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Environmental Microchanges in WiFi Sensing

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***Abstract*—Using WiFi's Channel State Information for human activity recognition—referred to as WiFi sensing—has attracted considerable attention. But despite this interest and many publications over a decade, WiFi sensing has not yet found its way into practice because of a lack of robustness of the inference results. In this paper, we quantitatively show that even "microchanges" in the environment can significantly impact WiFi signals, and potentially alter the ML inference results. We therefore argue that new training and inference techniques might be necessary for mainstream adoption of WiFi sensing.**

I. Introduction

WiFi (IEEE 802.11) signals—like any electromagnetic signal—are altered by the environment through absorption, reflection, and scattering [1]. With the recent advancements in machine learning (ML), such altered WiFi signals have been shown to be capable of inferring human activities, recognize gestures, estimate the number of people in a room, and even reconstruct spoken words [1]. With cameras and wearable sensors having their own disadvantages, the ubiquitousness of WiFi along with its inconspicuousness, makes WiFi sensing a promising approach. But despite this enormous promise and a large volume of literature [2], WiFi sensing is still a largely academic discipline and has not matured into practice.

Hurdle on the path to practice: A receiver extracts Channel State Information (CSI) data from the received WiFi signals [3], keeping track of variations in the amplitude and/or phase over different frequencies. This data is processed by machine learning (ML) models to infer what activities might have led to the received CSI amplitude- and phase variations. To this end, an ML model is first trained using labeled CSI data and then used to classify previously unseen data [3]. However, it has been widely observed that ML models trained with WiFi signals from human activities of interest in one environment do not provide robust inference in a different environment, even for the same human subjects and activities. The impact of such *explicit* or "macrochanges" in the environment on WiFi sensing is now recognized to be a major challenge and efforts to mitigate it are actively being pursued [4].

But what has not been studied until now is the impact of "microchanges" in the environment on WiFi signals, and how they impact inference robustness. It is usually assumed that changes in WiFi signals due to small environmental changes are also small and have no impact on ML inference, especially since modern ML techniques are inherently robust. To the best of our knowledge, this is the first paper that draws attention to the impact microchanges in the environment have on WiFi signals, and shows that such changes are significant. Such microchanges could be changes in the position of furniture by as small as a few centimeters, or small changes in temperature or humidity. Almost all previous work is based on data collected over short durations (at most a few hours), which is then used for both training and inference. These short durations often conceal potential microchanges. In contrast, we have collected data over multiple days—to reflect real-life usage—that highlight the impact of microchanges. Our results indicate the need for rethinking how ML models should be trained for WiFi sensing and for expanding the potential set of training and inference inputs.

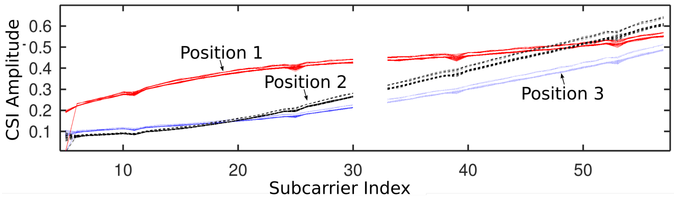

Fig. 1: CSI for different positions of an armchair in a room.

II. Visualizing Environmental Microchanges

We study two very common types of environmental microchanges and show their relevance to CSI data: 1) *Object displacements*: Objects in the environment might slightly change their positions, *e.g.*, a chair might move by a few centimeters. 2) *Atmospheric changes:* The indoor atmospheric conditions, *e.g.*, humidity or temperature, drift over time.

Object displacements: To study the impact of object displacements, we recorded approximately 170 WiFi frames, corresponding to a few seconds of time. This data was recorded in a room that included, besides other furniture, an armchair. We used a WiFi access point as a transmitter and a Raspberry Pi using the Nexmon [5] firmware as a receiver. During measurement, no one was present in the room. After the measurement, we moved the armchair by a few tens of centimeters, and repeated the measurement for two additional positions of the chair. The resulting distribution of the CSI amplitudes over different subcarriers, which correspond to different frequencies used by the WiFi network, are depicted in Figure 1. Here, the CSI amplitude has been normalized to lie between 0 and 1, and subcarriers that do not carry any information (*e.g.*, guard subcarriers) have been removed (hence the small gap in Figure 1). For each position of the armchair, there are approximately 170 curves that lie in such a close proximity that they cannot be distinguished from each other in the figure. However, the curves belonging to different positions of the armchair have unique shapes, illustrating that even such a minor change considerably alters the WiFi signals.

Further, we collected CSI data inside an office with an area of 12m × 6m, with two WiFi Access Points (APs). The office was occupied by up to six people engaged in different activities. The WiFi signal data was collected continuously

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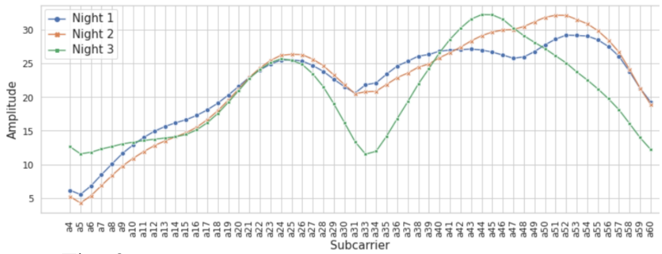

Fig. 2: Cumulative CSI recorded over different nights.

for a 74-hour period. During the 3 nights in the 74 hours under consideration, the room was unoccupied. To show that the CSI data nevertheless changed—even when there was no motion/activity in the room—for every subcarrier, we computed the sum of CSI amplitudes of all frames received in a night. Figure 2 shows these sums for the 3 different nights. Note that the CSI data changes considerably between different nights in the same office room, despite the "macro environment" remaining constant across the nights. These changes could be again related to small object (*chairs*) displacements during the day, and/or atmospheric (temperature/humidity) changes.

A WiFi sensing based *clock*: To further analyze such CSI changes, we partition the CSI amplitudes of all subcarriers for all the three nights into 10 groups (called *folds* in ML parlance) and used 9 folds for training and 1 fold for testing six different, commonly used classifiers, *viz.*,, Support Vector Machines (SVM), Decision Trees (DT), Convolutional Neural Networks (CNN), k-Nearest Neighbor (k-NN), Weighted k-NN (wk-NN), and Random Forests (RF). During the night we ensured that no objects (*e.g.,* furniture) in the room was moved. According to popular belief in the WiFi sensing research, in the absence of such displacement, all CSI amplitudes should be stable. To debunk this, we used the classifiers to infer the time at night from CSI, based on how the temperature, humidity, and other unknown environmental parameters changed during the course of the night and impacted the WiFi signals. There were 11 different classes: 8p.m., 9p.m., . . ., 6a.m.

If time could be accurately inferred solely based on WiFi signals, it would establish that significant changes in CSI values occur even without any macrochanges in the environment that prior research on WiFi sensing has primarily focused on. Table I displays the average recognition abilities of the six ML models trained on folds from the same night. In particular, it shows that the SVM and CNN models achieve an F1-Score of over 86% in recognizing the specific hour of the night.

TABLE I: CSI-based Hour Recognition

Model	Precision	Recall	Specificity	F1-Score	Accuracy
SVM	86.9	86.8	98.7	86.8	86.8
k-NN	79.2	78.6	97.9	78.9	78.6
Wk-NN	79.3	78.8	97.9	79.0	78.8
RF	80.7	80.5	98.1	80.6	80.5
DT	53.0	52.7	95.3	52.9	52.8
CNN	86.4	86.5	98.1	86.4	86.5

Impact of atmospheric changes: We have also studied how temperature and humidity, in particular, influence CSI data used for WiFi sensing. While the impact of temperature and humidity on wireless signal strength has been studied in the past [6], its impact on WiFi sensing (CSI data) has not been sufficiently investigated. We study their relationship using three different regression models (Gradient Boosting, Random Forest, and Linear Regressor) and show that a room's temperature and humidity may be accurately inferred from CSI data. Using the same 10-fold approach, in which each night is considered separately, our CSI-based linear regression model achieved an average root mean square error (RMSE) of 0.4 $^{\circ}C$ for temperature and 1.75% for humidity, and an average mean absolute error (MAE) of 0.3 $^{\circ}C$ for temperature and 1.35% for humidity (see Table II). Hence, there is an overall error of 3% in temperature estimation and 6% in humidity estimation in the setup we have studied. While we have focused on temperature and humidity alone, there could be additional unidentified factors that affect the CSI data, *e.g.,* the sensing device's temperature due to overheating.

TABLE II: CSI-based Temperature and Humidity Estimation

	Temperature		Humidity	
Model	RMSE	MAE	RMSE	MAE
Gradient	0.63	0.40	1.83	1.43
RF	0.60	0.44	1.81	1.40
Linear	0.40	0.30	1.75	1.35

III. Concluding Remarks

Most prior research on WiFi sensing have focused on mitigating the impact of environmental *macrochanges* on inference accuracy, while ignoring how *microchanges* might influence CSI data. Examples of such macrochanges involve a change in the room in which human activity or gestures are being recognized. Further, the data used for illustrating sensing results was limited to at most few hours, with a part of the data used for training ML models and the rest used for inference. With such limited time durations, the impacts of environmental microchanges were small. Using a variety of experiments and data collected over multiple days, we have demonstrated that small shifts in the furniture in a room, or changes in the room's temperature and humidity can cause large changes in CSI data. More factors contributing to such microchanges need to be investigated in the future. Our findings provide more insights into why inference in WiFi sensing continues to remain fragile, despite the availability of powerful ML models. To be able to transition WiFi sensing technology to practical scenarios, ML models might also need to take into account factors influencing environmental *micro*changes, such as temperature and humidity, which is currently not done. How inference robustness may be ensured in the presence of small changes in the room's configuration, such as changes in the position or orientation of a chair in the room, also needs to be studied in the future. Our results in this paper might motivate some of these studies.

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