Wi-PT: Wireless Sensing based Low-cost Physical Rehabilitation Tracking

Steven M. Hernandez[1]*, Md Touhiduzzaman[1]*, Peter E. Pidcoe[2] and Eyuphan Bulut[1]
[1]Department of Computer Science, Virginia Commonwealth University, Richmond, VA 23284, USA
[2]Department of Physical Therapy, Virginia Commonwealth University, MCV Campus, Richmond, VA 23220, USA
Email: {hernandezsm, touhiduzzamm, pepidcoe, ebulut}@vcu.edu

***Abstract*—Physical therapy (PT) exercises are critically important for the rehabilitation of patients with motor deficits. While rehabilitation exercises can be most effective when performed properly under the supervision of a physical therapist, it can be costly in terms of several aspects and may not be a viable option for all patients. At-home systems offer more accessible and less costly solutions to patients while also providing flexibility in scheduling prescribed exercises. However, current systems mostly depend on camera based solutions that have limitations (i.e., deployment cost, requiring patients to be in the sight of camera, potential privacy violations) or wearable solutions that are cumbersome and intrusive. To this end, in this paper, our goal is to leverage the WiFi infrastructure available in most indoor locations (i.e., homes, apartments, nursing homes, etc.) for tracking the exercises prescribed to patients during their rehabilitation. Our solution, *Wi-PT*, is based on the analysis of Channel State Information (CSI) captured from ambient WiFi signals, and uses deep learning models trained to recognize the prescribed physical therapy exercises. Through our experiments, we show that the proposed solution can successfully recognize different types of physical therapy exercises such as hand and finger movements, limb movements and movements performed with exercise equipment. Moreover, we show that our system can recognize the person performing different activities and can identify when they are at rest or actively performing an exercise.**

***Index Terms*—WiFi sensing, physical therapy, rehabilitation tracking, device-free.**

I. Introduction

Rehabilitation is the process of recovering a patient's health condition to its normal state after a period of illness. This is a critical process for patients affected by central nervous system disorders such as Parkinson's disease (PD) and cerebrovascular diseases (e.g., stroke). For example, stroke affects nearly 800,000 individuals each year in the U.S. and for approximately 600,000 of them, this is their first event [1]. Many survivors experience persistent difficulty with daily tasks as a direct consequence [2]. These include being less active, being less stable, moving slower as well as adopting inefficient movement patterns resulting in increased physical demands. Thus, more than two thirds of stroke survivors receive rehabilitation services after hospitalization. According to recent studies, patients can recover up to 91% functional ability if they start the rehabilitation within three months of the stroke [3]. Similarly, rehabilitation can also minimize secondary complications [4]. Thus, maintaining physical activity and performing rehabilitation treatment as early as possible is crucial for the recovery of a patient.

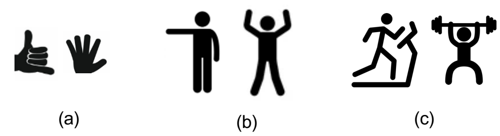


Fig. 1: Physical therapy exercises based on (a) wrist and finger movements, (b) whole body and limb movements, and (c) movements using equipment.

In current practice, rehabilitation treatment for a patient is usually performed under the supervision of a physical therapist who provides guidance to the patient when performing specific exercises and makes sure that each exercise is performed properly to ensure successful treatment. While such a practice with one on one attention from a physical therapy expert will ensure a quality treatment for the patients, it limits the application of rehabilitation treatment to a certain environment and comes with several costs (e.g., treatment cost, trip cost to the facility, dedication of specific time). Thus, alternative solutions which allow patients to perform such rehabilitation activities at home or outside of a dedicated rehabilitation facility can avoid such costs and provide a ubiquitous, and easily accessible solution. On the other hand, these alternative solutions should not reduce the quality of the treatment and must continue to give feedback to patients to ensure that rehabilitation exercises are performed properly and as prescribed. Note that clinical visits and expert based sessions can still be performed as needed but they can be performed less frequently.

The existing at-home systems mainly depend on wearable sensors or cameras located in the patients' houses [5], [6]. However, such solutions come with several issues (e.g., intrusive, privacy concerns). Alternative to these existing systems, in this paper, we propose a WiFi sensing based device-free physical rehabilitation tracking (*Wi-PT*) system for patients. There are a few other solutions that also rely on the analysis of radio-frequency (RF) signals; however, these systems require placement of special equipment (e.g., mmWave radar [7]), thus they are still costly. On the contrary, our goal is to leverage the WiFi infrastructure available in most indoor environments and houses for rehabilitation activity tracking, thus providing a low-cost and non-intrusive solution. Moreover, in order to

*Authors contributed equally.

This work is supported in part by National Science Foundation (NSF) Graduate Research Fellowship Program (GRFP) under Grant No. 1744624.

provide a thorough system, we target a solution that can (i) identify different types (e.g., hand, finger, limb) of exercises performed by the person, (ii) identify which person is performing the activity given, and (iii) verify if the person is actively exercising or resting for a period of time. We believe these are critical in tracking the person who is supposed to perform the physical rehabilitation activity as prescribed.

The rest of the paper is organized as follows. In Section II, we provide a background on WiFi sensing and discuss the related work. In Section III, we present the details of the proposed Wi-PT system. We evaluate the proposed system through experiments in Section IV. Finally, we provide our concluding remarks in Section V.

II. Preliminaries

A. Background on WiFi Sensing

WiFi sensing uses ambient WiFi radio signals to detect and sense physical properties of the environment. These RF signals propagate over multiple unique physical paths from a transmitter (TX) to a receiver (RX). These multipaths cause slight variations in the signal due to the RF signals reflecting off of surfaces and propagating through objects such as walls, furniture, and people within the environment.

Channel state information (CSI) is a signal metric captured in communication systems which use orthogonal frequency-division multiplexing (i.e., 802.11), to allow data-symbols to be encoded in multiple subcarrier frequency allowing for higher symbol throughput as well as resilience to signal fading and shadowing caused by multipath interference in the channel. CSI is modeled as $y^{(i)} = H^{(i)}x^{(i)} + \eta^{(i)}$, where i is the subcarrier index, x is the transmitted signal, y is the received signal, η is a noise vector, and H is a complex vector containing the CSI denoting the transformation change required from the input x to the output y. The complex CSI vector contains 64 subcarriers where 52 are data-subcarriers and 12 are null-subcarriers. The CSI value for each subcarrier is defined as a complex number with a real component ($H_r^{(i)}$) and an imaginary component ($H_{im}^{(i)}$). We can transform this raw CSI into amplitude, $A^{(i)} = \sqrt{(H_{im}^{(i)})^2 + (H_r^{(i)})^2}$, and phase, $\phi^{(i)} = atan2(H_{im}^{(i)}, H_r^{(i)})$.

Leveraging these signal features, WiFi sensing has been applied in various applications [8]–[10] including but not limited to localization, human activity recognition and crowd counting. In this paper, we focus on rehabilitation specific physical activities and propose a system which can not only recognize different kinds of physical therapy exercises but also can recognize the person who is performing them using a low-cost solution with an edge-based ML model inference.

B. Related Work

Thanks to the ubiquity of Internet of Things (IoT) devices, there have been many smart health and assistive solutions developed to track the activities of patients during a rehabilitation process. These solutions can be categorized into two major approaches. In the first approach, the studies [11]–[14] consider a wearable sensor attached to the body of the patient. These sensor usually contain an Inertial Measurement Unity (IMU) that can measure accelerometer, gyroscope and magnetometer readings and can obtain different directional and angular movements of the limbs of the patients. However, patients may feel uncomfortable with wearing these sensors and may not deal with charging them as needed.

In the second approach, the studies use camera based solutions (e.g., Kinect [15], RGB camera [16], depth camera [17]) and through the analysis of collected frames, detailed patient movements and poses can be detected. While such systems are non-intrusive as they do not require a device worn by the patient, they have certain limitations and drawbacks. For example, they can only track a person when the person is in the sight of the camera. These systems can also pose a privacy risk to users as they not only detect the movements of people but also their faces and the environment they live in. Finally, they can be costly to deploy especially for large areas where multiple cameras need to be deployed to obtain sufficient coverage.

In addition to these major approaches, there is also relatively new but growing number of studies that rely on RF signals and radar imaging. These studies [7], [18], [19] rely on specific signals (e.g., FMCW [18], mmWave [7], [19]) and deep learning based analysis of signal features. These solutions can be more effective than previous solutions as even the activities that are performed out of sight can be detected because RF signals can penetrate through some obstacles as well as bounce off of some other objects in the environment and reach out out of sight locations. On the other hand, these solutions require special equipment (e.g., mmWave radar) which can be costly. Different from these systems, our solution relies on already available ambient WiFi signals found in most indoor areas. Additionally, the proposed system can use low-cost microcontrollers to capture the signals, preprocess them, and make predictions directly on-board.

III. Proposed Wi-PT System

A. CSI Data Collection

In order to collect CSI data, we use the WiFi-enabled ESP32 microcontrollers and the ESP32-CSI Toolkit [20]. These microcontrollers provide a small-size, low-cost, and standalone solution compared to other existing methods, which require a host laptop with an updated Network Interface Card (NIC); thus, they can be easily deployed anywhere. We transmit frames from an ESP32 transmitter and then collect WiFi CSI from a separate ESP32 receiver at a rate of 100Hz.

B. Preprocessing and Machine Learning Model Development

Once the CSI data is collected and labeled with the performed exercise, we begin by performing some preprocessing steps. First, we denoise the incoming CSI signal by applying a moving average across each subcarrier independently using a window of size w. After this, we use the Principal Component Analysis (PCA) to achieve both dimensionality reduction and

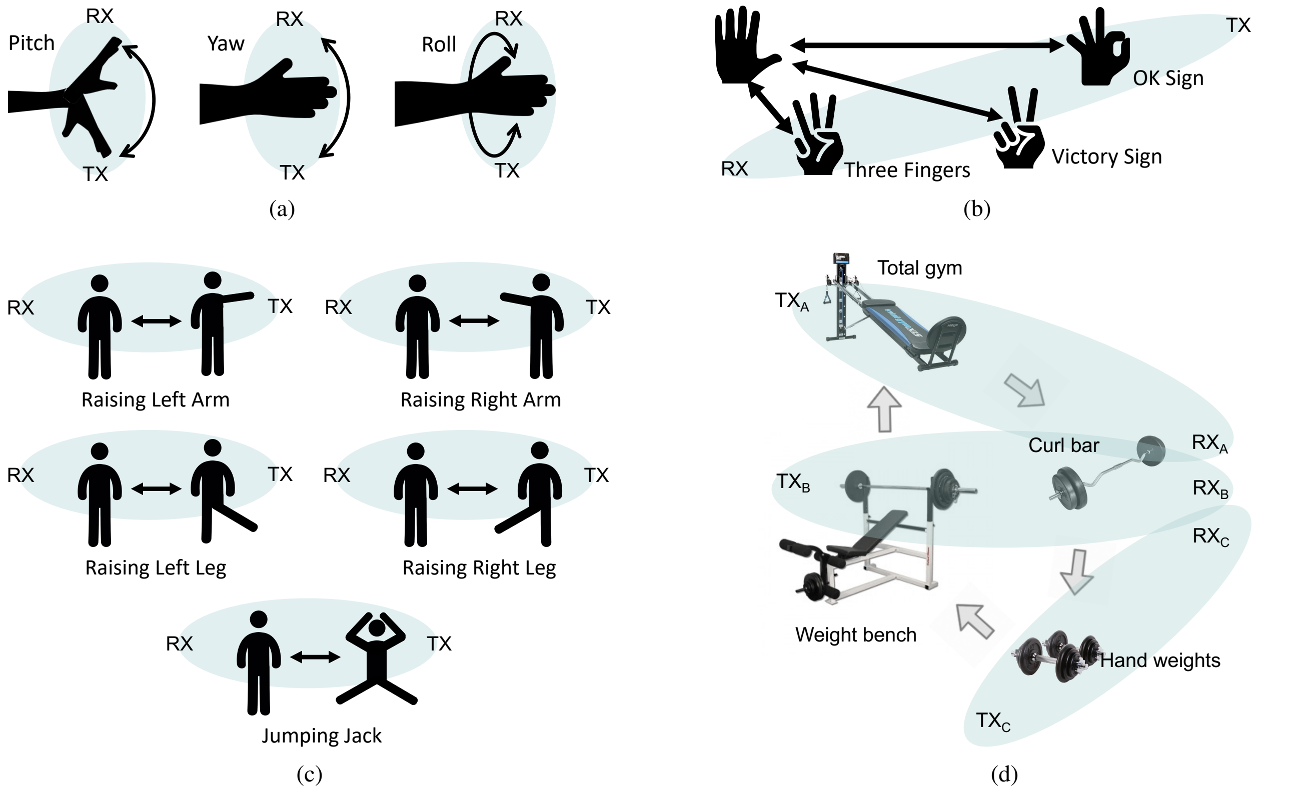


Fig. 2: Experimental design with TX/RX pairs illustrated for four different categories of activities: (a) hand and wrist movements, (b) finger movements, (c) full-body and limb movements, (d) exercise equipment usage movements.

further reduce the amount of noisy data used as input into the machine learning model.

After this preprocessing, we train a machine learning classifier model $\mathcal{M}$ using a Dense Neural Network (DNN) architecture with four dense layers for the equipment based exercises and two dense layers for the other actions. We apply a dropout layer between each dense layer to prevent overfitting. Finally, we use Stochastic Gradient Descent (SGD) to optimize the loss function $\mathcal{L}(x, y) = \frac{1}{N}\sum_{i=1}^{N}\left(\mathcal{M}(x_i) - y_i\right)^2$, where $\mathcal{M}(x_i)$ is the model prediction for input CSI x_i and y_i is the true class for the i-th CSI measurement.

IV. Evaluation

A. Data sets

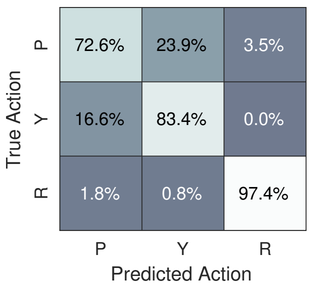
In order to evaluate the proposed Wi-PT system, we have collected CSI measurements for four physical therapy scenarios, each with different scales from small finger movements up to larger scale movements with full exercise equipment. Table I gives an overview of the four new data sets with the activities being tracked, number of repetitions of each activity, number of TX/RX links and finally the number of volunteers who performed these activities.

1) Wrist dataset: For our first data set, we collected CSI data for three hand movements using one volunteer. The movements are pitch (P), yaw (Y), and roll (R) of the palm around the wrist as illustrated in Fig. 2a. The volunteer repeated each hand movement multiple times for a duration of 10 seconds each time and in a round-robin fashion over 22 repetitions with 5 seconds of pauses while in the line of sight (LOS) of a single TX/RX pair. The TX/RX pair is placed vertically across the palm of the volunteer with a distance of 50 centimeters in between.

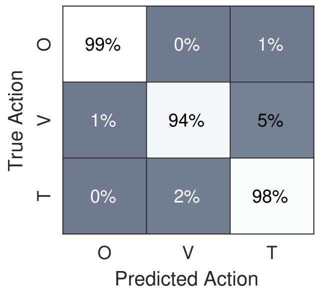
TABLE I: Information about the collected physical therapy experiment data sets.

Data set	Activities	Reps.	Links	Volunteers
Wrist	• Pitch (P) • Yaw (Y) • Roll (R)	22	1	1
Finger	• OK Sign (O) • Victory Sign (V) • Three Fingers (T)	20	1	1
Whole-body	• Raise Left Arm (LA) • Raise Right Arm (RA) • Raise Left Leg (LL) • Raise Right Leg (RL) • Jumping Jack (JJ)	10	1	1
Equipment	• Hand weights (HW) • Total gym (TG) • Curl bar (CB) • Weight bench (WB)	6	3	5

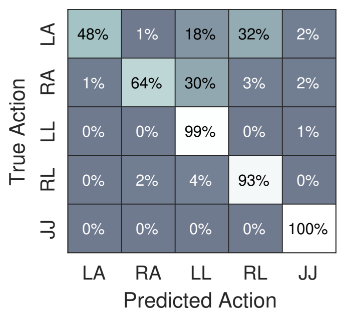
2) Finger dataset: In our next experimental dataset, we consider small scale finger movement tracking. For this experimental data collection, we collected CSI from a single TX/RX pair while a single volunteer performed three finger-based movements, namely, OK sign (O), Victory sign (V), Three Fingers (T) as illustrated in Fig. 2b. These gestures are repeated in a round-robin fashion for 20 repetitions, while



(a) Wrist Movements (Accuracy: 85.21%)



(b) Finger Movements (Accuracy: 97.13%)



(c) Whole-body Movements (Accuracy: 80.65%)

Fig. 3: Confusion matrix for (a) wrist movements, (b) finger movements, (c) whole-body movements

each action is performed for a duration of 5 seconds and with 5 seconds of pauses in between the successive actions. The single pair of TX/RX is placed horizontally across the palm of the volunteer with a distance of 60 centimeters in between.

3) Whole-body dataset: Our third experimental dataset includes full-body calisthenics movements which focus on the movements of the limbs. One volunteer performed five activities in the LOS of a single TX/RX pair repeated 10 times in a round-robin fashion, namely, raising left arm (LA), raising right arm (RA), raising left leg (LL), raising right leg (RL), and jumping jack (JJ) as illustrated in Fig. 2c. Each of these activities involves repeatedly moving from a static position to the active position over a period of 10 seconds and with 10 seconds of rests in between successive actions. The TX/RX pair is placed across the left-to-right direction of the body of the moving volunteer at the eye-level height and with a distance of 2.4 meters in between TX and RX.

4) Equipment-based dataset: Here, we collected data during exercises performed with different pieces of equipment. Uniquely for this dataset, we also collected data using multiple volunteers in order to test the system's performance in terms of person identification accuracy. More specifically, we asked 5 volunteers to perform exercises (i.e., hand weights (HW), total gym (TG), curl bar weight (CB), weight bench (WB)) one by one at four different stations in the same room (as shown in Fig. 2d). We asked each of the volunteers to perform each exercise for 10 seconds and rest the same amount of time and repeat this activity/inactivity 6 times in total at each station. We used three different TX/RX pairs located at different locations. We collected CSI data from each of these activities and developed deep learning models for three different detection tasks, namely, (i) the equipment used by the person, (ii) the identity of the person using it, and (iii) if the person is actively exercising or not. We used 4 repetitions of the exercise by each person as training data and remaining 2 repetitions for testing.

B. Experiment Results

1) Wrist results: For our first dataset, the three wrist movements are found to be classifiable with an overall accuracy of 85.21% using our optimized deep neural network model. The roll wrist activity is found to be more accurately classified (i.e., with 97.4% accuracy), and the pitch action of the wrist is found to be most prone to being confused with the yaw wrist action as shown in Fig. 3a.

As the TX/RX pair is placed vertically (i.e., at the top and bottom of the hand), the signals get the thinner view of the palm from this angle and, to our understanding, it causes these two movements to be less recognizable, while rolling actions provide the signals a broader view of the back of the palm to make recognizing this motion more accurately.

2) Finger results: For our next data set, we have achieved an overall accuracy of 97.13% when classifying the three multi-finger gestures. The model is optimized so well that it recognizes the three gestures from a horizontal angle of view of the wireless network across the human palm. All of these three gestures involve the thumb finger's movement, but the other three involved fingers make the gestures unique when classified during our evaluation.

The two slightly confused gestures among the three gestures are the three-finger sign and the victory-sign (i.e., two-finger sign) which is 5% in the worst case as depicted in the confusion matrix in Fig. 3b. In both of these gestures, thumb and little fingers are moving commonly and only the movement of the ring finger makes the difference, so it is understandable that these two gestures are more likely to be confused than with the other gesture.

3) Whole-body results: The activities performed for our whole-body data set can be divided into three subgroups: (i) arm movements, (ii) leg movements, and (iii) jumping jack which involves both arms and legs along with a whole body jumping motion. Our model successfully classifies the two actions of the leg movements along with the jumping jack movement with at least 93% accuracy and at best with 100% accuracy. However, the arm movements are found to be more challenging to distinguish from the other movements. The confusion matrix in Fig. 3c shows that the worst accuracy is found with the left-arm movement at 47.65%, while 31.74% left-arm moves are wrongly classified as right-leg movement and 29.80% right-arm movements are wrongly classified as the left-leg movement. The model confusion between the left and right arms and legs can be due to the fact that raising any leg sidewise (left or right) makes the body tilt towards the opposite side. Therefore, the arm movement at that opposite side is likely to be confused as a leg movement at that side, especially if the TX/RX pair is close enough to the body.

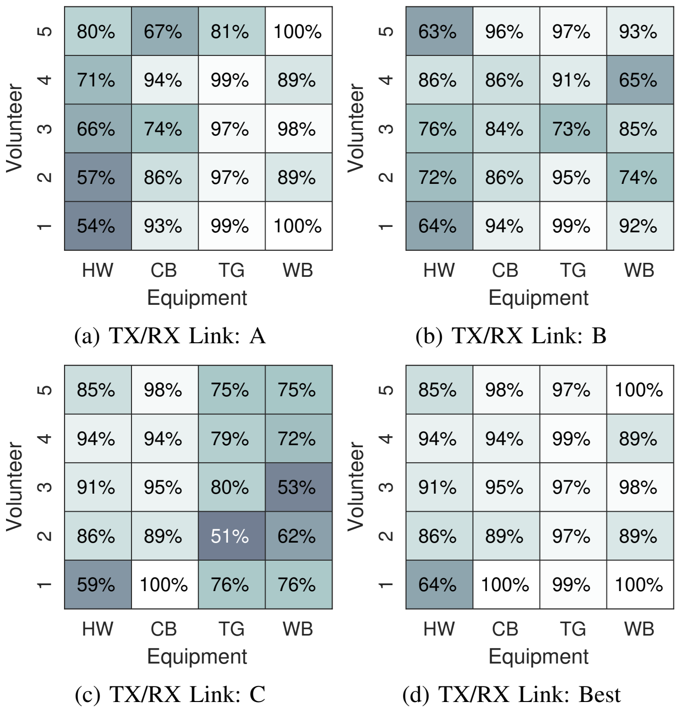


Fig. 4: Accuracy per TX/RX link when predicting active versus resting states for each pair of volunteers and equipment. Each link is better with distinct sets of equipment, thus using the best link allows for greater accuracy across all equipment.

Considering this, it can be possible to increase the accuracy of our model by increasing the distance between the pair of TX/RX. Until then, the best overall accuracy achieved by our DNN model to classify five of the mentioned simultaneous actions is 80.65%.

4) Equipment-based results: For our equipment-based dataset, we collected data from multiple volunteers, and as such, we can review the accuracy of our model with respect to each volunteer individually. We begin our analysis by evaluating the ability of our model to distinguish both active and resting states for each pair of volunteers and equipment. The results in Fig. 4a-c shows the accuracy when using each TX/RX link as illustrated in Fig. 2d. From the heatmap figures, we can see that link A achieves the greatest accuracy across volunteers for the TG and WB equipment while link C achieves the highest accuracy across volunteers for HW and CB equipment. While link B achieves slight improvements for some of the volunteer/equipment pairs, there is no consistent behaviour where it achieves greater accuracy than the other TX/RX links. As such, while link B does not itself achieve the greatest accuracy, it can still help improve the overall system.

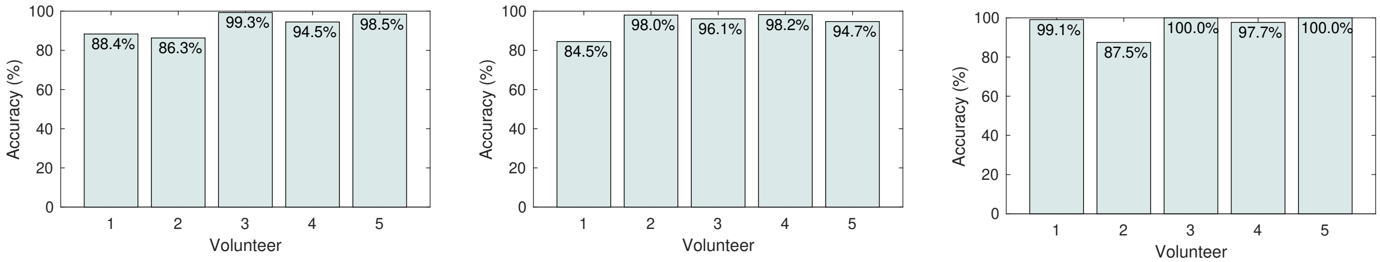
Fig. 4d shows the best overall accuracy achieved across each of the three TX/RX links. From here, we can see that HW achieves a low accuracy (i.e., 64%) for volunteer 1. This may be due to inconsistencies in the actions being performed between different repetitions. With additional data collections, we expect that these inconsistencies should be better handled by the model. Even so, we can see that the HW equipment achieves consistently lower accuracy for all volunteers compared to other equipment. We expect this is due to the small movements of the hand weights compared to the activities performed at the other equipment locations.

Next, we consider how well our system can predict which equipment is being used per volunteer. For this evaluation, we only use the active dataset for equipment identification. Fig. 5 shows the accuracy of a multi-class classifier predicting the four different equipment stations using CSI captured with each TX/RX link. We can see that all three links can successfully identify the equipment with an average accuracy greater than 93%. This demonstrates that even though only certain equipment is placed in the LOS of each TX/RX link, the models can still successfully distinguish which equipment is being used from any given link. Thus, we can see that link positioning is unimportant for equipment identification.

When exercise equipment is used by different people, then it can be important that an exercise tracking system is able to distinguish which person is using the equipment at any given time. As such, in Fig. 6, we show the accuracy of a multi-class classifier when predicting the five different volunteers at each given equipment station. From this, we can see that no single TX/RX link achieves high prediction accuracy for person identification at all equipment locations. This is because person identification relies on understanding details such as height, weight, and the way in which a volunteer performs each activity. As such, we find that the highest achieved accuracy for each TX/RX link corresponds directly to the equipment most closely located in the LOS of the TX and RX. This is because equipment located in the NLOS may have environmental noise such as fans as well as the physical movements being performed which may overshadow the human identifying traits that could more easily be seen in the LOS. Overall, the greatest accuracy that we can achieve for HW is 85.6% while all other equipment achieves greater than 91.1% respectively.

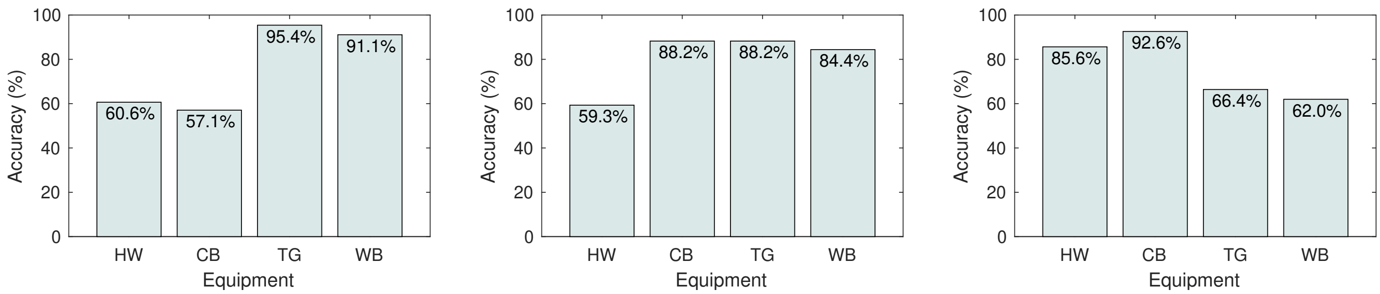
V. Conclusion

In this work, we proposed a non-intrusive WiFi sensing based physical rehabilitation activity tracking system. We discussed issues with existing methods and presented a low-cost and device-free method that can use ubiquitous WiFi signals for tracking physical activities. Using the proposed Wi-PT system, we collected and evaluated four new WiFi sensing physical therapy datasets: (i) wrist movements, (ii) finger movements, (iii) whole-body movements, and (iv) equipment-based exercise movements. We demonstrated that each of these scales of movements can be tracked by Wi-PT at high accuracies. Furthermore, with the equipment-based exercise movements, we considered multiple volunteers and multiple TX/RX link pairs. Through this, we demonstrated that we can not only recognize the activity/exercise, but also identify the person performing the exercise, which can be an important feature when different patients use the same equipment at different times. In our future work, we will collect additional data sets with multiple volunteers, develop environment-



(a) TX/RX Link: A (Average: 93.39%) (b) TX/RX Link: B (Average: 94.32%) (c) TX/RX Link: C (Average: 96.85%)

Fig. 5: Accuracy per TX/RX link when predicting four different equipment stations.



(a) TX/RX Link: A (Average: 76.05%) (b) TX/RX Link: B (Average: 80.02%) (c) TX/RX Link: C (Average: 76.65%)

Fig. 6: Accuracy per TX/RX link when predicting which of the five volunteers is using each individual pieces of equipment.

independent models [21], and evaluate the proposed system for tracking physical therapy patients over longer periods of time.

References

[1] C. W. Tsao, A. W. Aday, Z. I. Almarzooq, A. Alonso, A. Z. Beaton, M. S. Bittencourt, A. K. Boehme, A. E. Buxton, A. P. Carson, Y. Commodore-Mensah *et al.*, "Heart disease and stroke statistics—2022 update: a report from the american heart association," *Circulation*, vol. 145, no. 8, pp. e153–e639, 2022.

[2] J. Park and T.-H. Kim, "The effects of balance and gait function on quality of life of stroke patients," *NeuroRehabilitation*, vol. 44, no. 1, pp. 37–41, 2019.

[3] K. B. Lee, S. H. Lim, K. H. Kim, K. J. Kim, Y. R. Kim, W. N. Chang, J. W. Yeom, Y. D. Kim, and B. Y. Hwang, "Six-month functional recovery of stroke patients: a multi-time-point study," *International journal of rehabilitation research.*, vol. 38, no. 2, p. 173, 2015.

[4] G. Abbruzzese, R. Marchese, L. Avanzino, and E. Pelosin, "Rehabilitation for parkinson's disease: current outlook and future challenges," *Parkinsonism & related disorders*, vol. 22, pp. S60–S64, 2016.

[5] M. A. R. Ahad, A. D. Antar, and O. Shahid, "Vision-based action understanding for assistive healthcare: A short review." in *CVPR Workshops*, 2019, pp. 1–11.

[6] Q. Wang, P. Markopoulos, B. Yu, W. Chen, and A. Timmermans, "Interactive wearable systems for upper body rehabilitation: a systematic review," *Journal of neuroengineering and rehabilitation*, vol. 14, no. 1, pp. 1–21, 2017.

[7] S. An and U. Y. Ogras, "MARS: mmWave-based Assistive Rehabilitation System for Smart Healthcare," *ACM Transactions on Embedded Computing Systems (TECS)*, vol. 20, no. 5s, pp. 1–22, 2021.

[8] Y. Ma, G. Zhou, and S. Wang, "WiFi sensing with channel state information: A survey," *ACM Computing Surveys (CSUR)*, vol. 52, no. 3, pp. 1–36, 2019.

[9] S. M. Hernandez, D. Erdag, and E. Bulut, "Towards Dense and Scalable Soil Sensing Through Low-Cost WiFi Sensing Networks," in *Proc. of 46th IEEE Conference on Local Computer Networks (LCN), Edmonton, AB, Canada, October 4-7*, 2021, pp. 549–556.

[10] S. M. Hernandez and E. Bulut, "Adversarial Occupancy Monitoring using One-Sided Through-Wall WiFi Sensing," in *IEEE International Conference on Communications (ICC), Montreal, QC, Canada, June 14-23*, 2021, pp. 1–6.

[11] O. Postolache, D. J. Hemanth, R. Alexandre, D. Gupta, O. Geman, and A. Khanna, "Remote monitoring of physical rehabilitation of stroke patients using IoT and virtual reality," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 2, pp. 562–573, 2020.

[12] J. Qi, P. Yang, A. Waraich, Z. Deng, Y. Zhao, and Y. Yang, "Examining sensor-based physical activity recognition and monitoring for healthcare using internet of things: A systematic review," *Journal of biomedical informatics*, vol. 87, pp. 138–153, 2018.

[13] G. Bhat, N. Tran, H. Shill, and U. Y. Ogras, "w-HAR: An activity recognition dataset and framework using low-power wearable devices," *Sensors*, vol. 20, no. 18, p. 5356, 2020.

[14] V. Bianchi, M. Bassoli, G. Lombardo, P. Fornacciari, M. Mordonini, and I. De Munari, "IoT wearable sensor and deep learning: An integrated approach for personalized human activity recognition in a smart home environment," *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 8553–8562, 2019.

[15] X. Yu and S. Xiong, "A dynamic time warping based algorithm to evaluate kinect-enabled home-based physical rehabilitation exercises for older people," *Sensors*, vol. 19, no. 13, p. 2882, 2019.

[16] M. S. Aung, S. Kaltwang, B. Romera-Paredes, B. Martinez, A. Singh, M. Cella, M. Valstar, H. Meng, A. Kemp, M. Shafizadeh *et al.*, "The automatic detection of chronic pain-related expression: requirements, challenges and the multimodal EmoPain dataset," *IEEE Transactions on Affective Computing*, vol. 7, no. 4, pp. 435–451, 2015.

[17] D. Leightley, J. Darby, B. Li, J. S. McPhee, and M. H. Yap, "Human activity recognition for physical rehabilitation," in *IEEE International Conference on Systems, Man, and Cybernetics*, 2013, pp. 261–266.

[18] F. Adib, C.-Y. Hsu, H. Mao, D. Katabi, and F. Durand, "Capturing the human figure through a wall," *ACM Transactions on Graphics (TOG)*, vol. 34, no. 6, pp. 1–13, 2015.

[19] A. Sengupta, F. Jin, R. Zhang, and S. Cao, "mm-Pose: Real-time human skeletal posture estimation using mmWave radars and CNNs," *IEEE Sensors Journal*, vol. 20, no. 17, pp. 10 032–10 044, 2020.

[20] S. M. Hernandez and E. Bulut, "Lightweight and standalone IoT based WiFi sensing for active repositioning and mobility," in *21st International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*, Cork, Ireland, Jun. 2020.

[21] S. M. Hernandez and E. Bulut, "WiFederated: Scalable WiFi Sensing Using Edge-Based Federated Learning," *IEEE Internet Things Journal*, vol. 9, no. 14, pp. 12 628–12 640, 2022.