

LTE and Wi-Fi systems exhibit different channel characteristics due to the different propagation environments. Thus, although existing works have shown the high positioning accuracy of the Wi-Fi CSI fingerprinting, it is still unclear what accuracy the LTE-CSI fingerprinting can achieve. The first results of the LTE-CSI fingerprinting are presented in [6], where the positioning accuracy is on the meter level, comparable to the RSRP fingerprinting. The latest LTE-CSI fingerprinting results are provided in [7], where the mean distance errors of 0.47 and 19.9 meters are achieved for indoor and outdoor scenarios, respectively. The performance is much worse than the centimeter-level accuracy achieved by the Wi-Fi CSI fingerprinting as reported in [4].

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In this paper, we investigate the positioning accuracy of the LTE-CSI fingerprinting with the following contributions:

- To the best of our knowledge, we demonstrate for the first time that the centimeter positioning accuracy is achievable for the LTE-CSI fingerprinting. To obtain the results, we examine the factors affecting the positioning accuracy, under whose guide a LTE-CSI fingerprinting system is implemented for performance assessment.

- We propose a novel phase compensation method to improve the quality of CSI, which plays an important role to achieve the centimeter positioning accuracy as shown by the experimental results.

II. FACTORS AFFECTING POSITIONING ACCURACY

Except for channel characteristics, the design of CSI fingerprinting system has a major impact on the positioning accuracy. In this section, we examine the design aspects that affect the positioning accuracy by comparing the CSI fingerprinting system designed for Wi-Fi systems with centimeter-level accuracy [4] and the CSI fingerprinting systems designed for LTE systems with meter-level accuracy [6], [7], respectively. The aim is to guide us to build a high-accuracy LTE-CSI fingerprinting system.

A. POSITIONING ALGORITHM

The positioning algorithms in [4] and [6], [7] are different, where [4] employs a time reversal based algorithm while [6] and [7] employ machine-learning algorithms, specifically the K-nearest neighbor (KNN) algorithm and the multi-layer perceptron method, respectively. Considering that the fingerprint matching problem involved in the CSI fingerprinting system is essentially a classification problem, we will employ a machine learning algorithm to improve the positioning accuracy and reduce the complexity of online positioning.

B. CSI QUALITY

In [4] both channel amplitude and phase are employed for fingerprinting, while [6] and [7] only use channel amplitude. To exploit the phase information, the phase distortions should be compensated. In [4], a phase correction algorithm is proposed to estimate and compensate the phase distortions. For the CSI fingerprinting problem, however, we find that the impact of phase distortions can be eliminated without estimating the distortions, which motivates us to propose a novel low-complexity phase compensation algorithm.

C. FINGERPRINT GRANULARITY

The granularity of the fingerprint dataset restricts the positioning accuracy. Apparently, in order to achieve the centimeter-level accuracy, a fingerprint dataset with centimeter-level granularity is generally necessary. In [4] the fingerprint dataset has the granularity of 5 cm, while in [6] the fingerprint granularity is 0.5 m and in [7] the granularity is 1.2 m and 5 m in indoor and outdoor cases, respectively.

To explore the potential of LTE-CSI fingerprinting, we need to build a centimeter-level fingerprint dataset.

D. EVALUATION APPROACH

Given the fingerprint dataset and positioning algorithm, the positioning accuracy depends on how to select the testing points, specifically whether the testing points are selected from the reference points or not. The testing and reference points are identical in [4] but different in [6], [7]. This will degrade the accuracy of latter to a certain extent. From the perspective of practical applications, it is more reasonable to consider different reference and testing points because a user can be arbitrarily located in practice. We will evaluate the impact of different evaluation approaches on the positioning accuracy.

III. LTE-CSI FINGERPRINTING SYSTEM

In this section we first propose a phase compensation method to eliminate the impact of CSI phase distortions, and then describe the implementation of a high-accuracy LTE-CSI fingerprinting system.

A. CSI PHASE COMPENSATION

1) NECESSITY OF PHASE COMPENSATION

We use the downlink CSI from a single base station (BS) to a mobile station (MS) for positioning, where the BS has N_b antennas and the MS has N_r antennas. For LTE system, the cell-specific reference signals (CRSs) are employed for CSI estimation. It should be highlighted that different from Wi-Fi signals that are transmitted in burst mode, the LTE CRSs are transmitted continuously, which are always accessible for positioning service without the need of network authentication. In each LTE subframe with the duration of 1 ms, there are four orthogonal frequency division multiplexing (OFDM) symbols containing CRSs, which are evenly spaced in the frequency domain of each OFDM symbol. The total number of CRSs, denoted by N_c, depends on the bandwidth of the system. For instance, $N_c = 100$ and 200 for the bandwidth of 10 MHz and 20 MHz, respectively.

To build the fingerprint dataset, the experimental area is mapped by N_p predetermined reference points. The MS is placed on the reference points one by one, and the corresponding downlink CSI is estimated. The frequency channel response over the k-th CRS from the b-th transmit antenna to the r-th receive antenna at the p-th reference point can be expressed as

$$h_{p,b,r,k} = \sum_{l=1}^{L_{p,b,r}} a_{p,b,r,l} e^{-jw_c \tau_{p,b,r,l}} e^{-jk\Delta_f \tau_{p,b,r,l}}, \qquad (1)$$

where $L_{p,b,r}$ is the number of multipath components (MPCs), $a_{p,b,r,l}$ and $\tau_{p,b,r,l}$ are the gain and propagation delay of the l-th MPC, respectively, w_c is the carrier frequency, and Δ_f is the frequency spacing between adjacent CRSs. The parameters $L_{p,b,r}$, $a_{p,b,r,l}$ and $\tau_{p,b,r,l}$ may differ for different reference points p and antennas b, r. For notational

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simplicity, we omit the subscripts p, b and r for these parameters in the sequel.

The channel estimation in a practical receiver may suffer from synchronization error, sampling clock drift, frequency offset, phase noise, and received noise [9], [10]. Taking these impairments into account, the estimate of $h_{p,b,r,k}$ at time t can be expressed as

$$
\begin{aligned}
&\hat{h}_{p,b,r,k}(t) \\
&= e^{j(w_d t + \phi(t))} \sum_{l=1}^{L} a_l e^{-jw_c(\tau_l + \delta(t))} e^{-jk\Delta_f(\tau_l + \delta(t))} + n_{r,k}(t) \\
&= \underbrace{e^{j(w_d t + \phi(t) - w_c \delta(t))} e^{-jk\Delta_f \delta(t)}}_{\text{Phase distortion}} h_{p,b,r,k} + n_{r,k}(t), \quad (2)
\end{aligned}
$$

where w_d is the carrier frequency offset, $\phi(t)$ is the time-varying phase noise, $\delta(t)$ combines the time-varying synchronization error and sampling clock drift, and $n_{r,k}(t)$ is the received noise.

In order to improve the positioning accuracy, we often need to estimate the CSI multiple times, say N_s times, for the same reference point. Then, the acquired CSI at the p-th reference point can be expressed as

$$
\mathcal{F}_p = \left\{ \widehat{\mathbf{H}}_p(t_s) \right\}, \quad s = 1, \ldots, N_s, \quad (3)
$$

where $\widehat{\mathbf{H}}_p(t_s) = [\hat{\mathbf{h}}_{p,1,1}(t_s), \ldots, \hat{\mathbf{h}}_{p,N_b,N_r}(t_s)] \in \mathbb{C}^{N_c \times N_b N_r}$, which consists of the estimated channels between $N_b N_r$ antenna pairs over N_c CRSs, and $\hat{\mathbf{h}}_{p,b,r}(t_s) = [\hat{h}_{p,b,r,1}(t_s), \ldots, \hat{h}_{p,b,r,N_c}(t_s)]^T \in \mathbb{C}^{N_c \times 1}$, which is the estimated channels between a pair of antennas over N_c CRSs.

The expression of channel estimation given in (2) indicates a severe problem if the channel estimate is directly used for positioning. Specifically, it is shown that even when the real channel $h_{p,b,r,k}$ is fixed over time and the noise $n_{b,r,k}(t)$ is ignored, the estimated channel $\hat{h}_{p,b,r,k}(t)$ is still time varying. This leads to the mismatch between the channels for building the offline fingerprint dataset and for online positioning.

2) PHASE COMPENSATION METHOD

One way to circumvent the phase distortion problem is to only use the amplitude information, noting that $|\hat{h}_{p,b,r,k}(t)| = |h_{p,b,r,k}|$ is time invariant as shown in (2). However, this approach discards the phase information, which may degrade the performance.

In order to exploit the phase information, phase compensation is generally indispensable. In OFDM-based communication systems, phase compensation has been received extensive studies, where the phase distortion is first estimated and then compensated to facilitate coherent data detection. The CSI fingerprinting system has different task from the communication system, which aims to maintain time-invariant fingerprint rather than data detection. Such a change allows us to design a low-complexity phase compensation method without the need of phase distortion estimation. The basic idea of the proposed method is to conduct a relative phase compensation for each individual online or offline CSI. In particular, we use the phase of $\hat{h}_{p,b,r,k-1}(t)$ to compensate the

phase of $\hat{h}_{p,b,r,k}(t)$. To illustrate the principle of the proposed phase compensation method, we ignore the noise $n_{b,r,k}(t)$ in the sequel of this subsection, but the proposed method can be directly applied to the case with noise and will be used for the experimental performance assessment in the next section, where both noise and phase distortion are included.

Specifically, with the channel estimates $\hat{h}_{p,b,r,k-1}(t)$ and $\hat{h}_{p,b,r,k}(t)$, we compensate the phase of $\hat{h}_{p,b,r,k}(t)$ as

$$
\bar{h}_{p,b,r,k}(t) = \hat{h}_{p,b,r,k}(t) \cdot \frac{\hat{h}^*_{p,b,r,k-1}(t)}{|\hat{h}_{p,b,r,k-1}(t)|}, \quad (4)
$$

where $\bar{h}_{p,b,r,k}(t)$ is the new channel estimate after phase compensation. Upon substituting (2), we can derive $\bar{h}_{p,b,r,k}(t)$ as

$$
\begin{aligned}
\bar{h}_{p,b,r,k}(t) &= \hat{h}_{p,b,r,k}(t) \cdot e^{-j(w_d t + \phi(t) - w_c \delta(t))} e^{j(k-1)\Delta_f \delta(t)} \\
&\quad \cdot e^{-j\theta_{p,b,r,k-1}} \\
&= e^{-j\Delta_f \delta(t)} h_{p,b,r,k} e^{-j\theta_{p,b,r,k-1}}, \quad k \geq 2, \quad (5)
\end{aligned}
$$

where $\theta_{p,b,r,k-1}$ is the phase of the real channel $h_{p,b,r,k-1}$.

It is shown from (5) that the compensated channel estimate $\bar{h}_{p,b,r,k}(t)$ still includes a time varying phase term $e^{-j\Delta_f \delta(t)}$, which, however, is a common term for all the compensated channels over the CRSs with $k \geq 2$. Thus, we can further normalize $\bar{h}_{p,b,r,k}(t)$ by the phase of the compensated channel over an arbitrary CRS k, say $\bar{h}_{p,b,r,2}(t)$, as

$$
\bar{\mathbf{h}}_{p,b,r}(t_s) = e^{-j\bar{\theta}_{p,b,r,2}} [\bar{h}_{p,b,r,2}(t_s), \ldots, \bar{h}_{p,b,r,N_c}(t_s)]^T, \quad (6)
$$

where $\bar{\mathbf{h}}_{p,b,r}(t_s) \in \mathbb{C}^{(N_c-1) \times 1}$, and $\bar{\theta}_{p,b,r,2}$ is the phase of $\bar{h}_{p,b,r,2}(t)$. By replacing $\hat{\mathbf{h}}_{p,b,r}(t_s)$ with $\bar{\mathbf{h}}_{p,b,r}(t_s)$, we can update $\widehat{\mathbf{H}}_p(t_s)$, as defined below (2), as $\overline{\mathbf{H}}_p(t_s) \in \mathbb{C}^{(N_c-1) \times N_b N_r}$. Then, the acquired CSI at the p-th reference point can be updated as

$$
\mathcal{F}_p = \left\{ \overline{\mathbf{H}}_p(t_s) \right\}, \quad s = 1, \ldots, N_s. \quad (7)
$$

Remark 1: The proposed phase compensation method exploits the property of CSI-fingerprinting task to avoid the estimation of phase distortion. For online positioning, we only need to implement the proposed method once for the online estimated CSI, whose complexity is independent of the size of the offline fingerprint dataset. By contrast, the phase compensation algorithm proposed in [4] requires the estimation of phase distortion between the online estimated CSI and each CSI in the offline fingerprint dataset. Thus, its online processing complexity for phase compensation scales with the size of the offline fingerprint dataset, which is much higher than the proposed method.

Remark 2: It can be found from (6) that the proposed method scarifies one dimension of CSI to realize the relative phase compensation. Nevertheless, this has minor impact on the positioning accuracy due to the large dimension of LTE CSI.

Remark 3: The proposed method includes two steps of phase compensation as given by (4) and (6), both of which multiply the channel to be compensated with a phase of

other channel. Thus, the statistical distribution of the noise involved in the estimated channel does not change after the compensation. As aforementioned, the impact of noise is taken into account in the experiments in the next section.

B. IMPLEMENTATION OF LTE-CSI FINGERPRINTING SYSTEM

We develop a LTE-CSI fingerprinting system to assess the positioning accuracy. It follows the same design principle as exist fingerprinting systems, i.e., operating in two stages including offline building of fingerprint dataset and online positioning. But the implementation of the system incorporates the factors analyzed in Sec. II, which is described as follows.

1) OFFLINE BUILDING OF FINGERPRINT DATASET

The employed positioning algorithm has impact on the building of fingerprint dataset. For example, if the positioning is conducted by measuring the correlation between channels, e.g., the time reversal based algorithm in [4], then the acquired CSI can be directly used as fingerprint dataset. If machine learning is used for positioning, then the fingerprint dataset can be formed by the learned features or models according to the employed methods [3], [5].

We use the Random Forest (RF) method as an example to show the effectiveness of machine learning for fingerprint-based positioning. RF is effective to deal with large datasets (consider that we will create a fingerprint dataset with centimeter-level granularity and hundreds of dimensions for each channel) since it can work with subsets of data. Meanwhile, RF does not require data preprocessing, e.g., normalization, so that the channel amplitude and phase information can be directly used as attributes. The implementation of RF follows the work in [8]. Since RF works on real-valued attributes [8], we set the amplitudes and phases of $\overline{\mathbf{H}}_p(t_s)$ as the input attributes. Based on the subsets created by Bootstrap Aggregation, T decision trees are trained in parallel, and the outputs of these trees are finally combined by the voting algorithm. The trained model is then saved at the MSs for positioning. Since only the learned features instead of the raw channel data $\overline{\mathbf{H}}_p(t_s)$ are stored, the required memory size at MSs is generally not large.

The detailed considerations regarding fingerprint granularity and evaluation approach will be elaborated in the next section.

2) ONLINE POSITIONING

When a MS conducts positioning at time t, it first estimates the real-time LTE CSI $\widehat{\mathbf{H}}_p(t)$. Then, it can calibrate the estimated CSI by using the proposed phase compensation algorithm, and obtains the compensated CSI estimate $\overline{\mathbf{H}}_p(t)$. Finally, the amplitude and phase parts of $\overline{\mathbf{H}}_p(t)$ are extracted as the input attributes to the trained RF model, and the output of the model is the final positioning result.

IV. EXPERIMENT RESULTS

We conducted the experiments in a lab office at the local campus. A rectangular experimental area with $1\,\mathrm{m} \times 0.675\,\mathrm{m}$ was considered. In order to improve the fingerprint granularity, we mapped the experimental area by $N_p = 588$ uniformly scattered reference points with 5 cm vertical spacing and 2.5 cm horizontal spacing. These reference points were generated by an antenna scanner. The experiment environment, reference point layout, and system setup are shown in Fig. 1.

We designed a prototype system equipped with $N_r = 2$ antennas to receive LTE signals from a public macro BS operated by China Unicom, which is located out of the campus. According to our measurements, we find that the BSs deployed around the campus may have one or two antennas. In order to obtain a conservative positioning accuracy, we only estimate and utilize the CSI from one antenna of the macro BS. The radio frequency part of the prototype system was implemented on AD-FMCOMMS2, which is an evaluation board of the radio frequency transceiver chip AD9361. AD9361 is a popular radio frequency chip used in LTE BSs, which has adjustable carrier frequency from 70 MHz to 6 GHz. The baseband processing was implemented on ZedBoard, an evaluation board of the Xilinx all programmable SoC chip Zynq-7020. Zynq-7020 involves dual-core ARM processors and programmable logics, with which we can implement the baseband processing algorithms on chip. To reduce the implementation complexity for real-time processing, we estimated the channels only once in each subframe, which is reasonable for positioning because the movement of indoor users within a subframe (i.e., 1 ms) is negligible. The considered LTE system has the bandwidth of 20 MHz, which includes $N_c = 200$ CRSs. Thus, we can obtain a channel estimate with the size of 200×2 every millisecond.

To reflect the impact of the factor "evaluation approach" as discussed in Section II-D, we carried out two channel measurement campaigns on different days. In the first measurement, denoted by "CH-1", we controlled the scanner to move the antennas to each reference point, and then estimated the channels for 10 seconds per reference point, which corresponds to $N_s = 10,000$ channel estimates for each reference point. In the second measurement, denoted by "CH-2", we drove the scanner to generate a continuous movement of antennas in the experimental area. The movement distance was 16 meters, from which we sampled 16,000 testing points with the granularity of 1 mm. Note that most of these testing points are outside of the 588 reference points, which can reflect the real-life positioning scenarios and is thus of practical importance.

We consider the following two performance metrics.

1) *Mean classification accuracy (MCA)*: A positioning is called a correct classification if the closest reference point to the testing point is found. This metric measures the probability of correct classification.
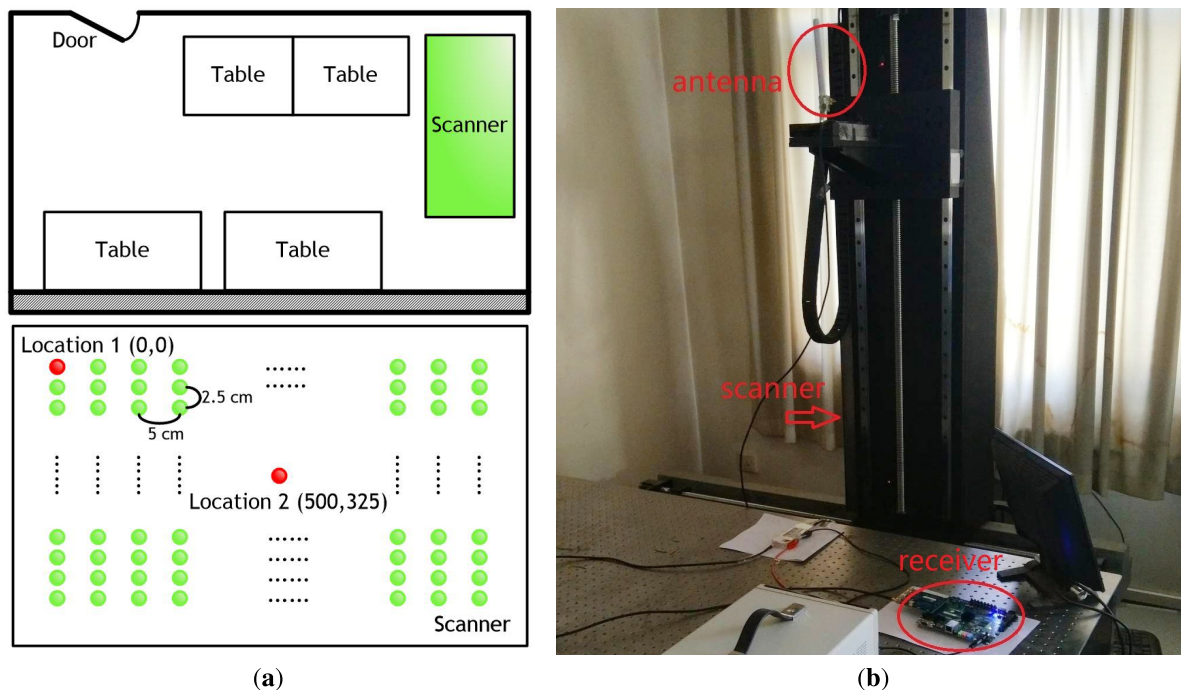
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(a)   (b)

FIGURE 1. (a) Experiment environment and reference point layout (b) Experiment system and setup.

2) *Mean Absolute Error (MAE)*: This metric measures the distance between the positioning estimate and the real position.

For comparison, except the proposed positioning scheme using RF algorithm with $T = 100$ decision trees, two relevant schemes are also considered, which employ the time-reversal (TR) based algorithm in [4][1] and the KNN algorithm in [6] with $K = 2$, respectively. For every algorithm, we consider three kinds of CSI for positioning: 1) only use amplitude (denoted by "AM"), 2) use both amplitude and uncompensated phase (denoted by "uCP"), and 3) use both amplitude and compensated phase with the proposed compensation method (denoted by "CP").

A. EVALUATION WITH CH-1

We first evaluate the performance under CH-1. We randomly select 60 samples from the 10, 000 channel estimates for each of the $N_p = 588$ reference points, where 30 samples are used to build the fingerprint dataset for training and the remaining 30 samples are used for testing. It can be found that the testing points are selected from the N_p reference points in this setup, which is a widely used evaluation approach, e.g., in [4].

The evaluation results are presented in Table 1, where the MCA of KNN cannot be measured and thus is not shown since KNN outputs K closest reference points. We consider different numbers of adjacent CRSs to reflect the LTE systems with different bandwidths. For the proposed RF based scheme, it can be observed that using channel amplitude

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[1]We choose the method in [4] for comparison because it can provide a centimeter-level accuracy, which is relevant to the focus of the paper.

can achieve comparable performance to using both amplitude and compensated phase when the bandwidth is large, while the gap between them increases with the decrease of bandwidth. It indicates that adequate high-quality channel features, no matter amplitude or phase, are indispensable for accurate positioning. If the phase is not compensated, using phase is harmful compared to only using amplitude. Comparing the three schemes, we can find that the RF based scheme has the best performance, which achieves very high positioning accuracy, for instance, MCA is 99.50% and MAE is 0.41 mm when $N_c = 200$. A reason for the good performance is that we use CH-1 for evaluation, where the reference points and testing points are identical, and moreover the channels for training and testing are measured simultaneously. To remove the impact, we further use CH-2 to evaluate the performance in the next subsection.

B. EVALUATION WITH CH-2

We next use the CSI in CH-2 for testing while the fingerprint dataset is generated by CH-1 as before. Now the testing points are sampled from a continuous movement trajectory, the overwhelming majority of which are taken outside of the reference points. Meanwhile, CH-1 and CH-2 are measured on different days, which can reflect the impact of fingerprint degradation over time. The evaluation results are presented in Table 2 in the unit of centimeter.

By comparing Table 1 and 2, we can observe the performance degradation caused by using CH-2 for testing. The proposed positioning system still outperforms the other two systems. It is shown that with the channel amplitudes and the phases compensated by the proposed method, the developed

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TABLE 1. Positioning results under CH-1.

CRSs (N_c)	25	50	100	200
MCA RF-AM	78.38%	92.69%	98.05%	99.53%
MCA RF-uCP	12.57%	22.17%	32.97%	51.04%
MCA RF-CP	82.10%	93.25%	98.13%	99.50%
MCA TR-AM	6.72%	12.59%	22.47%	44.07%
MCA TR-uCP	38.36%	60.31%	76.49%	84.65%
MCA TR-CP	57.25%	78.06%	91.84%	96.67%
MAE RF-AM (mm)	51.32	8.43	1.64	0.39
MAE RF-uCP (mm)	290.19	219.38	166.74	69.26
MAE RF-CP (mm)	29.35	7.86	1.25	0.41
MAE TR-AM (mm)	340.12	274.28	213.20	93.84
MAE TR-uCP (mm)	166.65	78.72	30.12	12.27
MAE TR-CP (mm)	90.14	40.28	13.34	4.57
MAE KNN-AM (mm)	318.62	236.34	146.99	59.26
MAE KNN-uCP (mm)	252.07	196.21	159.45	131.35
MAE KNN-CP (mm)	40.84	13.30	7.56	5.42

TABLE 2. Positioning results under CH-2.

CRSs (N_c)	25	50	100	200
MAE RF-AM (cm)	21.30	16.21	11.65	10.15
MAE RF-uCP (cm)	37.78	32.03	27.80	22.29
MAE RF-CP (cm)	21.32	14.59	10.04	8.71
MAE TR-AM (cm)	45.52	34.47	31.62	25.71
MAE TR-uCP (cm)	29.24	24.84	21.67	17.26
MAE TR-CP (cm)	25.06	21.93	17.58	16.35
MAE KNN-AM (cm)	40.16	33.21	27.49	19.86
MAE KNN-uCP (cm)	35.34	31.89	28.33	27.48
MAE KNN-CP (cm)	22.46	20.94	19.67	17.49

positioning system can achieve a centimeter-level accuracy for $N_c = 200$ (i.e., 20 MHz bandwidth), where the MAE is 8.71 cm.

C. COMPLEXITY COMPARISON

We finally compare the complexity of the three algorithms in terms of mean execute time (MET) during the online positioning stage, where the algorithms were run in Matlab on a computer with Intel® Core™ i9-7900X CPU (3.30 GHz). The MET of RF-CP, TR-CP and KNN-CP was obtained as 6.50 ms, 1.30 s, and 2.71 s, respectively. We can find that RF-CP has much lower complexity than others due to both the proposed phase compensation method and the advantage of machine learning in reducing online-processing complexity.

V. CONCLUSION

In this paper we investigated the positioning accuracy of the LTE-CSI fingerprinting system. By analyzing the impact of positioning algorithm, CSI quality, fingerprint granularity, and evaluation approach on the positioning accuracy, we implemented a LTE-CSI fingerprinting system under the guide of the four aspects, where a novel phase compensation method was proposed. The experiment results showed that

the centimeter-level positioning accuracy is achievable for the LTE-CSI fingerprinting system.

VI. ACKNOWLEDGMENT

REFERENCES

[1] A. Khalajmehrabadi, N. Gatsis, and D. Akopian, "Modern WLAN fingerprinting indoor positioning methods and deployment challenges," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 3, pp. 1974–2002, 3rd Quart., 2017.

[2] L. Gui, M. Yang, H. Yu, J. Li, F. Shu, and F. Xiao, "A Cramer–Rao lower bound of CSI-based indoor localization," *IEEE Trans. Veh. Technol.*, vol. 67, no. 3, pp. 2814–2818, Mar. 2018.

[3] X. Wang, X. Wang, and S. Mao, "Deep convolutional neural networks for indoor localization with CSI images," *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 1, pp. 316–327, Jan. 2020.

[4] C. Chen, Y. Chen, Y. Han, H.-Q. Lai, and K. J. R. Liu, "Achieving centimeter accuracy indoor localization on WiFi platforms: A frequency hopping approach," *IEEE Internet Things J.*, vol. 4, no. 1, pp. 122–134, Nov. 2017.

[5] J.-Y. Lee, C. Eom, Y. Kwak, H.-G. Kang, and C. Lee, "DNN-based wireless positioning in an outdoor environment," in *Proc. IEEE ICASSP*, Apr. 2018, pp. 3799–3803.

[6] 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, pp. 1–18, Dec. 2018.

[7] H. Zhang, Z. Zhang, S. Zhang, S. Xu, and S. Cao, "Fingerprint-based localization using commercial LTE signals: A field-trial study," in *Proc. IEEE VTC-Fall*, Sep. 2019, pp. 1–5.

[8] Y. Wang, C. Xiu, X. Zhang, and D. Yang, "WiFi indoor localization with CSI fingerprinting-based random forest," *Sensors*, vol. 18, no. 9, pp. 2869–2891, Aug. 2018.

[9] Y. Tian, H. Duan, and Y. He, "Passive localization via on-the-air LTE signals," in *Proc. IEEE ICC Workshops*, May 2019, pp. 1–6.

[10] Y. Tian, Y. He, and H. Duan, "Passive localization through channel estimation of on-the-air LTE signals," *IEEE Access*, vol. 7, pp. 160029–160042, 2019.

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YAFEI TIAN (Member, IEEE), received the B.S. degree in electronics engineering and the Ph.D. degree in signal and information processing from Beihang University, Beijing, China, in 2001 and 2008, respectively. He was a Visiting Scholar with the University of Southern California, Los Angeles, CA, USA, from 2010 to 2011. He is currently an Associate Professor with the School of E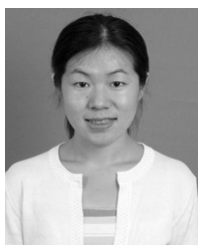lectronics and Information Engineering, Beihang University. His research interests include 5G cellular systems, MIMO precoding and interference mitigation, passive localization, and wireless sensing.

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