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PhysiFi: WiFi Sensing for Monitoring Therapeutic Robotic Systems

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***Abstract*—Patients recovering from limb-impairing strokes require consistent and precise physical therapy (PT) to regain mobility and functionality. Autonomous rehabilitation robots are increasingly adopted during recovery, offering a scalable solution to reduce the burden on physical therapists while assisting patients in performing prescribed exercises accurately. However, the effectiveness of these treatments often relies on professional supervision to ensure patients follow the robot's movements properly, which could be challenging considering the ongoing shortage of physical therapists. Current PT monitoring systems primarily rely on camera-based technologies, which usually raise concerns due to potential privacy violations and high deployment costs, or wearable devices that are intrusive and uncomfortable for patients. To address these limitations, we propose *PhysiFi*, a novel approach that leverages ubiquitous WiFi signals available in most indoor environments, such as homes, rehabilitation centers, and assisted living facilities. By analyzing Channel State Information (CSI) from ambient WiFi signals and employing deep learning models, PhysiFi can track and recognize exercises performed by patients with rehabilitation robots. Our experiments demonstrate that PhysiFi can accurately identify prescribed exercises and evaluate whether patients are following the robot's movements correctly, providing a non-intrusive, privacy-preserving, and cost-effective alternative for monitoring physical therapy sessions.**

***Index Terms*—WiFi sensing, robot activity recognition, physical therapy, channel state information.**

I. Introduction

Physical therapy involves using physical stimuli through various exercises, stretches, and massages to improve mobility for individuals with limited or impaired motor skills. In the United States alone, more than 795,000 people suffer from a stroke each year. Strokes result in reduced mobility for more than half of survivors over the age of 65 [1]. Patients encounter various limitations, including restricted ability to perform exercises and weakness or paralysis in limbs. Physical therapy is the recommended method of recovery for most stroke victims. Patients often struggle to perform exercises independently and require assistance from a therapist. In recent years, rehabilitation centers have begun utilizing autonomous rehabilitation robots to assist patients with exercises. Studies show that patients receiving robot-aided treatment experience more effective care than those relying on manual therapy [2], [3]. Consistent physical therapy is also known to reduce the likelihood of complications in stroke patients [4].

Most physical therapy treatments require in-person visits with a therapist who may engage directly in the treatment through manual physical therapy techniques, such as massaging, assisting with stretching, or guiding limb exercises. Physical therapy becomes more effective when exercises are performed with a higher number of repetitions, a task where autonomous rehabilitation robots often surpass human professionals [2]. This advantage has driven the growing adoption of autonomous robots in rehabilitation. As it is illustrated in Fig. 1, the patient's limb requiring rehabilitation is typically strapped to the robot, which either passively acts (guiding the affected limb with no resistance from the patient) or actively (the affected limb guides the robot's action) [5]. The professional remains in the room to ensure active patient participation, which is essential for effective treatment. While this approach combines the precision of robotic assistance with the expertise of a therapist, it restricts patients to treatments that require direct professional supervision.

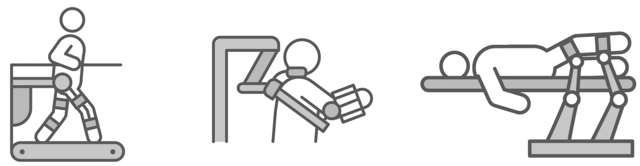


Fig. 1: Usage of robots in various rehabilitation exercises.

In recent years, there has been a significant drop in the number of practicing physical therapists, with vacancy rates reaching 17% [6]. In 2021 over 22,000 physical therapists left the practice. This shortage has resulted in increased wait times for patients requiring treatment [7]. Alternative monitoring solutions that enable patients to perform exercises with the assistance of a robot, without requiring a professional's presence, would significantly increase patient accessibility. Note that professionally monitored sessions can still be administered as needed but can be performed less frequently.

In this study, we propose *PhysiFi* system that aims to facilitate the monitoring of robot-assisted physical therapy sessions using the analysis of ambient WiFi signals. The proposed system utilizes a WiFi transmitter and a receiver which exchange WiFi packets not only to recognize the movements of the robotic arm but also to understand the compliance by the patients to those movements by their limbs attached to the robot's arm. This is achieved by recognizing signal amplitude patterns obtained from the Channel State Information (CSI) over WiFi subcarriers through a deep learning method [8]. Since the proposed system targets both the high-level movements of the robot and the low-level differences (i.e., compliance of the human to robotic movements that mimic prescribed exercises), we use a neural network architecture that combines the features extracted from earlier layers (i.e., early exit) as well as later layers. Experimental results show that through such a hybrid learning structure, we can achieve an effective recognition model that not only understands the compliance of the people to the robotic movements but is also robust to different people performing the activities.

The rest of the paper is organized as follows. We first talk about the robot setup used, and provide an overview of WiFi sensing and related studies in Section II and highlight the differences of this study. In Section III, we then provide the proposed method in which we describe the data collection process, preprocessing steps and the developed machine learning model. Next, we provide the evaluation results in Section IV. Finally, we provide our concluding remarks and discuss on future work in Section V.

II. Background

A. Robotic Arm

All experiments were performed using the ABB GoFa™ CRB 15000 Collaborative Robot [9]. The GoFa Robot is a high-capacity collaborative robot and can be used in various industrial applications. Thanks to lightweight and flexible (i.e., articulated on six axes) design, it can also be leveraged in assisting the rehabilitation exercises. Besides its main features such as over 1.5 meter extensibility of the arm and easy programmability, it is also designed to collaborate with surrounding objects and humans safely, which is another reason why we used it in our study. While it can be used in different types of rehabilitation exercises, in this work, we mainly considered arm based rehabilitation exercises where we secured the human arm to the robot arm with a cotton sling designed to stabilize and position the arm.

B. WiFi Sensing

WiFi sensing method relies on the usage of collected CSI data from ambient WiFi signals [10]. The collected CSI data is used to extract amplitude and phase values over WiFi subcarriers. Then, after removing anomalies and performing some smoothing (e.g., window averaging) and calibration operations (specifically for phase values to remove the random offsets [11], [12]), a neural network is trained using this data. The neural network learns unique features from the CSI patterns associated with different activities and thus can recognize them successfully [13].

The CSI matrix is formed with the sum of multiple paths that the signal propagates between a transmitter and a receiver and it is formulated as:

$$H(t) = \sum_{i=1}^{N} \alpha_i(t) e^{-j2\pi f \frac{d_i(t)}{c}}$$

where N represents the number of paths, $d_i(t)$ denotes the length of the i-th path, $\alpha_i(t)$ is the complex variable that consists of the phase and amplitude attenuation information, f is the carrier frequency, and c is the speed of light.

Initial WiFi sensing studies that rely on CSI have used Intel 5300 Network Interface Card (NIC) and the Linux 802.11n CSI Tool [14]. However, this has changed with the recently developed lightweight standalone solutions [15], [16]. In this study, we use ESP32 microcontrollers as TX and RX devices to setup our system and use ESP32-CSI-tool [17] to extract the CSI data from the receiver. We then compute the amplitude values and use them only to develop our WiFi sensing system.

C. Related Work

WiFi sensing has recently been considered in many application domains including human activity recognition [18], [19], occupancy monitoring [20], [21], security [22], [23], physical therapy [24], and agricultural sensing [25], [26]. It has also been considered for robotic activity recognition very recently [27], where recognition of eight different robotic arm movements have been targeted. The authors also study recognition of movements by two robot arms in [28] where they also use audio and video data to increase the accuracy. However, in these studies, there is no human involvement considered together with the robotic movements as in the robot-assisted physical therapy exercises considered in our study.

Apart from WiFi sensing based studies, monitoring of robot-assisted rehabilitation and human-robot interaction have been studied heavily from various aspects including robotic hardware [29], sensing technologies [30], and patient engagement [31]. Machine learning techniques [32] are also utilized not only for the recognition of the movement intention, but also for controlling the human–robot interaction and providing a quantitative assessment of motor functions. However, these studies consider physiological (e.g., electroencephalogram (EEG), electrocardiogram (ECG)) or physical (e.g., force/position information from robot) data collected during the rehabilitation sessions.

Different from these studies, we propose a non-invasive solution based on WiFi CSI data only. To the best of our knowledge, this is the first work that leverages WiFi sensing method to not only recognize the robotic movements but also to assess the compliance of the human movements to the robotic movements. This is achieved by benefiting from both the low-level features extracted in earlier layers and also the high-level features in the later layers. Note that, there are some works that study early exit models within the context of human activity recognition systems [33]. However, these studies look at whether the latency and memory can be reduced in these systems without affecting the recognition performance significantly. Thus, these studies do not directly consider the benefit from both low-level and high-level features jointly, which perfectly fits to our context in this study.

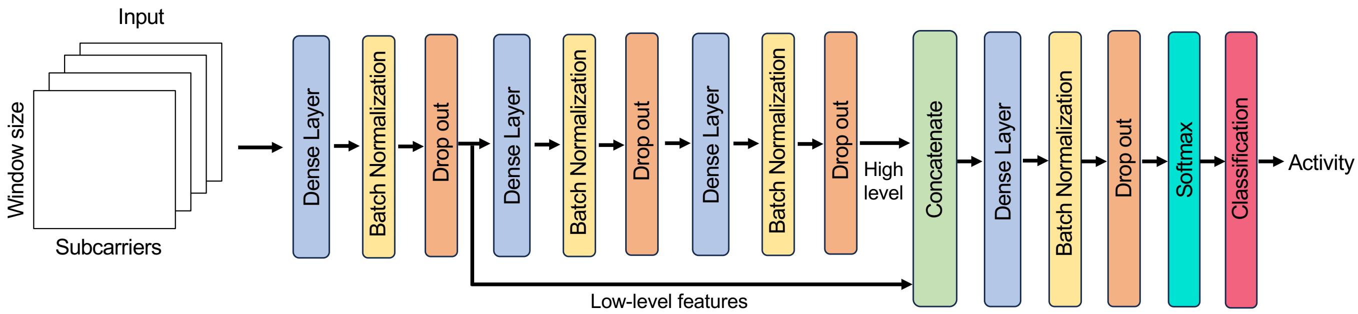


Fig. 2: Proposed model architecture that combines low-level and high-level features.

III. Proposed Solution

In this section, we first talk about the assumed rehabilitation setup and how the robot is used for assistance. Then, we discuss how the CSI signals are used and processed. Finally, we elaborate on the proposed approach and the associated neural network model developed for recognition and quality assessment of patient's exercises.

A. Rehabilitation Setup

We assume a scenario in which a rehabilitation patient with a limb impairment will be performing their exercises with the assistance from the robotic arms. To this end, our goal is to develop a WiFi sensing system that can not only recognize the movements performed by the robotic arm but can also recognize if the movements are properly performed. Note that, for example, if the rehabilitation exercises are arm based movements, the arm of the patient will be strapped to the robot's arm, which will be programmed to perform movements that will help the patient perform the prescribed physical therapy exercises.

B. CSI Pre-Processing

The collected raw CSI data is processed to first obtain the amplitude values for each subcarrier and to get rid of some anomalies to facilitate the feature extraction. There are 64 subcarriers in the collected CSI data, however only 52 of them include non-zero and meaningful values, thus we filtered the others out. We then used both Hampel filter and window-averaging methods to remove the anomalies and smooth out the temporal transitions in the data. Hampel filter [34] is computed by

$$\hat{h}_i = \begin{cases} h_i & |h_i - med_w(h_i)| \leq \sigma \times k \\ med_w(h_i) & \text{otherwise}, \end{cases} \tag{1}$$

where $med_w(h_i)$ is the median of values in a window of size w that ends at ith data, k is constant (we used $k = 3$), and σ is the standard deviation of residuals ($r_i = h_i - med_w(h_i)$) computed by:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_i - \bar{r})^2},$$

where $\bar{r}$ is the mean of residuals. After removing the anomalies, window averaging method then computes

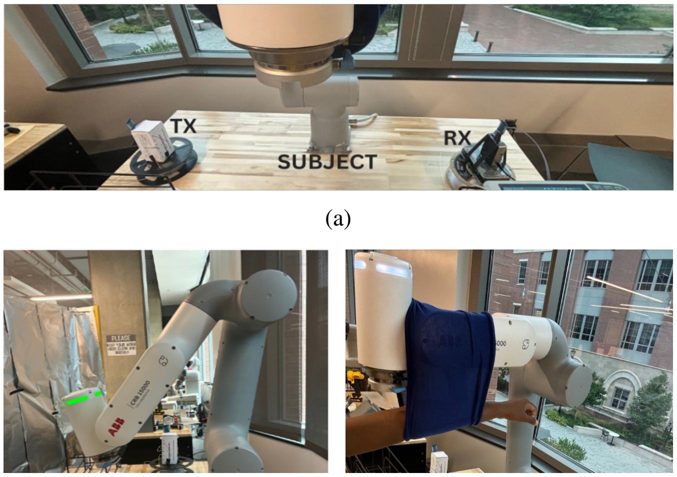
$$\hat{h}_i = \frac{1}{w}\sum_{j=0}^{w-1} h_{i-j} \tag{2}$$

for each data point collected.

In order to capture the temporal patterns in the data, we generate sliding window based data points using a window size of 100. Note that this refers to one sec of each recorded movement as we use 100 Hz of packet generation rate at the transmitter device. Following this step, we split this windowed data points into training and test portions. In order to reduce the dimensionality of the dataset and identify most critical data points, we apply principal component analysis (PCA) to training dataset and transform the test dataset using the fitted PCA parameters on training data. Note that PCA should not be applied to all dataset before split as it will create correlation between the training and test portions. Next, we use this filtered, denoised and split datasets for training and testing of developed neural network model.

C. Model Architecture

For the sake of having a simple yet efficient architecture, we develop a sequential deep neural network (DNN) based model. Since our goal is to recognize not only the high-level features (e.g., robotic arm movements) but also the low-level features (e.g., compliance by the human arm), we propose a model that can recognize both of them simultaneously. Since the earlier layers in a DNN model will help extract low-level features, we take an early exit and combine it with the features obtained from later layers. The proposed model architecture is illustrated in Fig. 2. The input is a window (W) of the amplitude values from all non-zero subcarriers. We use a dense layer with relu activation, followed by a batch normalization and dropout layers, and get an exit to obtain low-level features. We then repeat this pattern two more times to further extract high-level features. We then combine these low-level and high-level features and repeat the dense layer, batch normalization and dropout layer pattern one more time and use softmax to obtain the class predictions at the end.



(a)

(b)

(c)

Fig. 3: Setup showing (a) TX (transmitter) and RX (receiver) placement, (b) Robot only scenario, and (c) Robot with strapped arm scenario.

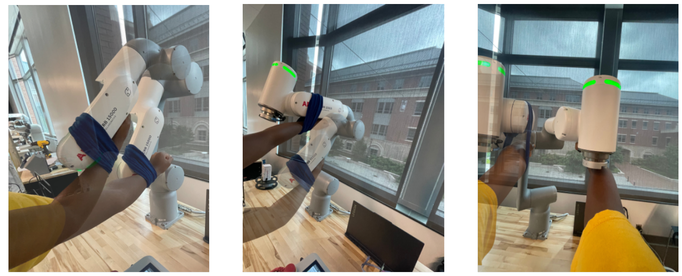
IV. Evaluation

In this section, we evaluate the performance of the proposed PhysiFi system. We begin with describing the experimental setup and data collection process. Then, we discuss how the model training is performed and present the model prediction results for different scenarios.

A. Experimental Set up and Data Collection

We start with collecting WiFi CSI data for three different rehab exercises. To this end, we consider three basic movements shown in Fig. 4, namely, (i) Forward-Inward, (ii) Up-Down, and (iii) Left-Right. These movements are performed in three different scenarios but always with the same number of repetitions. That is, each of these movements are continuously performed for 5 seconds with a 5 second transition before the next one. We then repeat this sequence 15 times. In the first scenario, we consider only robotic movements (Fig. 3b). In the second scenario, we consider a human arm strapped to the robot arm while performing each of these movements (Fig. 3c). Here, we also assume human is following the robot arm's movements properly (i.e., full compliance). In the third scenario, we consider the human arm strapped to the robot arm again but it is not following the robot's movements properly i.e., when robot arm is going left, human arm is trying to stay static or trying to go right (while still strapped). Note that the human arm still moves to where the robot arm goes as it is strapped, however, lack of compliance creates differences in the movements.

During each of these experiments, we used our ESP32 CSI tool [15], [17] to collect CSI data from the ambient WiFi signals. We installed one ESP32 in transmitter (TX) mode and one ESP32 in receiver (RX) mode on the sides of the table that the robot is on, as shown in Fig 3a. The TX device is set to send 100 packets per second to the RX device. RX is



(a)

(b)

(c)

Fig. 4: Performed exercises (a) Forward-Inward, (b) Up-Down, (c) Left-Right.

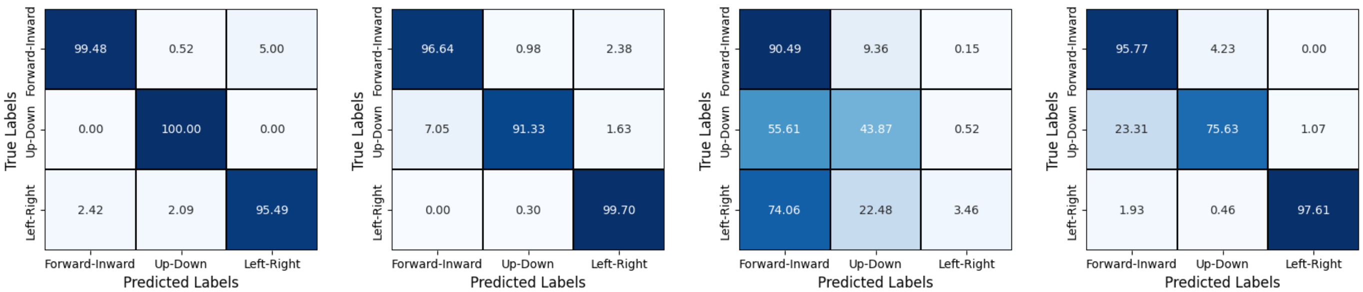
connected to a Raspberry Pi device which then receives the extracted CSI data and stores it. As it is shown in Fig. 3b, we also used an aluminum foil room divider to mitigate the impact of other environmental movements in our large and shared lab environment.

B. Model Training

The proposed neural network model is trained with the 70% of the collected data for the robot only scenario. We used Adam optimizer with a learning rate of 0.001 and cross entropy loss as the loss function. We performed training up to 100 epochs with a batch size of 128. We also used an early stopping mechanism based on validation accuracy, which stops the training if no improvement is achieved for 10 consecutive epochs. We then tested the trained model on the remaining 30% of robot only scenario as well as on the entire data collected from scenarios with the human arm strapped to the robot arm. Note that the model architecture is designed to utilize both the low-level and high-level features from the robotic movements. Thus, the expectation is to be able to recognize the robot movements properly even when the human arm is involved and performing a full compliance to the robot movements. On the other hand, in the case of no compliance by the human arm, we want the model to fail in recognizing robot movements or prescribed exercises.

C. Performance Results

Our results are provided in Table I and Fig. 5, with the latter showing the confusion matrices obtained from predictions made for each scenario. In the robot only scenario, as expected, we obtain a very high accuracy (i.e., 98.5%) when it is tested on the remaining 30% of the robot only scenario. When a person is involved with a strapped arm to these robot arm movements and following the movements properly i.e., in full compliance without showing any resistance, the model trained on robot only scenario provides 95.9% accuracy. This shows that we can understand the full compliance by the person while doing the prescribed exercises. This is because when we test the scenario where the same person does not properly follow the robot movements, the prediction accuracy goes down to 44.2%, which is close to totally random prediction accuracy for three classes. Note that in this scenario the human arm



(a) (b) (c) (d)

Fig. 5: Confusion matrices for different scenarios: (a) robot only, (b) volunteer one (full compliance), (c) volunteer one (no compliance), and (d) volunteer two (full compliance).

TABLE I: Prediction Results in Different Scenarios

	Scenario	**Accuracy (%)**
a	Robot only	98.5%
b	Strapped Arm with full compliance (Volunteer 1)	95.9%
c	Strapped Arm without compliance (Volunteer 1)	44.2%
d	Strapped Arm with full compliance (Volunteer 2)	90.2%

is still strapped to the robot arm and thus still performing the movements more or less the same way. However, due to the resistance by the human arm, the system notices the non-compliance in movements, thus produces a lower accuracy. This information can then be utilized by the physical therapists to understand if the patient performed the prescribed exercises properly.

In order to test the system's robustness with another person, we also collected and tested data when a second person performs the same robot arm movements with the strapped arm with full compliance. The accuracy is slightly lower but still high enough (i.e., 90.2%) to consider that there was a full compliance by the person while performing the robot assisted exercises. Note that the predictions happen every one sec in our current results. That is, if larger prediction intervals are tolerable and can be used, much higher accuracies can be achieved using techniques like majority voting [24]. We can also use multiple TX-RX pairs or devices with antenna arrays to further increase the accuracy [35].

Looking at the confusion matrices in Fig. 5, we can also observe the success in predictions made by the trained model across different classes, particularly in Fig. 5a and Fig. 5b. When another person uses the system, as shown in Fig. 5d, we observe some confusion for *Up-Down* movement, while the other class predictions are successful. In our future work, we will look at this issue further and will also collect more data with the robot scenario and increase the complexity of the model for a better accuracy distribution across all classes. Finally, in case of no compliance, the confusion matrix in Fig. 5c also shows that the learning process did not work well, resulting in biased predictions favoring one class (i.e., *Forward-Inward*).

We should also remark that in order to assess the advantage offered by the proposed model architecture that jointly considers both low-level and high-level features, we obtained results with models that exclusively use either only low-level features (i.e., a single dense layer followed by batch normalization and dropout layers) or high-level features (i.e., three dense layers each followed by batch normalization and dropout layers). The results indicate that the proposed model consistently outperforms these alternatives. The performance gap was particularly notable in the case of the second volunteer, where models using only low-level or high-level features achieved accuracy levels of 80–82%. In future work, we plan to further investigate this performance comparison in detail and explore optimizations for the proposed model, including techniques such as weighted integration of low-level and high-level features.

V. Conclusion

In this work, we have studied CSI based WiFi sensing solution in a robot-assisted physical therapy setting. More specifically, we have explored whether we can monitor the compliance of the subjects to the prescribed exercises, which are performed by the robotic arm while the human limb is strapped to the robot's arm. Our initial results show that with a DNN model that is trained to recognize not only the high-level features of the robotic movements but also the low-level features, we can recognize the compliance of the human subjects successfully. Our results also show that the proposed solution works for different people, confirming that it can be a generalized solution. We believe that this study can potentially open a new horizon to WiFi sensing studies in the context of recognizing robotic movements as well as its utilization for automatic monitoring of physical therapy sessions without the presence of a therapist.

In our future work, we aim to explore a wider range of movements with the robotic arm (including different limb movements and multiple robot arms) and evaluate our system with a larger group of volunteers (potentially with real rehabilitation patients) to evaluate its generalizability and robustness. Additionally, we plan to investigate whether our model can effectively recognize partial compliance, where the human introduces resistance during certain movements only while performing the others correctly. This would provide deeper insights into the proposed system's ability and robustness in understanding compliance across different movements. Finally, we would like to explore if the proposed solution can also be leveraged for intention recognition which is currently achieved with sensors and motion signals [36] and used to assist the users in completing the desired movements.

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