Wi-Wheat: Contact-free Wheat Moisture Detection with Commodity WiFi

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***Abstract*—In this paper, we present a non-destructive and economic wheat moisture detection system with commodity WiFi. First, we experimentally validate the feasibility of wheat moisture detection by using CSI amplitude and phase difference data. We then design Wi-Wheat system, where data preprocessing, feature extraction and support vector machine (SVM) classification are implemented for CSI processing module. For data preprocessing, we employ outlier detection, data normalization and eliminating noise for obtaining clear CSI amplitude and phase difference data. Then, we consider principal component analysis (PCA) based feature extraction for Wi-Wheat system. For SVM classification, Gaussian radial basis function (RBF) is used as the kernel function for wheat moisture detection. The experimental results show the Wi-Wheat system can achieve higher classification accuracy for LOS and NLOS scenarios.**

***Index Terms*—Channel state information (CSI); Commodity WiFi; phase difference; wheat moisture detection; machine learning; support vector machine (SVM).**

I. Introduction

With the increase in population and social mobility, the demand for food will be doubled by 2050 [1]. Globally, more than two billion tons of grain are harvested annually [2]. The harvested grains need to be stored safely to meet the future food demand of the population, and in particular, to deal with emergency needs such as disaster and famine. Safe storage of grains can be accomplished by manipulating two important physical factors: temperature and moisture content [2]. Compared with temperature monitoring, grain moisture detection is more challenging for different phases of the grain distribution chain between the consumer and producer.

The existing grain moisture content measurement techniques can be roughly classified into two categories, namely, destructive methods [3] and non-destructive methods [4]–[9]. Destructive methods for determining the moisture level in grain require oven drying for specific time periods at specified temperature with the existing methods. Because such methods are tedious and time-consuming, they are not suitable for general use in the grain trade, while other faster testing methods have been developed. On the other hand, non-destructive methods mainly exploit magnetic or electric properties to measure the grain moisture content. Moreover, the non-destructive technique is less time-consuming and requires less man power, as grain or food items can be directly used without any processing like cleaning or crushing. However, the detection devices for non-destructive methods are usually complex with a high cost.

Recently, channel state information (CSI) based sensing, detection, and recognition techniques have been successfully applied for many applications, such as fall detection, activity recognition, breathing and heart rate monitoring, and indoor localization [10]. CSI can provide fine-grained channel information, which reflects indoor channel characteristics such as multipath effect, distortion, and shadowing fading. Furthermore, compared with received signal strength (RSS), CSI amplitude and phase difference data are considerably more stable. Such CSI information can now be easily extracted from off-the-shelf WiFi network interface cards (NIC), such as the Intel WiFi Link 5300 NIC. Motivated by the existing CSI sensing techniques and the easy access with commodity WiFi, we propose to use CSI amplitude and phase difference data for contact-free wheat moisture detection.

In the paper, we present a non-destructive and economic wheat moisture detection system with commodity WiFi, namely Wi-Wheat. The proposed system does not need any dedicated device, thus having low cost with easy deployment. We first introduce the CSI background and experimentally prove the feasibility of wheat moisture detection using CSI amplitude and phase difference data. We then present the detailed design of the proposed Wi-Wheat system, which consists of CSI extraction and CSI processing. CSI amplitude and phase difference data are first extracted from the receiver NIC through the device driver, when the transmitter sends a number of packets to the receiver. Once the CSI data is collected, the CSI processing module of Wi-Wheat consists of data preprocessing, feature extraction, and training-based support vector machine (SVM) classification. For data preprocessing, we employ outlier detection, data normalization, and noise removal to obtain calibrated CSI amplitude and phase difference data. For feature extraction, we utilize the principal component analysis (PCA) technique, which not only retains the core data characteristics, but also reduces the input data dimension. For SVM classification, the Gaussian radial basis function (RBF) is used as the kernel function for wheat moisture detection. We also present our experiment results to validate the performance of the proposed scheme.

The main contributions of this paper are summarized below.

- We validate the feasibility of using fine-grained CSI amplitude and phase difference data for wheat moisture measurement. To the best of our knowledge, this is the first work that leverages CSI data to detect wheat moisture content level.

- We design the Wi-Wheat system, including its CSI extraction and processing modules. We also implement the Wi-Wheat system on two off-the-shelf laptop computers with commodity WiFi cards.
- We conduct experiments with real grain to validate the performance of the proposed Wi-Wheat system. The experiment results show that Wi-Wheat can achieve considerably high classification accuracy in both line-of-sight (LOS) and non-line-of-sign (NLOS) scenarios.

The remainder of this paper is organized as follows. The related work is reviewed in Section II. The preliminaries are discussed in Section III. We present the Wi-Wheat system design in Section IV and evaluate its performance in Section V. Section VI concludes this paper.

II. Related Work

A. Wheat Moisture Measurement

According to the measurement technology, the existing methods on wheat moisture measurement can be classified into drying method [3], capacitance method [4], resistance method [5], microwave method [6], [7], and neutron method [8]. The oven-drying method [3] is widely used in practice. Although this method is quite accurate, it is only suitable for the laboratory environment; it does not meet the requirements of online moisture detection in the field. The capacitive moisture detection method [4] is also popular, but its performance is limited by the fact that the measurement values are not only sensitive to the temperature, but also to the grain flow velocity and grain compactness in the dryer. Moreover, the measurement values can also be affected by many other factors in grain moisture measurement. For example, the method needs to implement sensor recalibration after a long time of use.

For the resistance method [5], the online resistance grain moisture detector is designed based on the model of the relationship between measurement frequency and grain moisture and the nonlinear correction method of temperature. The detector consists of a lower computer and a upper computer. The lower computer mainly senses the grain resistance values based on V/F conversion. The upper computer is focused on the conversion of moisture and frequency and nonlinear correction of temperature. The microwave method [6], [7] and neutron method [8] have several advantages, such as high accuracy, fast detection speed, non-destructive, and noninvasive measurements. Moreover, they can easily measure the the grain internal moisture. However, the measurement device is complex with a high cost.

B. CSI-based Sensing Systems

CSI-based sensing systems have been widely used for indoor localization and device-free sensing. Fingerprinting based indoor localization techniques that use CSI data have become the mainstream methods recently. For example, the FIFS [11] and DeepFi [12] systems employ CSI amplitude values for indoor localization; the PhaseFi [13] system exploits calibrated CSI phase data and the BiLoc system [14] incorporates bimodal CSI data as fingerprints, respectively, for indoor localization with a deep autoencoder network. Moreover, the CiFi system [15] considers phase difference values for indoor localization, where a deep convolution network is incorporated for learning the CSI image data, for improving localization accuracy and reducing the data storage requirement.

On the other hand, CSI based device-free sensing systems are also popular, which mainly includes activity recognition, fall detection, and vital sign monitoring. For activity recognition, the E-eyes system implements device-free location-oriented methods for recognizing household activities based on CSI amplitude [16]. For recognizing spoken words, the WiHear system exploits specialized directional antennas to measure CSI variations caused by lip movements [17]. The CARM system provides a CSI based speed model and activity model for identifying the relationship between human activity and CSI dynamics [18]. For fall detection, WiFall [19] and RT-Fall [20] utilize CSI amplitude and phase differences to detect the fall of certain objects, respectively. For vital sign monitoring, PhaseBeat [21] and TensorBeat [22] use CSI phase differences to estimate a single or multiple persons' respiration rates. In recent works Wi-Fire [23] and Wi-Metal [24], the authors employ CSI data to detect fire events and metal objects, respectively.

III. Preliminaries and Feasibility

The OFDM technique is widely adopted in the Physical Layer (PHY) or modern wireless communication systems, such as LTE and WiFi [25], [26]. In OFDM, the total spectrum (e.g., 20 MHz or 40 MHz in IEEE 802.11n) is divided into multiple orthogonal subcarriers [12], [22]. Moreover, data is transmitted on subcarriers to deal with frequency selection fading in indoor environments. Recently, OFDM have been exploited for wireless sensing such as indoor localization and activity recognition, where rich CSI data can be extracted from open-source devices for certain WiFi chipsets.

For the WiFi OFDM PHY in the 2.4 GHz or 5 GHz bands, the subcarriers can be regarded as narrowband flat fading channels, which are stable for RF sensing. The channel frequency response of the i_{th} subcarrier can be written as

$$h_i = |h_i| \exp\{j\angle h_i\}, \tag{1}$$

where $|h_i|$ and $\angle h_i$ are the amplitude and phase information for the ith subcarrier, respectively. In this paper, the Wi-Wheat system leverages CSI amplitude and phase difference data for device-free wheat moisture detection. The device driver for the Intel WiFi Link 5300 NIC with 802.11n can provide CSI from 30 subcarriers among the 56 subcarriers used in the PHY.

To validate the feasibility of using the fine-grained CSI data for wheat moisture measurement, we collect CSI amplitude and phase difference data for wheat piles with different moisture content levels. In this experiment, we consider wheat moisture content level of 13% as the critical moisture content (MC). We measure the CSI amplitude and phase difference data for normal wheat moisture content level of 11% as well as abnormal moisture content levels of 14.7% and 16.5%, as the WiFi signal propagates through the wheat pile. As shown in Fig. 1, there are small changes in CSI amplitude when the wheat moisture content level is increased from 11% to 16.5%. Moreover, Fig. 2 presents the CSI phase difference data when wheat moisture content level is changed. It can be seen that for wheat moisture content level of 14.7%, the CSI data is quite different from that when the moisture content level is 13%. Thus, we can see that CSI data can be leveraged for measuring the wheat moisture content level.

IV. Overview of the Wi-Wheat System

A. Wi-Wheat System Architecture

The Wi-Wheat system architecture is illustrated in Fig. 3, which includes two main parts: (i) CSI extraction and (ii) CSI processing. For CSI extraction, we leverage two mobile devices equipped with Intel WiFi link 5300 NIC: one as transmitter and the other as receiver. The transmitter is configured to operate in the injection mode and the receiver in the monitor mode. The 5 GHz CSI data can be extracted from the receiver, where CSI amplitude and phase difference data are thus obtained.

The CSI processing part includes three main functional modules, which are data preprocessing, features extraction, and SVM classification. CSI data preprocessing mainly consists of outlier detection, data normalization, and noise removal to obtain calibrated and clear CSI data sequences. For feature extraction, we exploit the PCA technique to extract CSI sequence features, which not only retains the main characteristics, but also reduces the dimension space of the CSI data. Finally, SVM classification is utilized for wheat moisture detection, where a nonlinear classifier with the Gaussian RBF kernel function is incorporated to achieve high classification accuracy. Based on the detection result, alarm messages may be sent to the warehouse manager once the wheat moisture content level is over the critical threshold.

B. Wi-Wheat Design Methodology

In this section, we present the design methodology of the Wi-Wheat system, including its data preprocessing, features extraction, and SVM classification modules.

1) Data Preprocessing: The data preprocessing module includes outlier detection, data normalization, and noise removal for calibrating the captured CSI data.

- Outlier detection: There are usually some abnormal values in the captured CSI amplitude and phase difference traces. Anomaly detection is performed to detect bad data values, which should be replaced from the raw CSI data. In Wi-Wheat, we adopt the Pauta criterion method to detect and remove outliers. The detailed process is presented as follows.

Step 1: let X_i, $i = 1, 2, ..., n$, be the the ith sample of CSI amplitude or phase difference from a subcarrier. We compute the arithmetic mean value as

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i. \tag{2}$$

Step 2: we then calculate the residual V_i as in (3) and the standard deviation σ of CSI amplitudes or phase differences as in (4).

$$V_i = X_i - \bar{X}, \;\; i = 1, 2, ..., n \tag{3}$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2}. \tag{4}$$

Step 3: for all X_i, $i = 1, 2, ..., n$, if $|V_i| > 3\sigma$, then we regard X_i as an abnormal value and replace it with the arithmetic mean value $\bar{X}$.

Step 4: repeat the above 3 steps till all samples are detected.

- Data normalization: In order to improve the detection accuracy, the input values should be limited in the range (0, 1) for SVM classification. Thus we choose to normalize the amplitudes or phase differences of CSI data. The normalized value Y_i is computed as

$$Y_i = \frac{X_i - X_{mean}}{X_{max} - X_{min}}, \tag{5}$$

where X_i represents the raw data, X_{mean} is the average value of the amplitudes, X_{max} and X_{min} are the maximum and minimum of CSI amplitudes or phase differences over a period of time after outlier removal.

- Noise elimination: Before applying feature extraction techniques, we choose the magnitude-squared Chebyshev Type II filter for further removing environment noise. We define the response function of the Chebyshev Type II filter as

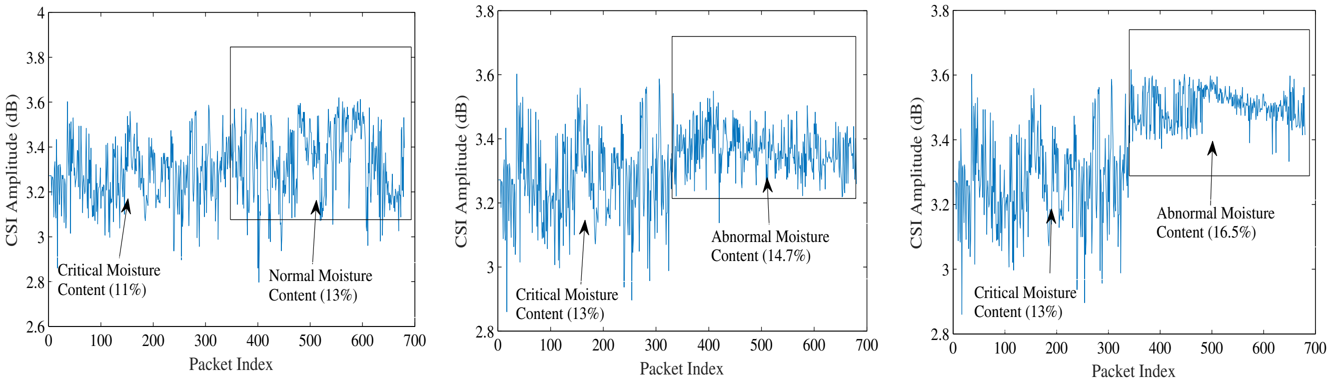
$$|H(j\omega)|^2 = \frac{\epsilon^2 C_N^2(\frac{\omega_s}{\omega})}{1 + \epsilon^2 C_N^2(\frac{\omega_s}{\omega})}, \tag{6}$$

where ϵ, $0 < \epsilon < 1$, is the amplitude frequency ripples in the stopband, ω_s describes a frequency scaling constant, N is the order number of the polynomial $C_N^2(\frac{\omega_s}{\omega})$, and

$$C_N(x) = \begin{cases} \cos(N\cos^{-1}(x)), & \text{if } |x| \le 1 \\ \cosh(N\cosh^{-1}(x)), & \text{if } |x| > 1. \end{cases} \tag{7}$$

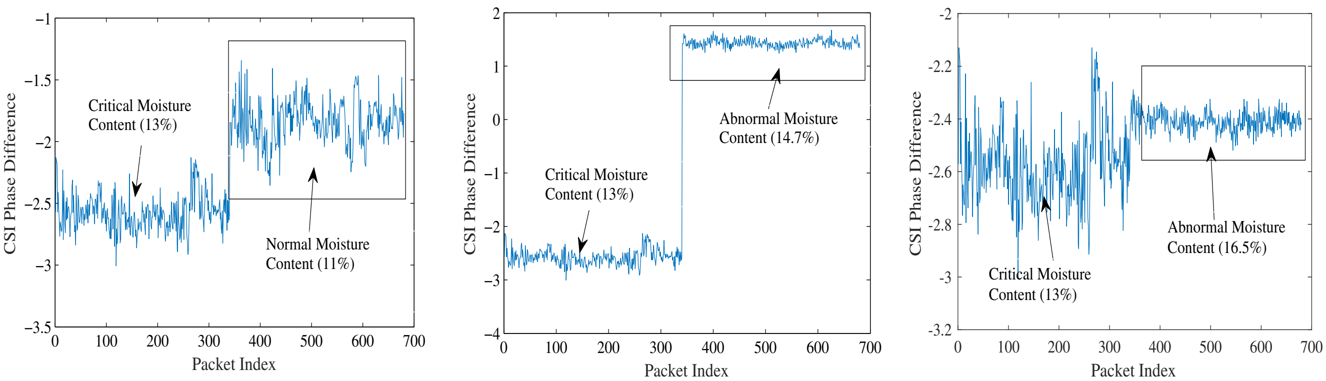
2) Feature Extraction: The PCA technique is employed in Wi-Wheat for feature extraction, which can not only focus on the main data characteristics but also decrease the input data dimension [18]. For CSI amplitude and phase difference data, we can compute p principal components for each CSI data sequence using the PCA method. The matrix with size $p \times n$ can thus be obtained. We set $p = 12$ for all the experiments reported in this paper. The procedure is described in the following.

- Preprocessing: Because the static components have been removed in the previous data preprocessing procedure, we



(a) Critical MC 11% and Normal MC 13% (b) Critical MC 13% and Abnormal MC 14.7% (c) Critical MC 13% and Abnormal MC 16.5%

Fig. 1. CSI amplitude measurements when wheat moisture content changes.



(a) Critical MC 13% and Normal MC 11% (b) Critical MC 13% and Abnormal MC 14.7% (c) Critical MC 13% and Abnormal MC 16.5%

Fig. 2. CSI phase difference measurements when wheat moisture content changes.

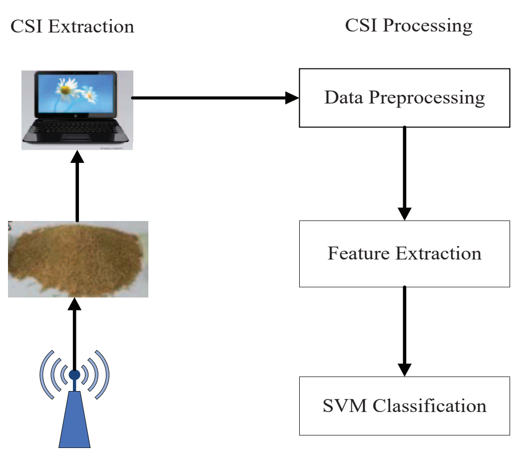


Fig. 3. The system architecture of Wi-Wheat.

employ the processed CSI amplitude or phase difference data to create CSI matrices as

$$Z = \begin{bmatrix} z_{11} & z_{12} & z_{13} & \cdots & z_{1n} \\ z_{21} & z_{22} & z_{23} & \cdots & z_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & z_{m3} & \cdots & z_{mn} \end{bmatrix}, \quad (8)$$

where m is the number of subcarriers, z_{ij} denotes the processed CSI amplitude or phase difference for subcarrier i recorded for packet j.

- Calculate the correlation matrix: We compute $\frac{1}{n}Z^TZ$ to obtain the correlation matrix, with size $n \times n$.
- Calculate eigenvectors: With the correlation matrix $\frac{1}{n}Z^TZ$, we apply eigen decomposition to compute the eigenvectors v_i, $i = 1, 2, ..., p$.
- Reconstruct the signal: We build a new CSI matrix using the correlation matrix and the eigenvectors, as $z_i = v_iZ$, where z_i is the ith principal component and v_i is the ith eigenvector.

3) SVM Classification: SVM is employed to classify the processed CSI data for wheat moisture detection [27]. We randomly divide the processed data into two groups to train and test, and then find a hyperplane in the n-dimensional data space. The training procedure is as follows.

Step 1: we use $f(x)$ to represent the classification function, which is defined by

$$f(x) = \text{sign}(\omega^T x + b), \quad (9)$$

where ω^T and b are the classification surface function parameters (ω^T is the normal vector and b is the offset), and x is the extracted feature from CSI amplitude or phase difference data.

Step 2: let y that takes 1 or -1 to represent two different categories (i.e., 1 and -1 mean normal and abnormal for Wi-Wheat, respectively), and add a certain constraint on the normal vector ω (see (9)). With Lagrangian multiplier α, the new objective function is formulated as

$$\mathcal{L}(\omega, b, \alpha) = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{n} \alpha_i (y_i(\omega^T x_i + b) - 1), \qquad (10)$$

where $\mathcal{L}(\omega, b, \alpha)$ is the objective function, n is the size of the training set, and α is the Lagrangian multiplier.

Step 3: we seek the maximum interval between the two boundary ends or the extreme dividing line to determine ω and b. Then the problem of finding the classification function is transformed into an optimization problem for ω and b. We can determine the final classification function as follows.

$$\max_{\alpha} W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} y^{(i)} y^{(j)} \alpha_i \alpha_j \langle x^{(i)}, x^{(j)} \rangle \quad (11)$$

$$s.t. : 0 \leq \alpha_i \leq C, \;\; i = 1, 2, ..., n \qquad (12)$$

$$\sum_{i=1}^{n} \alpha_i y^{(i)} = 0, \qquad (13)$$

where C is the penalty coefficient, and α_i and α_j are the Lagrangian multipliers.

Step 4: only two components α_i and α_j are selected in each iteration, while the other components remain constant. After obtaining α_i and α_j, the other components are then improved by α_i and α_j. We obtain a maximum margin hyper plane classifier as

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} y_i \alpha_i \langle x^{(i)}, x \rangle + b \right). \qquad (14)$$

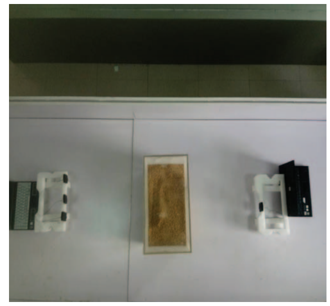
For wheat moisture detection using CSI amplitude or phase difference data, the problem is not linearly separable due to the complexity indoor environments. We can leverage the Gaussian RBF as kernel function for mapping processed CSI data into a high dimensional feature vector space. The new SVM classifier is defined as

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} y_i \alpha_i K\langle x^{(i)}, x \rangle + b \right), \qquad (15)$$

where the RBF kernel function $K\langle\rangle$ is given by

$$K\langle x^{(i)}, x \rangle = \exp\left\{ -\frac{1}{2\sigma^2} \left\| x - x^{(i)} \right\|^2 \right\}, \qquad (16)$$

where σ is the standard deviation.



(a) The LOS Scenario

(b) The NLOS Scenario

Fig. 4. Experimental setup.

V. Experimental Results and Discussions

We implement the Wi-Wheat system with off-the-shelf laptops and WiFi cards. The prototype consists of an HP ProBook 4411s laptop with 2.1GHz Intel (R) Pentium 2 CPU and 2GB RAM as receiver, and a Sony PCG-6S1T laptop as a transmitter. Both laptops use the Unbuntu 12.04 operation system, and are equipped with Intel Link 5300 WiFi NIC. To obtain 5 GHz CSI data, we set the transmitter in the injection mode and the receiver in the monitor mode. We inject packets from the transmitter, using one antenna, to the receiver with three antennas. Our experiments are conducted over a period of six months. For the experimental setup shown in Fig. 4, we test both LOS and NLOS scenarios in a computer laboratory environment.

In general, wheat can be safely stored for up to a year when the moisture content is under a temperate climatic condition, i.e., between 12% and 13% wet basis [2]. Thus, we choose wheat a moisture content level 13% as the critical value for the SVM classifier. If wheat moisture content is larger than the critical value, it is regarded as abnormal. Moreover, we utilize 100 samples to train the SVM classifier and other samples are used for testing.

Fig. 5 shows the accuracy of classification for the LOS scenario using either CSI amplitude (left) or phase difference data (right), respectively. When CSI amplitude data is used, we can see that as the wheat moisture content level is increased from 11% to 16.5%, the classification accuracy also increases from 94% to 97%. On the other hand, using phase difference data, the the classification accuracy is the highest, i.e., 98%, when the wheat moisture content level is 14.7%. The proposed Wi-Wheat system can achieve high classification accuracy for LOS scenario using CSI amplitude or phase difference data.

In Fig. 6, we present the accuracy of classification for the NLOS scenario using CSI amplitude (left) and phase difference data (right), respectively. Similarly, we can see that the classification accuracy using CSI amplitudes increase from 93% to 96% as the wheat moisture content level is increased from 11% to 16.5%. Moreover, for Wi-Wheat with CSI phase difference data, a 95% classification accuracy is achieved for every wheat moisture content level. The experimental results also validate the effectiveness of the Wi-Wheat system for the NLOS scenario.

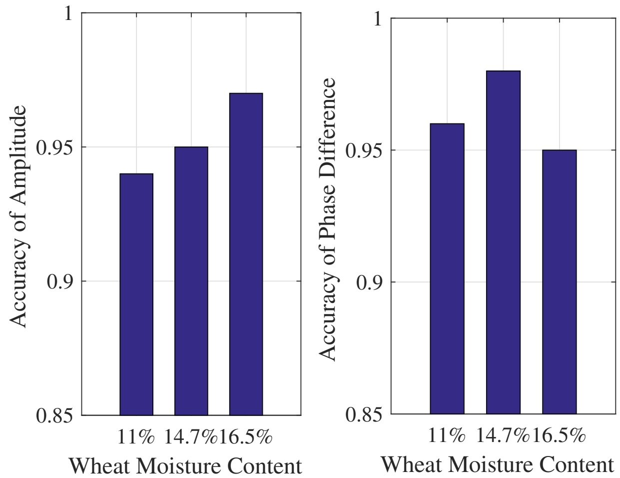


Fig. 5. Accuracy of Classification for the LOS Scenario: Amplitude (left) and Phase Difference (right) results.

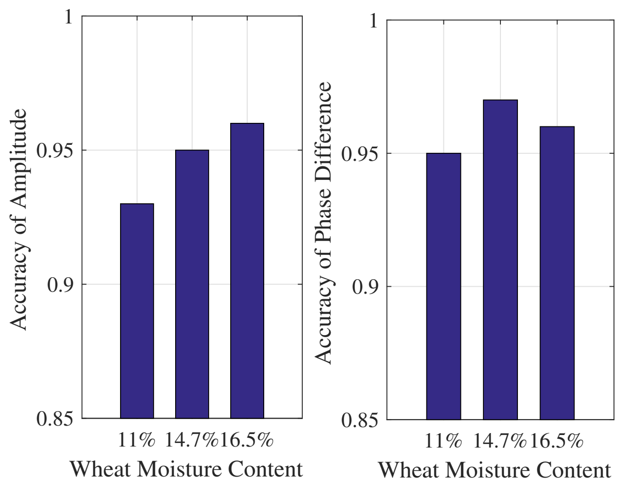


Fig. 6. Accuracy of Classification for the NLOS Scenario: Amplitude (left) and Phase Difference (right) results.

VI. CONCLUSIONS

In this paper, we proposed Wi-Wheat, a device-free wheat moisture detection system with commodity WiFi. We first introduced CSI preliminaries and validated the feasibility of using CSI amplitude and phase difference data for wheat moisture detection. We then presented the design of Wi-Wheat, including CSI extraction and CSI processing. Our experimental study demonstrated the efficacy of the proposed Wi-Wheat system, which can achieve high classification accuracy for both LOS and NLOS scenarios.

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