WiHumidity: A Novel CSI-Based Humidity Measurement System

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Abstract. Atmospheric humidity is one of the most important environmental attributes for weather condition. It affects the economy of nature as well as human life. Many environmental processes are affected by this attribute. For example, rice has the most powerful photosynthesis when the atmospheric humidity is in between 50% and 60%. For most of the human being, the humidity in between 20% and 80% is good to have a healthy life. Consequently, humidity measurement methods are urgently required. The existing methods are neither convenient for large scale deployment due to the high cost nor accurate enough to use. Recently, researchers found that humidity has a direct effect on radio propagation. This observation is undoubtedly useful to measure humidity in the environment. However, the humidity estimation based on received signal strength indicator (RSSI) is easily affected by the temporal and spatial variance due to multipath effect. Meanwhile, the change of radio signals incurred by RSSI-based systems is not that much obvious when the transmitter and receiver are in close distance. As a result, it is challenging to measure humidity in indoor environments. In this work, we provide a novel system, namely WiHumidity, to tackle this problem. The system utilizes the special diversity of channel state information (CSI) to alleviate multipath effect at the receiver. Extensive experiments have been conducted to verify the effectiveness of WiHumidity. The experimental results verify that on average, WiHumidity can achieve 79% measurement accuracy.

Keywords: Humidity measurement · Channel state information · Received signal strength indicator

1 Introduction

Wireless network technologies [1–3] have been developing rapidly in recent years. At the same time, people are increasingly concerned about the relationship between their health and nature. Atmospheric humidity strongly influences economic sectors as well as plays an important role in a variety of environmental processes.

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Besides hygrometer [4] and weather satellites [5], the existing humidity measurement methods are typically developed based on the idea of wireless signal attenuation. The accuracy of hygrometers is very high. However, due to the high cost, hygrometers are not suitable for large-scale deployment. On the other hand, meteorological measurement near the Earth surface is not accurate. The humidity measurement methods based on wireless signal attenuation require the use of several tens of GHz band and special equipments. These special equipments are quite expensive, and hence these methods are not suitable for large-scale deployment. Consequently, the necessity of an accurate and low-cost method to measure atmospheric humidity is high.

Wireless technologies are capable to identify the changes of environments. One application that utilizes this idea is [6]. This system exploits the change of wireless signal to measure rainfall. The heavier the rainfall the more attenuation is caused to the wireless channel. Based on the same principle, wireless network technologies can be used to measure atmospheric humidity [7]. However, there are still two problems with this idea. First, due to the small attenuation caused by water vapor, measurement over a long distance is required to have a significant amount of attenuation. A typical experimental distance can be upto several kilometers. It is inconvenient to conduct measurements over such long distance in one shot. Second, a very high frequency and special device have been used, which is not common in life.

There are some humidity measurement systems [8,9], which are developed based on the received signal strength indicator (RSSI) concept of radio signals. There are many problems associated with RSSI-based measurement systems. First, RSSI is measured from the RF signal at a per-packet level, the accurate value of which is difficult to obtain. Some surveys [10–12] show that the variance of RSSI can be upto 5 dB in 1 min. Second, multipath effect of the radio signal always exists, especially in indoor environments. RSSI is easily affected by this effect. In theory, a model to measure the humidity using the received power can be established. However, in practice, RSSI value is not monotonic due to multipath effect. Consequently, the RSSI-based propagation model is invalid in short distance.

In order to tackle these challenges, we utilize channel state information (CSI) instead of RSSI of wireless signals in designing our system. And, unlike in [8,9], we redefine a new propagation model to accommodate these issues. Our proposed WiFi signal-based humidity measurement system is based on the new propagation model, and we name our system as WiHumidity. In the system, two Commercial Off-The-Shelf (COTS) WiFi devices are used, one of which is a sender (e.g., a router) and another one is a receiver (e.g., a laptop). The sender continuously emits signals and the receiver continuously receives signals. We conduct the humidity measurement experiments over a short distance on 5 GHz radio band.

Our refined propagation model has an unknown parameter, the value of which is greatly dependent on the environment. Since the model parameter is unknown, we cannot directly apply the new model to predict the humidity of a certain place. Consequently, we adopt a supervised machine learning algorithm, i.e., Support Vector Machine (SVM) to build a learning model that infers the relationship between CSI samples and humidity. Once we establish the model using training data, we verify the effectiveness of our model using test data. The main contributions of this paper are summarized as follows.

- We develop a supervised learning model that concludes the relationship between CSI samples and humidity of a certain place, and can measure humidity accurately. To the best of our knowledge, this is the first work that has used fine-gained PHY layer information in orthogonal frequency division multiplexing (OFDM)-based systems to build a propagation model so as to improve the performance of atmospheric humidity measurement.
- Since the refined propagation model has an unknown parameter, it cannot be directly applied to measure humidity of a certain environment. Consequently, we develop a supervised learning model that concludes the relationship between CSI samples and humidity of a certain place.
- We implement our method in commercial 802.11 Network Interface Cards (NICs), and conduct extensive experiments in typical indoor environments to show the feasibility of our design.
- Experimental results demonstrate that WiHumidity can measure atmospheric humidity effectively and accurately. The average measurement accuracy can be upto 79%.

The rest of this paper is organized as follows. We first provide some background information related to the content of this paper in Sect. 2, which includes the detailed explanation of CSI and the traditional wireless signal propagation model. In Sect. 3, the refined propagation model based on CSI is introduced. In Sect. 4, we present the detailed design description of our CSI-based humidity measurement system. Followed by the experimental setup, we evaluate the performance of our system in Sect. 5. Finally, Sect. 6 concludes the paper with some directions on future research.

2 Preliminaries

In this section, we provide a detailed description of CSI and the general wireless signal propagation model.

2.1 Elaboration of CSI

CSI represents the channel properties of a communication link. In wireless communications, the radio signal is affected by surrounding physical environments. The combined effect of reflections, diffractions and scattering is revealed by CSI. In frequency domain, the narrow band flat-fading channel model is

$$y = Hx + n, \tag{1}$$

where y and x are the received and transmitted signal vectors, respectively. n is the additive white Gaussian noise vector, and H is the CSI matrix. The noise is often modeled as to have circular symmetric complex normal distribution with $n \approx cN(0, S)$. Thus, H in the above formula can be estimated as $H = \frac{y}{x}$.

2.2 General Radio Propagation Model

Previous studies [8,9,13] have indicated that many weather attributes can affect the transmission of electromagnetic waves. Precipitation, water vapor, oxygen, snow, mist and fog are the typical notions of weather attributes. Diffraction, refraction, absorption and scattering caused by these weather factors can affect the electromagnetic waves and cause attenuation to radio signals. Hence, the current widely distributed wireless communication network technologies have opened a new door to measure environmental attributes. Quite a lot of research have been conducted in this context for many different purposes, such as rainfall measurement [6,14–16], etc.

The research results in the field of Physics show that oxygen and water vapor are the main absorbing gases, especially in lower atmosphere [17]. Although other atmospheric molecules have definite effect on radio signals, their impacts are too small to be ignored. Hence, the attenuation γ due to dry air and water vapor can be described as follows.

$$\gamma = A_w + A_o = 0.1820 f_{GHz} N^{''}(f), \tag{2}$$

where A_w is the attenuation amount caused by the water vapor, and A_o is the attenuation amount caused by the dry air. $N^{''}(f)$ is the imaginary part of the frequency-dependent complex refractivity, which is a function of pressure, temperature and water vapor density. And, $N^{''}(f)$ is given by

$$N^{''}(f) = \sum_i S_i(.)F_i(.) + N_D^{''}(f), \tag{3}$$

where $S_i(.) = S_i(p, T)$ (the function of pressure and temperature) is the strength of the ith frequency line; $F_i(.) = F_i(p, T, f)$ (the function of pressure, temperature and frequency) is the line shape factor; and $N_D^{''}(f)$ represents the dry continuum due to pressure induced nitrogen absorption and the Debye spectrum [18]. Hence, according to (2) and (3), we can obtain

$$\gamma = 0.1820 f (\sum_i S_i(.)F_i(.) + N_D^{''}(f)). \tag{4}$$

Reorganizing (4), we obtain

$$\sum_i S_i(.)F_i(.) = \frac{\gamma}{0.1820 f} - N_D^{''}(f). \tag{5}$$

The right hand part of (5) does not have any variable related to humidity. However, both $S_i(.)$ and $F_i(.)$ have parameters, which are related to humidity. As for $S_i(.)$ and $F_i(.)$, the precise expression can be found in [18].

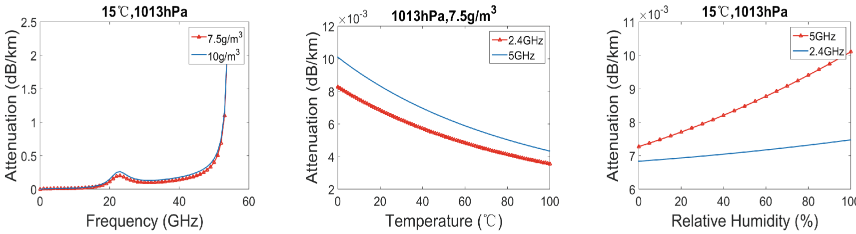
3 Proposed Refined Radio Propagation Model

In this section, we utilize the fine grained CSI instead of RSSI of radio signals to build a propagation model, and accommodate the issues relevant to humidity measurement in the model. Before proposing the new refined model, we discuss about the deficiencies of the existing RSSI-based propagation model.

3.1 Deficiencies of the RSSI-based Model

According to (4), we have plotted some figures, that characterize this model. As illustrated in Fig. 1(a), maximum attenuation occurs at around 22 GHz band within the range of [0 ∼ 40] GHz frequency band. In theory, water vapor has a resonance line at 22.235 GHz channel. Hence, at ∼22 GHz band, the signal loss is caused predominantly by the water vapor. Consequently, [22 ∼ 23] GHz electromagnetic wave was used for the experiments in [8]. Figure 1(b) shows us the relationship between attenuation and temperature. Below 100°C, the higher the temperature, the smaller the attenuation.

Figure 1(c) shows us the important information in this context. The functional relationship between the attenuation and humidity is monotonic. The higher the humidity, the larger the attenuation. At the same time, one important key point is, the attenuation ratio is relatively low (in the order of 10^{-3}) at 2.4 GHz frequency or at 5 GHz frequency band compared to that in Fig. 1(a). Consequently, in order to obtain obvious and measurable attenuation value, the measurement distance is often several kilometers long even at ∼5 GHz frequency band[1].

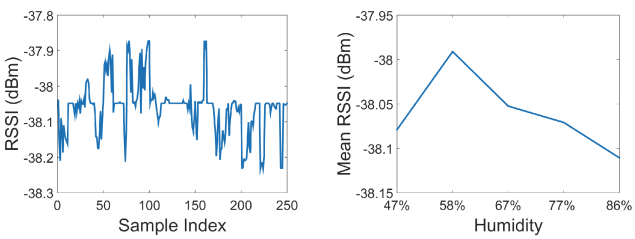


(a) The relationship between frequency and attenuation ratio (dB/km).

(b) The relationship between temperature and attenuation ratio (dB/km).

(c) The relationship between humidity and attenuation ratio (dB/km).

Fig. 1. The RSSI-based model.



(a) RSSI comparison with the varying humidity samples.

(b) RSSI comparison with the varying humidity.

Fig. 2. The relationship between humidity and RSSI of the signal.

[1] The higher the frequency band, the larger the attenuation value.

We chose a confined space, which is 4 m long and 2 m high. We used humidifier to adjust the humidity in this small space. Then, we collected data for five different humidity values. 50 samples were collected at each humidity value. In total, there were 5 different humidity points and their corresponding 250 samples. The distance between TX and RX was set to 3 m. Figure 2(b) describes the changing trend of RSSI for different humidity values. Whereas, in Fig. 2(a), we show the RSSI variance w.r.t. different humidity samples.

We conducted some experiments to emphasize the deficiencies of this model further. The distance between TX and RX was set to 3 m. In total, we collected 5 different humidity values and 50 samples for each humidity value. Figure 2(b) describes the changing trend of RSSI for different humidity values. Whereas, in Fig. 2(a), we show the RSSI variance w.r.t. different humidity samples.

To summarize, the greater the humidity, the greater the attenuation ratio. In theory, the RSSI value is monotonically decreasing with humidity. However, in Fig. 2, we see the fluctuations in terms of this trend. There are two reasons which contribute to this observation. First, the attenuation ratio is relatively low even at 5 GHz band, which is obvious in Fig. 1(c). Second, multipath effect always exists, especially in the indoor environment.

3.2 CSI-Based Model

In order to address the problems with the RSSI-based model, we refine the propagation model here. Comparing with RSSI, CSI can better reflect the quality of the channel. Denoting the CSI-based attenuation by CSI_{eff} and replacing γ with CSI_{eff} in (5), we can obtain

$$\sum_i S_i(.)F_i(.) = \frac{\alpha \cdot |CSI_{eff}|}{0.1820f} - N''_D(f), \tag{6}$$

where CSI_{eff} is given by

$$\mathrm{CSI}_{eff} = \frac{1}{K}\sum_{k=1}^{K}(\frac{f_k}{f_0} \times |H_k|), \quad k \in (-15, 15). \tag{7}$$

α is an unknown factor which is greatly dependent on the environment. f_0 is the central frequency. Respectively, f_k and $|H_k|$ are the frequency and amplitude of the kth subcarrier. The reason to replace γ by CSI_{eff} is that it can exploit the frequency diversity to compensate the small-scale fading effect.

4 System Design

Using the refined CSI-based propagation model described in the previous section, we propose a system that measures humidity in a certain place effectively. We name our system as WiHumidity. Although the model provides the relationship between the humidity of a certain place and CSI of wireless signal, our system is

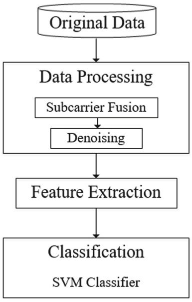


Fig. 3. The system flow diagram.

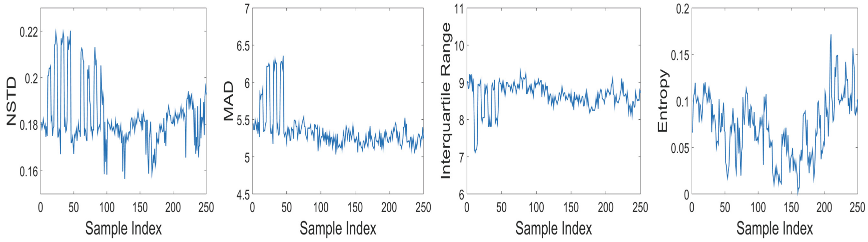
based on the supervised machine learning algorithm. Supervised learning algorithm requires some training data to build a prediction model, and test data to validate the model. In the following discussions, we provide the detailed description of our system including the methodology. Figure 3 shows the functional flow diagram of our system. There are mainly two components in the system, the functionalities of which are described as follows.

4.1 Data Collection and Processing

In a typical environment, CSI is easily influenced by human activities, and hence CSI needs filtering to reduce noise. We choose a confined space in the indoor environment, in which there are N_T number of transmit antennas and N_R number of receive antennas. WiFi NIC(s) of the receiver(s) report(s) CSI values over 30 OFDM subcarriers of the 20 MHz wide WiFi channel. This leads to 30 CSI samples with dimension $N_R \times N_T$ per humidity value. Consequently, the number of collected CSI samples for one humidity value is $30 \times N_R \times N_T$.

4.2 Feature Extractioin and Classification

In order to cope with the randomness of data, we collect a set of samples for each humidity value. Seven features of the collected $30 \times N_R \times N_T$ CSI samples (for per humidity sample) are used to build a classification model. These seven features are: (1) mean value, (2) normalized standard deviation (NSTD), (3) median absolute deviation (MAD), (4) interquartile range (IR), (5) maximum value, (6) skewness, and (7) signal entropy. As shown in the next section, none of the features alone can determine the corresponding humidity value effectively. Taking all features jointly into account, we apply a supervised machine learning algorithm, i.e., SVM to make a definite decision about the corresponding humidity.



(a) NSTD (b) MAD (c) IR (d) Entropy

Fig. 4. The change of individual feature value w.r.t. different humidity samples.

5 Experiments and Performance Evaluation

In this section, we first describe the details of the experimental settings and the implementation of our system, WiHumidity. Then, to justify the effectiveness of WiHumidity, we show the results of our experimentation.

5.1 Experimental Settings

For the experiment, we design a confined space, the size of which is 4 m long and 2 m high. We use humidifier to adjust the humidity of environment in this small space. One TP-LINK router acts as the TX. A desktop of DELL with 2.4 GHz dula-core CPU as the RX, and implements WiHumidity. The desktop is equipped with Intel WiFi Link 5300(iwl5300) 802.11n NICs. In order to avoid the interference from the neighboring bands, we conduct our experiment on 5 GHz band. Moreover, we implement our system on the MATLAB platform, and evaluate the system in a typical laboratory room. Then, we collect data to evaluate the performance of our system. In order to ensure the diversity of data, 50 samples are collected for each humidity value.

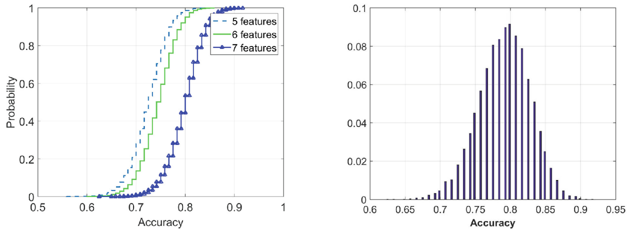
5.2 Experimental Results

5.2.1 Signal-Level Analysis of the Collected Data

Previous works [9,13] have proved that water vapor can cause attenuation to radio signals, which leads to the change in RSSI or CSI values. However, to the best of our knowledge, no model based on CSI has been established before. This is the first work that has established the relationship between humidity and CSI. The key of the humidity measurement problem is to extract features from the CSI samples to discriminate different humidity values. We select four different features of the CSI samples to show the variation with different humidity values. From Fig. 4, for different humidity values, we can find obvious difference in terms of a feature value. It implies that different humidity values have different variation of CSI.

5.2.2 The Final Measurement Performance

As mentioned previously, a total of 250 CSI-humidity samples are collected. To establish a classification model, 120 of them are used for training, the rest (130) are to test. Finally, we run the classification process for 10000 times. As demonstrated in Fig. 5, WiHumidity can achieve detection accuracy 79% on average. The highest accuracy can be even upto 91%. Figure 5(a) shows comparison of three features combination. Figure 5(b) is the pdf plot for the measurement accuracy when all seven features are taken into account in building the SVM classification model. One of the outstanding works, in this context, is to predict the humidity following the relation in (6). However, there is an unknown factor α in this equation, which can be determined using the relations in (5) and (6). Then, the results of the proposed classification model can be verified with that of the proposed CSI-based propagation model. We would like to leave this work as our future study. Furthermore, we have not compared the results of our classification model with that of a RSSI-based measurement model. This is because the short distance over which we have conducted our experiments, and the RSSI-based models are not applicable for the short distance. Moreover, it requires specialized expensive equipments which are not easy to obtain.



(a) CDF (b) PDF

Fig. 5. Accuracy of our SVM classification model.

6 Conclusions and Future Work

In this paper, we proposed an effective and low-cost humidity measurement system. Having noticed several drawbacks of the existing RSSI-based humidity measurement systems, we proposed a refined CSI-based propagation model. To the best of our knowledge, this is the first work that used fine-gained PHY layer information (CSI) in OFDM-based systems to build a propagation model for improving the performance of atmospheric humidity measurement. Since the refined model has an unknown parameter and it is greatly dependent on the environment, we used SVM learning model to predict the humidity. Comprehensive experiments were conducted to verify the effectiveness of the learning model in predicting humidity. The average measurement accuracy that we obtained was around 79%. The accuracy of the prediction can be further improved by using better machine learning algorithm.

As a continuation of this work, our first objective is to improve the measurement accuracy of the system. Perhaps, we can use higher frequency radio signals to improve the accuracy. Furthermore, we can conduct more comprehensive experiments at different environments while considering different distance between the TX and the RX to verify the new CSI-based propagation model further.

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