2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovations

WiFit: Ubiquitous Bodyweight Exercise Monitoring with Commodity Wi-Fi Devices

Shengjie Li[*†‡], Xiang Li[*†‡], Qin Lv[§], Guiyu Tian[*†‡], Daqing Zhang[*†‡]
[*]*Key Laboratory of High Confidence Software Technologies(Ministry of Education)*
[†]*Peking University Information Technology Institute(Tianjin Binhai)*
[‡]*School of Electronics Engineering and Computer Science, Peking University, Beijing, China*
[§]*Department of Computer Science, University of Colorado Boulder, Boulder, USA*
{lishengjie, lixiang13, wavey, dqzsei}@pku.edu.cn, Qin.Lv@colorado.edu

***Abstract*—Bodyweight exercises are effective and efficient ways to improve one's balance, flexibility, and strength without machinery or extra equipment. Prior works have been successful in monitoring aerobic exercises and free-weight exercises, but are not suitable for ubiquitous bodyweight exercise monitoring in order to provide fine-grained repetition counting information in each exercise set. In this work, we propose WiFit, a bodyweight exercises monitoring system that supports accurate repetition counting using a pair of commodity Wi-Fi devices without attaching anything to the human body. We first analyze the movement patterns of bodyweight exercises and couple them with detailed Doppler effect modeling to determine the most effective system settings. Then, by leveraging the human activity Doppler displacement stream extracted from Wi-Fi CSI signal, we have developed an impulse-based method to segment and count the number of repetitions, and analyzed specific features for classifying different types of bodyweight exercises. Extensive experiments show that WiFit achieves 99% accuracy for repetition counting and 95.8% accuracy for exercise type classification.**

***Index Terms*—Wi-Fi, Ubiquitous, Bodyweight exercise, CSI**

I. Introduction

Bodyweight exercises, such as push-up, sit-up, and squat, are effective and efficient forms of strength training to maintain good health and fitness [1]. They have become increasingly incorporated into people's daily routines. In order to provide exercisers with useful feedbacks and improve their exercise experience, a robust and easily-deployable solution which can accurately monitor and evaluate such bodyweight workout sessions is highly desirable.

In the past few years, researchers have proposed a number of solutions that use cameras [2], wearable and mobile devices [3], [4], or RFIDs [5] to monitor people's exercises. However, camera-based systems have privacy concerns and light requirements. Wearable and mobile device based systems require attaching devices to the user's body, which would be inconvenient and uncomfortable during bodyweight exercises. RFIDs attached to free-weight equipment may be appropriate for free-weight exercises, but not for bodyweight exercises. Given the limitations of these solutions, it is longing for a bodyweight exercise monitoring system that is easy to deploy and without any attaching requirements.

This work is sponsored by National Key Research and Development Plan under Grant No.2016YFB1001200.

With the ubiquitous availability of Wi-Fi devices, a number of Wi-Fi based activity recognition systems exist in the literature [6]–[8]. They focus mainly on detecting human activities such as falls, daily activities, or direction of movement. However, unlike existing works, bodyweight exercise monitoring requires knowing not only the occurrence of exercises, but also fine-grained information such as number of repetitions of each type of exercises. Since a single workout session typically consists of multiple sets of bodyweight exercise repetitions, along with other non-exercise activities, it is critical for a bodyweight exercise monitoring system to detect/segment not only each set of exercise but also each repetition in that set. To achieve this goal, we could utilize the basic physical phenomenon called Doppler effect. Given a pair of Wi-Fi transmitter and receiver, the human body can reflect Wi-Fi signals to the receiver, and movement of the human body introduces a Doppler frequency shift on the reflected Wi-Fi signal. By capturing this Doppler frequency shift in Wi-Fi signals [9], we could extract features that are characteristic of bodyweight exercises. By identifying and utilizing such features, we could then detect segments of repeated exercises and count the number of exercise repecitions accurately.

A number of challenges need to be addressed to build the bodyweight exercise monitoring system with commodity Wi-Fi devices. First, bodyweight exercises are freestanding exercises, and how people position themselves relative to the Wi-Fi devices can have a significant impact on the received Wi-Fi signal patterns. To obtain high-quality and robust Wi-Fi based Doppler effect features, it is important for us to investigate the optimal system design setting and provide clear guidance to users. Second, each exercise session is a mixture of multiple types of exercises and non-exercise activities. This calls for a fully automated approach that can accurately detect, segment, and characterize individual exercises in a workout session. In this work, we propose WiFit, a Wi-Fi based bodyweight exercise monitoring system that is robust and easily deployable. WiFit addresses all the above mentioned challenges and makes the following contributions:

- We take three typical exercise (sit-up, push-up, squat) as examples and investigate the most effective system setting to capture fine-grained bodyweight exercise movements using Wi-Fi based Doppler effect features. Specifically,

978-1-5386-9380-3/18/$31.00 ©2018 IEEE
DOI 10.1109/SmartWorld.2018.00114

Authorized licensed use limited to: Peking University. Downloaded on May 13,2021 at 06:17:21 UTC from IEEE Xplore. Restrictions apply.

we analyze the movement patterns of bodyweight exercises, and couple them with detailed Doppler effect modeling to determine how we can capture the exercises' features with commodity Wi-Fi devices accurately.

- We propose an impulse-based method based on Doppler displacement to automatically segment each exercise set in the activity stream as well as each repetition in the exercise set. Furthermore, we also build a SVM classifier for bodyweight exercise classification.
- We implement WiFit on commodity Intel 5300 Wi-Fi cards, and evaluate the system through extensive experiments with 20 different participants and a total of 4350 repetitions for three kinds of bodyweight exercises. WiFit performs well for the diverse population and exercises, achieving an accuracy of 99% in repetition counting and 95.8% in exercise classification [1].

II. Related Work

Our work is broadly related to research in three sub-areas: physical exercise monitoring systems, activity recognition with wireless signals, and activity recognition with Wi-Fi.

a) **Physical exercise monitoring systems:** The first group of related studies focus on monitoring physical exercises with wearable sensors, and mobile phones. There are wristband [10], and a number of other solutions [3]–[5], [11]. While all these systems rely on dedicated sensors or specific hardware for exercise monitoring, we argue that it is preferable not to require people to wear any devices during bodyweight exercises, and WiFit is designed with this objective. There are also camera-based systems for monitoring human exercises [2]. Due to privacy concerns and lighting condition requirements of the camera-based schemes, WiFit is more advantageous, also in terms of cost and deployment as a device-free Wi-Fi based solution.

b) **Activity recognition using wireless signals other than Wi-Fi:** The second group of related works aim at recognizing human activities [12]–[14] using various wireless signals other than commodity Wi-Fi. These systems deploy specialized hardware to track human motion and recognize human activities. For instance, WiTrack [12] tracks moving targets at sub-meter accuracy by isolating signals reflected off targets using FMCW radar. mTrack [13] accurately locates and tracks finger movement using customized 60GHz millimeter signals. Wideo [14] achieves fine-grained motion tracking using the WARP software-defined radio platform. While these systems leverage dedicated and expensive devices to achieve high accuracy, WiFit advances the state-of-the-art by extracting Doppler shifts on commodity Wi-Fi devices and obtaining fine-grained information about bodyweight exercise training.

c) **Activity recognition using Wi-Fi signals:** In recent years, with the availability of CSI on commodity Wi-Fi devices, significant progress has been made in device-free human tracking [8], [9], human activity recognition [7], [15], and vital sign monitoring [16]–[18]. Among the Wi-Fi CSI-based research works, both model-based [6], [9], [16]–[19] and pattern-based approaches [7], [15], [20] have been investigated. E-eyes [7] exploits subcarriers of CSI to recognize household activities such as washing dishes and taking a shower. RT-Fall [15] automatically segments fall-like activities from daily activity CSI stream and accurately detects the fall using a set of selected features. SEARE [20] utilizes CSI amplitude waveform shape to recognize exercise activities. In contrast, Zhang *et al.* [16]–[19] develop the Fresnel zone model based techniques to sense micro and macro human activities robustly. CARM [6] extracts speed-related features from CSI and proposes an effective machine learning framework to mitigate location-dependency in CSI-based activity recognition. WiDance [8] and IndoTrack [9] directly extract Doppler frequency shift with multiple antennas available on commercial Wi-Fi devices, which can obtain accurate human motion velocity and direction information. Different from [8], [9], WiFit goes one step further to leverage both Doppler velocity and displacement to recognize various activities and count the number of repeated activities accurately.

III. Doppler Effect for Fine-grained Bodyweight Exercise Monitoring

In this section, we present in detail how to obtain effective and robust Doppler effect features from Wi-Fi signals for fine-grained bodyweight exercise monitoring.

A. Wi-Fi CSI based Doppler Effect Model

Given a pair of Wi-Fi transmitter (TX) and receiver (RX), the Wi-Fi signal can propagate from the transmitter to the receiver via a direct path, or via path reflected by human, wall and other objects. The signal received at the receiver is a superposition of all path signals. This phenomenon is called multi-path propagation. Human movement can change the path length of the human reflection signal, and introduce a Doppler frequency shift to the received signal: $f_{Doppler} = f\frac{v_{path}}{c}$. Where f is the carrier frequency of the signal, v_{path} is the speed of path length change, and c is the propagation speed of light.

As Wi-Fi CSI characterizes both the amplitude attenuation and phase change when a signal propagates from the transmitter to the receiver, it also contains this Doppler frequency shift information. Considering only one signal, its CSI at time t_0 is $x(f, t_0) = A_0 e^{-j2\pi f \tau_0}$, where A_0 is the attenuation and τ_0 is the propagation delay. If the propagation path length changes at a speed of v, after a short time period t, the path length change $\Delta l_{path} = vt$ and the propagation delay change $\Delta\tau = \frac{vt}{c}$. When ignoring the attenuation change, the signal's CSI is $x(f, t_0{+}t) = A_0 e^{-j2\pi f(\tau_0 + \frac{vt}{c})} = x(f, t_0)e^{-j2\pi f\frac{vt}{c}}$. So the changing frequency of CSI reflects the Doppler frequency shift of the signal. For the multi-path propagation scenario, the CSI of each packet can be represented as follows:

$$x(f, t_0 + t) = \sum_{i=1}^{L} A_i e^{-j2\pi f(\tau_i + \frac{v_i t}{c})}, \tag{1}$$

[1]To see a demonstration video of the WiFit system in action, please visit YouTube: https://www.youtube.com/watch?v=WlU-5TGFQpo Youku: http://v.youku.com/v_show/id_XMzQ5NzExMTMzMg==.html

Authorized licensed use limited to: Peking University. Downloaded on May 13,2021 at 06:17:21 UTC from IEEE Xplore. Restrictions apply.

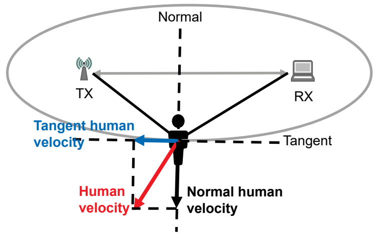


Fig. 1: Doppler velocity vs. actual human movement velocity.

where L is the number of propagation paths, τ_i is the propagation delay of the i^{th} path signal at time t_0, and v_i is the i^{th} path's length change speed. Based on (1), we can estimate the Doppler frequency shift introduced by the human movement with the frequency analysis on Wi-Fi CSI, and further estimate the path length change speed, also referred as *Doppler velocity*.

B. Doppler Velocity vs. Human Movement

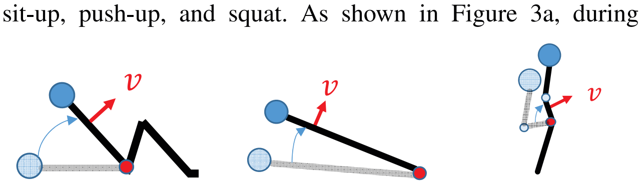
In order to use Doppler velocity for bodyweight exercise monitoring, we first need to understand the relationship between Doppler velocity and human movement. As illustrated in Figure 1, there exists an ellipse for the human target with foci at the transmitter and the receiver. Here, the human velocity can be decomposed into two components: the *tangent human velocity* and the *normal human velocity*. Only the normal human velocity would change the human reflection path length and introduce a non-zero Doppler velocity. This leads to two important observations:

- For the same human position and same magnitude of human velocity, changing the direction of human velocity can result in different decomposition of the normal human velocity, and the observed Doppler velocity would be different.
- For different human positions, the same human velocity would decompose into different normal human velocity, and the observed Doppler velocity would be different.

In other words, the observed Doppler velocity depends on not only the actual human movement, but also the relative position of the human movement and the transceivers. As such, how we position the system is crucial to ensure the extraction of effective and robust Doppler effect features.

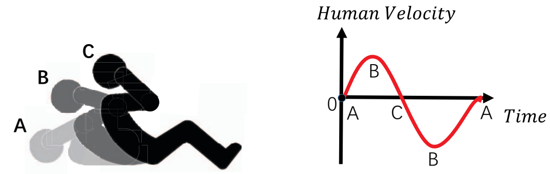
C. System Deployment for Bodyweight Exercise Monitoring

Understanding Human Velocity of Bodyweight Exercises: As illustrated in Figure 2, most bodyweight exercises can be abstracted as a circular motion where a part of the human body is fixed as the pivot point for kinetic stability and other parts of the human body perform a circular motion around this pivot point. Here, we consider three typical examples: sit-up, push-up, and squat. As shown in Figure 3a, during the process of sit-up, when the body moves from position A to position B, the magnitude of human velocity gradually increases, and when the body continues to move from B to C, the magnitude of human velocity gradually decreases to zero. Although not exactly symmetric, a similar change happens when the body returns from C to A. Thus, if we could obtain obvious Doppler velocity pattern corresponding to human velocity pattern shown in Figure 3b, we will get chance to characterize bodyweight exercise using Wi-Fi signal.



(a) Sit-up abstraction (b) Push-up abstraction (c) Squat abstraction

Fig. 2: Human velocity direction of bodyweight exercises.

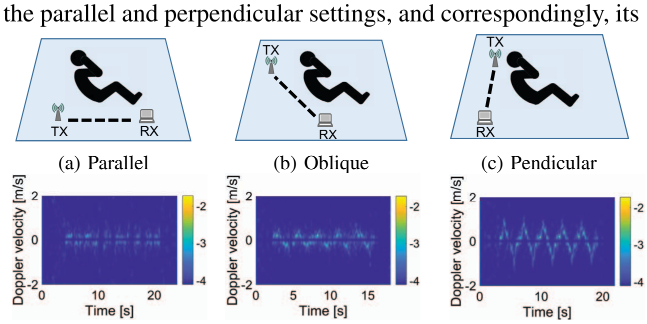


(a) Sequence of sit-up exercise (b) Human velocity magnitude

Fig. 3: Human velocity magnitude of bodyweight exercises.

System Deployment vs. Human Velocity Direction: Given a pair of Wi-Fi transceivers placed apart on the ground, we investigate three deployment strategies with regard to human velocity direction as Figure 4a-4c, in which the human body is parallel or oblique or perpendicular with the direct path. Correspondingly, Figure 4d-4f show the Doppler velocity spectrum obtained from real-world sit-up exercise under different deployment settings. We can see that, although the user performs the same sit-up exercise, the quality of Doppler velocity varies significantly, with the perpendicular setting achieving the best quality (clear periodic pattern).

The detailed reasoning is explained as follows: when the human body is parallel to the direct path as shown in Figure 5a. There is an angle θ between the human velocity and reflection plane (the blue shaded triangle). The human velocity v_{real} can be decomposed into the normal velocity v on the reflection plane and another tangent velocity (not shown). Only normal velocity change the reflection path length which can be expressed as $v = v_{real} \times cos(\theta)$. θ of parallel deployment is close to 90 degrees. It would result in near zero Doppler velocity which is difficult to be extracted and easily distorted by noise. In contrast, θ of perpendicular deployment is close to 0 degree and the normal velocity is largest as shown in Figure 5b. So significant changes of the Doppler velocity could be observed. As for oblique deployment, it has an angle θ that is in-between the parallel and perpendicular settings, and correspondingly, its

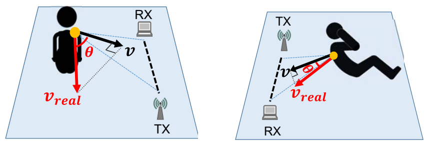


(a) Parallel (b) Oblique (c) Pendicular

(d) Parallel (e) Oblique (f) Perpendicular

Fig. 4: Doppler velocity of different deployment strategies.

Authorized licensed use limited to: Peking University. Downloaded on May 13,2021 at 06:17:21 UTC from IEEE Xplore. Restrictions apply.



(a) Parallel(left side view) (b) Perpendicular

Fig. 5: Velocity decomposition of different deployments.

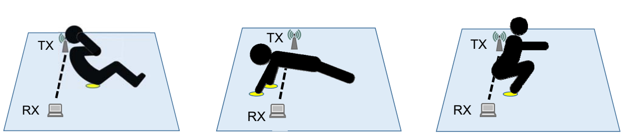
Doppler velocity changes fall in middle cases.

When come to push-up and squat, the reasoning process is similar to sit-up. Through extensive experiments, all of three kinds of exercises achieve better Dopper velocity pattern in the perpendicular deployment. The perpendicular deployments of three kinds of exercises are illustrated in Figure 6a-6c.

System Deployment vs. Human Position: Besides human velocity direction, the impact of human position should also be considered when deciding on the best system deployment. Here, we further investigate different deployment strategies with regard to human position along the mid-perpendicular line of the direct path. Specifically, for sit-up exercise, as shown in Figure 7a-7c, we consider three typical human positions, where the waist or chest or head is above the direct path. Figure 7d-7f show the corresponding Doppler velocity spectrum in real-world experiments. When the human is further away from the direct path, the magnitude of Doppler velocity becomes larger (easier to detect). But at the same time, the signal becomes weaker and the Doppler velocity spectrum becomes darker (harder to detect). It's because that: as the human moves further away from the direct path, the main human reflection area gradually changes from torso to head, which generates a weaker reflection signal due to the smaller reflection area. Therefore, the best system deployment needs to strike a balance between larger Doppler velocity changes and weaker/noisier reflection signal. We further conduct experiments with $10cm$ fine-grained increments in between waist, chest, and head. As a result, the chest deployment achieves the best performance for sit-up, capturing clear Doppler velocity patterns with larger magnitude and higher intensity. Similarly, we also have conducted lots of experiments for push-up and squat. It turns out that the best position for squat is when the user stands next to the direct path as shown in Figure 6b, and the best position for push-up is when the user's chest aligned with the direct path as shown in Figure 6c.

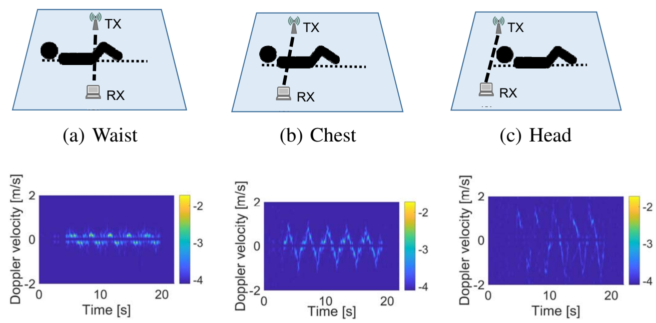
D. Doppler Displacement Extraction on Commodity Wi-Fi

So far, we have assumed that Doppler velocity is readily available from Wi-Fi CSI. In reality, we apply the Doppler-MUSIC method [9] to get the Doppler velocity spectrum which is used for analysis in previous section, as the example shown in Figure 8a. Then we further extract the strongest Doppler velocity from Doppler velocity spectrum as our valid



(a) Sit-up deployment (b) Push-up deployment (c) Squat deployment

Fig. 6: System deployment.



(a) Waist (b) Chest (c) Head

(d) Waist (e) Chest (f) Head

Fig. 7: Doppler velocity of different human positions.

Doppler velocity, because it represents the velocity of dominating reflection path signal introduced by major reflection area of human body. Figure 8b shows the extracted Doppler velocity from the corresponding spectrum in Figure 8a. After that, we could calculate the Doppler displacement from the Doppler velocity:

$$\begin{cases} d(z_0) = 0 \\ d(z_i) = d(z_{i-1}) + v(z_i) \times \Delta z, i > 0 \end{cases} \quad (2)$$

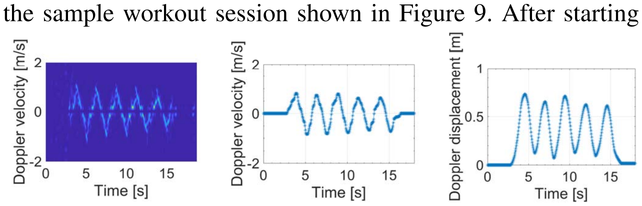
where z_0 is the system start time, $d(z_i)$ is the aggregated path length change since z_0, $v(z_i)$ is the extracted Doppler velocity at the i^{th} time interval, and Δz is the time interval between two consecutive Doppler velocity estimations. Figure 8c shows the Doppler displacement calculated from the Doppler velocity shown in Figure 8b. The Doppler displacement is smoother than Doppler velocity, and will be used in the next section for segmenting and counting bodyweight exercises.

IV. Bodyweight Exercise Segmentation, Counting, and Classification

Now, we are able to extract effective and robust Doppler effect features to capture fine-grained bodyweight exercise movements. However, more is needed for real-world monitoring of bodyweight exercises, where people tend to perform multiple sets of exercises of different types, along with non-exercise activities in a single workout session. Thus, it is important for WiFit to automatically segment and count the bodyweight exercise, then further classify each type of bodyweight exercises.

A. Bodyweight Exercise Segmentation and Counting

Key Observations: Due to the diversity of people's exercise routines, it is natural to expect that the system would collect signal of intermittent exercise and non-exercise activities in the exercise process. To illustrate this, let's take a closer look at the sample workout session shown in Figure 9. After starting



(a) Doppler spectrum (b) Doppler velocity (c) Doppler displacement

Fig. 8: Doppler displacement extraction

Authorized licensed use limited to: Peking University. Downloaded on May 13,2021 at 06:17:21 UTC from IEEE Xplore. Restrictions apply.

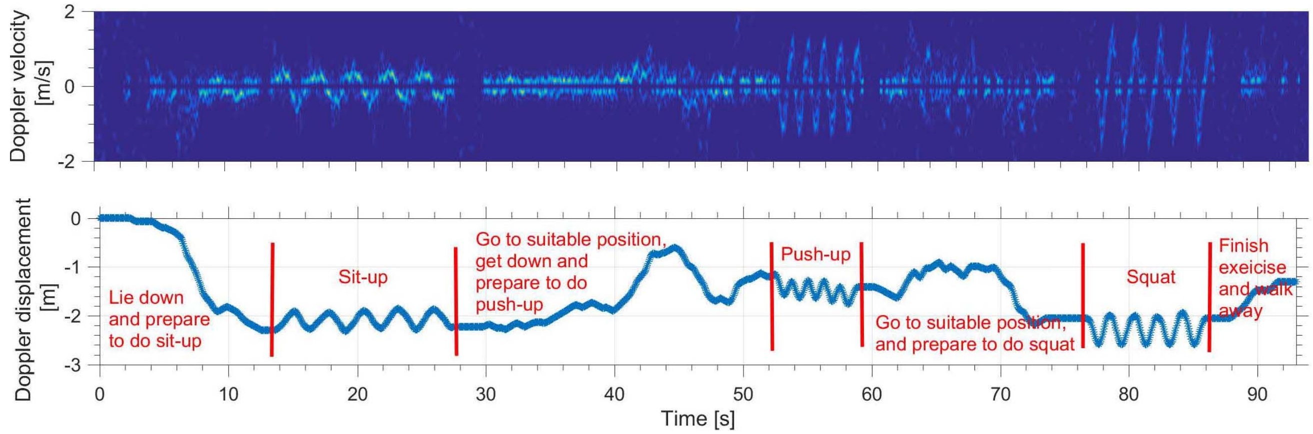


Fig. 9: A sample workout session consisting of multiple sets of bodyweight exercises and other activities. Upper figure shows the Doppler velocity spectrum, and below figure shows the corresponding Doppler displacement and annotated activities.

the system, the user first walks towards the system and then lies down to perform a set of sit-up exercise. After some rest, he gets up, walks around a little bit, then he gets down again to perform another set of push-up exercise. After that, he gets up again and adjust himself for squat. Finally, after finishing a set of squat exercise, he gets up and walks away. From the annotated Doppler displacement shown in Figure 9, we make the following three observations:

1) Each exercise repetition will cause an impulse pattern in Doppler displacement. The value of Doppler displace would increase (decrease) when the human body moves away from (towards) the direct path, i.e., positive (negative) Doppler velocity.
2) Compared with other non-exercise activities, bodyweight exercises are usually carried out in sets of repetitions, resulting in a short pause at the beginning of each set on the Doppler displacement, followed by a group of continuous and periodic impulses.
3) Within the same set of exercise repetitions by a user, the impulses should be similar to each other.

Based on these observations, we propose an impulse-based method to distinguish bodyweight exercises from other non-exercise activities, and further segment and count individual repetitions in each set of exercise.

Single Impulse Detection: Since each exercise repetition consists of moving away and returning back to the base posture, a target impulse in the Doppler displacement stream would have the form as shown in Figure 10, in which the three transition points A, B, C form an impulse, and the amount of displacement within an impulse would be symmetric. For example, when moving up and down in a sit-up repetition,

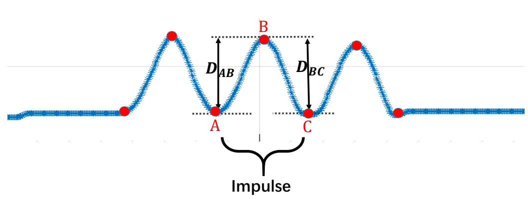


Fig. 10: A real-world example of impulse in sit-up exercise.

the corresponding Doppler displacement for moving up D_{AB} and down D_{BC} should be the same. Considering that the Doppler velocity estimation may have accumulative error, a target impulse should satisfy: $|D_{AB} - D_{BC}| < \delta_D$, where δ_D is empirically set to $0.3m$ in this work. Furthermore, considering the physical characteristics of the human body, each exercise repetition is expected to take a certain amount of time, i.e., not too fast or too slow. Therefore, a target impulse should satisfy: $\delta_{T_{min}} < T_C - T_A < \delta_{T_{max}}$, where T_A and T_C correspond to the time of point A and point C, respectively, $\delta_{T_{min}}$ and $\delta_{T_{max}}$ are the minimal and maximal threshold of repetition duration. In our system, we set $\delta_{T_{min}} = 1$ second and $\delta_{T_{max}} = 5$ seconds. Using the criteria above, WiFit continuously monitors the Doppler displacement stream and detects individual impulses by checking the three transition points, the difference of their displacement, and time duration.

Set of Impulses Detection: The single impulse detection process above can filter out most of the static and random activities. But it may still detect impulses caused by other non-exercise activities, such as sudden shake of the body, walking back and forth. To determine whether an impulse corresponds to a bodyweight exercise repetition, we make the following assumptions: (a) Bodyweight exercises are performed in sets of repetitive movements, and each set contains more than one exercise repetition. (b) There is a short pause before the start of each set, as the user gets ready in the base posture. (c) The gap between two consecutive repetitions is short (e.g., no more than 2 seconds in our setting). In other words, in real-world scenarios, the bodyweight exercises often occur as sets of impulses, which can be detected as follows:

1) If a new impulse occurs after a short pause and does not belong to the previous impulse set, it may be the first impulse of a new set.
2) A new impulse is added to the previous impulse set if it satisfies the following two requirements:
   - $T_{begin}^{(i)} - T_{end}^{(i-1)} < \delta_{interval}$, where $T_{begin}^{(i)}$ is the beginning time of a new impulse, $T_{end}^{(i-1)}$ is the ending time of the last impulse in the previous

Authorized licensed use limited to: Peking University. Downloaded on May 13,2021 at 06:17:21 UTC from IEEE Xplore. Restrictions apply.

impulse set, $\delta_{interval}$ is the maximum time gap allowed between two adjacent impulses in a set.

- The normalized similarity between the new impulse and impulses in the previous set should be high:

$$\frac{\sum_{j=1}^{n} DTW(Impulse_{now}, Impulse_j)}{\sum_{j=1}^{n} Len(Impulse_j)} < \xi$$

where n is the total number of impulses in the previous impulse set, each impulse is represented as a sequence of Doppler displacement values, and $Len(Impulse_j)$ is the length of the j^{th} impulse. DTW refers to the Dynamic Time Warping algorithm [21].

3) When no more new impulse can be added to the previous impulse set, and the number of impulses in the previous impulse set n is more than one, this set of impulses will be segmented out with n as the number of repetitions in this set. Otherwise, it will be discarded.

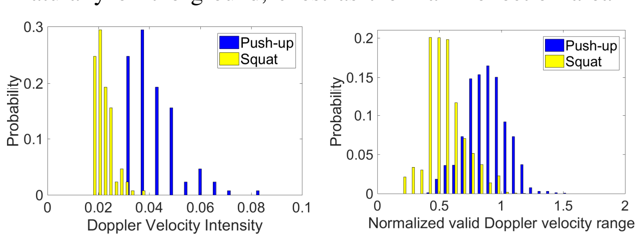
B. Bodyweight Exercise Classification

Given the segmented sets of impulses, which correspond to different sets of bodyweight exercise repetitions, we further classify them into the specific types of bodyweight exercises. In this work, we propose to extract the following features from real-time CSI streams for exercise classification: (1) normalized standard deviation of CSI amplitude, (2) normalized standard deviation of CSI phase difference between two antennas on the receiver, (3) entropy of CSI histogram, (4) change direction of Doppler Displacement, (5) Doppler velocity intensity, and (6) normalized valid Doppler velocity range. The first three features have been used and explained in previous works for activity classification [7], [15], [22]. Here we only elaborate on the other three new features.

• First, consider a standard sit-up exercise, it begins with the user lying on the floor, then elevating both the upper and lower vertebrae from the floor, before returning back to the floor again [1]. In this process, the human body first moves away from the direct path and then closer to the direct path. As such, sit-up impulses are positive, as shown in Figure 9. However, for push-up and squat exercises, the human body first moves closer to the direct path, then away from the direct path, resulting in negative impulses. So the first feature we choose here is the positive or negative direction of the impulse, which is effective to differentiate sit-up exercise from other two types of exercises.

• Next, compared with squat, the human body is at a lower height when doing push-up. With the Wi-Fi devices placed naturally on the ground, chest as the main reflection area in push-up has shorter reflection path than hip in squat. Note that the strongest Doppler velocity of the Doppler velocity spectrum represents the velocity of the dominating reflection path signal, and its value (referred to as Doppler velocity intensity) indicates the power of reflection path. So we choose Doppler velocity intensity as another effective feature. As shown in Figure 11a, the distributions of Doppler velocity intensity are quite different between push-up and squat, and push-up shows higher Doppler velocity intensity than squat.

• Further, consider push-up exercise, in which both the human torso and arms move but at different velocities, thus generating a much wider range of Doppler velocity on the Doppler spectrum. For squat exercise, the Doppler velocity is mainly generated by the human hip with a narrow range of Doppler velocity. This motivates the design of our third feature: the normalized valid Doppler velocity range (normalized by the strongest Doppler velocity extracted from the Doppler spectrum), which indicates the diversity of human velocity. Figure 11b shows the normalized valid Doppler velocity range distributions for push-up and squat exercises. It makes further improvement to differentiate push-up and squat. At last, all of the features along with the annotated labels are fed into the multi-class LibSVM classifier for exercise classification.



(a) Push-up vs. Squat (b) Push-up vs. Squat

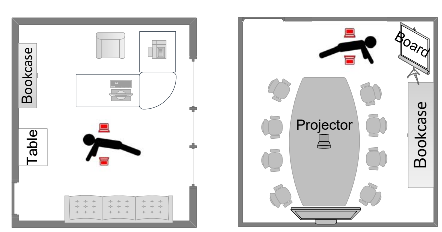
Fig. 11: Feature comparison of push-up and squat.

V. Evaluation

A. System Implementation and Experimental Setup

For WiFit system. we use two GIGABYTE miniPCs equipped with off-the-shelf Intel 5300 Wi-Fi cards as the transmitter and receiver [23]. The experiments are conducted in the 5 GHz frequency band utilizing a 20 MHz channel, and the sampling rate of CSI in WiFit is set to 200 Hz. We conduct experiments in two different environments as shown in Figure 12: a) an office room (4m×4m) with various furniture and electrical appliances, and b) a meeting room (6m×5m) with a big table and many chairs. Both rooms are typical indoor environments with rich multi-path.

The experiments were conducted over a period of three weeks. We have recruited 20 volunteers to perform the three types of bodyweight exercises naturally in various workout sessions. The 20 volunteers include 5 female and 15 male, aged 20–38, with a height range of $[157cm, 185cm]$ and a weight range of $[50kg, 100kg]$. Most of them have no prior knowledge of our system. In each workout session, a volunteer easily sets up two Wi-Fi devices by placing them on both sides of his/her body with a suggested direct path length of 1 m. The Wi-Fi devices can be replaced by personal devices in the real world (e.g., smart phone as transmitter and tablet as receiver).



(a) Office Room (b) Meeting Room

Fig. 12: System evaluation environments.

Authorized licensed use limited to: Peking University. Downloaded on May 13,2021 at 06:17:21 UTC from IEEE Xplore. Restrictions apply.

Exercise	Accuracy	FPR
Push-up	0.9944	0.0071
Sit-up	0.9864	0.0071
Squat	0.9902	0

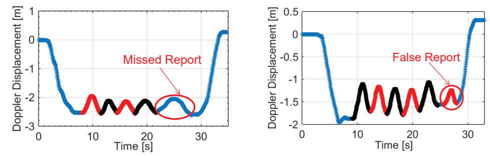
(a) R1

Exercise	Accuracy	FPR
Push-up	0.993	0.005
Sit-up	0.99	0
Squat	0.985	0.008

(b) R2

Direct Path	Accuracy	FPR
0.8m	0.9876	0.0075
1m	0.9903	0.0047
1.2	0.9944	0.0056

(c) R1



(d) Example of missed report (e) Example of false report

Fig. 13: (a), (b) show the repetition counting performance of office room(R1) and meeting room(R2); (c) shows the repetition counting performance of different direct path length; (d), (e) show the missed and false examples of report.

After that, he/she starts our system, and makes preparations, then performs several sets of bodyweight exercise of different types. Only a short pause is required before each set of exercise at the base posture. At other time, the volunteer can do any thing naturally for preparing the exercise. After finishing the exercise session, the volunteer leaves and stops our system. A camera is deployed in the environment to record the ground truth. Each volunteer performed each type of bodyweight exercises at least 10 sets with 5 repetitions in one set, resulting in 1450 repetitions(290 sets) per type, and in total 4350 repetitions of bodyweight exercises. In order to evaluate the exercise repetition counting performance, we use the metrics below:

$$accuracy = \frac{\#\ of\ correctly\ detected\ repetitions}{\#\ of\ repetitions\ that\ are\ performed} \quad (3)$$

$$FPR = \frac{\#\ of\ mistakenly\ detected\ repetitions}{\#\ of\ repetitions\ that\ are\ detected} \quad (4)$$

B. Repetition Counting Performance

Impact of Different Environments: To evaluate the robustness of our segmentation scheme, we evaluate the repetition counting performance in two different indoor environments, where both direct paths are set to 1m. Figure 13a-13b shows the results for each type of bodyweight exercise in two indoor environments. We can see that WiFit achieves good performance for all three types of exercises, with more than 98% accuracy and less than 1% FPR in both indoor environments. During the experiments, missed reports and false reports for counting only occur rarely at the end of a set of exercise. As shown in Figure 13d, when the volunteer was too exhausted to finish the last several repetitions in a set, the Doppler displacement deformed badly, which would lead to a missed report in our system. As to false alarms, they may occur when a volunteer finishes his exercise with other irrelevant body shaking actions. As shown in Figure 13e, after the volunteer completed his exercise of sit-ups, his body shook suddenly as he was standing up because of imbalance, causing an impulse that was similar to the previous sit-up repetitions, thus generating a false count for this set of exercise. Nevertheless, such missed report and false report occur rarely under our segmentation scheme.

Impact of Direct Path Length: Since exercisers may differ in their body shape and exercise style, they may adjust their Wi-Fi devices' placement and position them slightly different from the suggested 1m direct path length. Therefore, we also conducted experiments in the office room with two other direct path lengths: $0.8m$ and $1.2m$ so that further examine the counting performance and testify the robustness of our system. Five volunteers are asked to perform the same workout with each type of exercise 50 repetitions in different direct path length settings. The results of the different length settings are shown in Figure 13c. From the results, we can see that the counting accuracy stays high across different lengths of the direct path. This means that each user can choose the direct path length that is most comfortable for himself or herself and still get consistent counting performance.

C. Exercise Classification Performance

Next, we evaluate the exercise classification performance. As false repetition reports only occur rarely at the end of a set of exercise, and our classification scheme is based on the exercise set but not on the repetition, so we only consider the three target types of exercise for classification. Specifically, for each of three types of bodyweight exercises, we examine for all segmented sets of exercises that the fraction of sets that are correctly classified VS sets that are misclassified.

Impact of Different Environments: In order to evaluate the performance of different environments, 200 sets of each exercise type conducted by 20 volunteers are firstly gathered in the office room. Then the whole data are divided into two parts (18 volunteers as training set, 2 volunteers as testing set) for 10-fold cross validation to build the classification model. For the meeting room, we apply the same model trained in the office room to test the exercise data collected from 4 volunteers with 40 sets per exercise type. Figure 14a-14b shows the confusion matrix for the three exercise types in the two indoor environments. We first note that all the sit-up exercise cases are correctly classified. This is due to the impulse direction feature we used for effective classification. Our system also does a good job distinguishing the other two types of exercises, correctly classifying 95.8% and 94.6% of the push-up and squat exercises in the office room (R1). The classification performance in the meeting room (R2) drops a little but still holds a high accuracy while using the same model trained in the office room. The results clearly show that, based on the effective feature selection scheme, our system achieves high and stable activity classification performance for all three kinds of exercise in different environments.

Impact of Direct Path Length: We also evaluate the robustness of our classification model by varying the direct path length. The test data set is collected from five volunteers in another two length settings ($0.8m$, $1.2m$), same as the one used for counting performance evaluation under different length settings. The results are shown in Figure 14c-14d. We

Authorized licensed use limited to: Peking University. Downloaded on May 13,2021 at 06:17:21 UTC from IEEE Xplore. Restrictions apply.

Actual exercise	Predicted exercise		
	Push-up	Sit-up	Squat
Push-up	0.958	0	0.042
Sit-up	0	1	0
Squat	0.054	0	0.946

(a) Direct path = 1m in R1

Actual exercise	Predicted exercise		
	Push-up	Sit-up	Squat
Push-up	0.902	0	0.098
Sit-up	0	1	0
Squat	0.088	0	0.912

(b) Direct path = 1m in R2

Actual exercise	Predicted exercise		
	Push-up	Sit-up	Squat
Push-up	0.947	0	0.053
Sit-up	0	1	0
Squat	0.054	0	0.946

(c) Direct path = 0.8m in R1

Actual exercise	Predicted exercise		
	Push-up	Sit-up	Squat
Push-up	0.953	0	0.047
Sit-up	0	1	0
Squat	0.062	0	0.938

(d) Direct path = 1.2m in R1

Fig. 14: Exercise classification performance.

can see that the classification performance is only slightly affected by the direct path length. Again, this evaluation demonstrates that our system is robust against variations in the direct path length.

Impact of Different Participants: Since exercisers can differ in height, weight, and the way they exercise, we also evaluated the robustness of our system against individual diversity. First, we collected training data from 10 different volunteers to build the classification model. Then, in the testing phase, we apply this model to other 10 volunteers, and the evaluation results of individual participants are shown in Figure 15. Overall, our system maintains high classification accuracy (between 0.939 and 0.967) for all 10 participants.

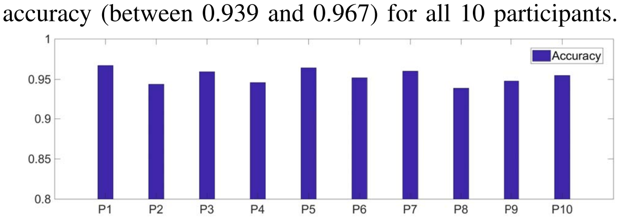


Fig. 15: Classification performance of different participants

VI. Conclusion

In this paper, we have developed WiFit, a ubiquitous bodyweight exercise monitoring system using only two commodity Wi-Fi devices. WiFit can automatically segment, count and recognize three typical bodyweight exercises. To build WiFit, we have studied the relationship between bodyweight exercises and Wi-Fi signal, and propose the best system deployment strategies in order to capture effective and robust Doppler effect features that correspond well to fine-grained bodyweight exercise movements. Moreover, we have proposed an impulse-based method to segment and count each exercise repetition. Based on the segmentation, we also extracted informative features to classify different types of bodyweight exercises. WiFit achieves an accuracy of 99% in repetition counting, and 95.8% in exercise classification. Building upon our initial success of effective bodyweight exercise monitoring using off-the-shelf Wi-Fi devices, we plan to investigate other interesting problems. For example, can we develop other features that could generalize in classification of more exercise types? Can we extend exercise monitoring in muti-user scenario? These would be our future work.

References

[1] J. S. Harrison, "Bodyweight training: A return to basics," *Strength & Conditioning Journal*, vol. 32, no. 2, pp. 52–55, 2010.
[2] W. Zhao, H. Feng, R. Lun, D. D. Espy, and M. A. Reinthal, "A kinect-based rehabilitation exercise monitoring and guidance system," in *"Proc. ICSESS'14"*, June 2014, pp. 762–765.
[3] X. Guo, J. Liu, and Y. Chen, "Fitcoach: Virtual fitness coach empowered by wearable mobile devices," in *"Proc. INFOCOM'17"*, May 2017, pp. 1–9.
[4] T. Hao, G. Xing, and G. Zhou, "Runbuddy: A smartphone system for running rhythm monitoring," in *"Proc. Ubicomp'15"*, 2015, pp. 133–144.
[5] H. Ding, J. Han, L. Shangguan, W. Xi, Z. Jiang, Z. Yang, Z. Zhou, P. Yang, and J. Zhao, "A platform for free-weight exercise monitoring with passive tags," *IEEE Transactions on Mobile Computing*, vol. 16, no. 12, pp. 3279–3293, Dec 2017.
[6] W. Wang, A. X. Liu, M. Shahzad, K. Ling, and S. Lu, "Understanding and modeling of wi-fi signal based human activity recognition," in *"Proc. MobiCom'15"*, 2015, pp. 65–76.
[7] Y. Wang, J. Liu, Y. Chen, M. Gruteser, J. Yang, and H. Liu, "E-eyes: Device-free location-oriented activity identification using fine-grained wifi signatures," in *"Proc. MobiCom'14"*, 2014, pp. 617–628.
[8] K. Qian, C. Wu, Z. Zhou, Y. Zheng, Z. Yang, and Y. Liu, "Inferring motion direction using commodity wi-fi for interactive exergames," in *"Proc. CHI'17"*, 2017, pp. 1961–1972.
[9] X. Li, D. Zhang, Q. Lv, J. Xiong, S. Li, Y. Zhang, and H. Mei, "Indotrack: Device-free indoor human tracking with commodity wi-fi," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 1, no. 3, pp. 72:1–72:22, Sep. 2017.
[10] (2017). [Online]. Available: https://www.fitbit.com/
[11] I. Pernek, K. A. Hummel, and P. Kokol, "Exercise repetition detection for resistance training based on smartphones," *Personal Ubiquitous Comput.*, vol. 17, no. 4, pp. 771–782, Apr. 2013.
[12] F. Adib, Z. Kabelac, D. Katabi, and R. C. Miller, "3d tracking via body radio reflections," in *"Proc. NSDI'14"*, 2014, pp. 317–329.
[13] T. Wei and X. Zhang, "mtrack: High-precision passive tracking using millimeter wave radios," in *"Proc. MobiCom'15"*, 2015, pp. 117–129.
[14] K. Joshi, D. Bharadia, M. Kotaru, and S. Katti, "Wideo: Fine-grained device-free motion tracing using rf backscatter," in *"Proc. NSDI'15"*, 2015, pp. 189–204.
[15] H. Wang, D. Zhang, Y. Wang, J. Ma, Y. Wang, and S. Li, "Rt-fall: a real-time and contactless fall detection system with commodity wifi devices," *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 511–526, Feb 2017.
[16] D. Zhang, H. Wang, and D. Wu, "Toward centimeter-scale human activity sensing with wi-fi signals," *Computer*, vol. 50, no. 1, pp. 48–57, Jan 2017.
[17] H. Wang, D. Zhang, J. Ma, Y. Wang, Y. Wang, D. Wu, T. Gu, and B. Xie, "Human respiration detection with commodity wifi devices: Do user location and body orientation matter?" in *Proc. Ubicomp'16"*, 2016, pp. 25–36.
[18] F. Zhang, D. Zhang, J. Xiong, H. Wang, K. Niu, B. Jin, and Y. Wang, "From fresnel diffraction model to fine-grained human respiration sensing with commodity wi-fi devices," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 2, no. 1, pp. 53:1–53:23, Mar. 2018.
[19] D. Wu, D. Zhang, C. Xu, H. Wang, and X. Li, "Device-free wifi human sensing: From pattern-based to model-based approaches," *IEEE Communications Magazine*, vol. 55, no. 10, pp. 91–97, Oct. 2017.
[20] X. Fu, J. Chen, X. Xie, L. Gui, L. Sun, and R. Wang, "Seare: A system for exercise activity recognition and quality evaluation based on green sensing," *IEEE Transactions on Emerging Topics in Computing*, vol. PP, no. 99, pp. 1–1, 2018.
[21] S. Salvador and P. Chan, "Toward accurate dynamic time warping in linear time and space," *Intelligent Data Analysis*, vol. 11, no. 5, pp. 561–580, 2007.
[22] S. Li, X. Li, K. Niu, H. Wang, Y. Zhang, and D. Zhang, "Ar-alarm: An adaptive and robust intrusion detection system leveraging csi from commodity wi-fi," in *"Proc. ICOST'17"*, 2017, pp. 211–223.
[23] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Tool release: Gathering 802.11n traces with channel state information," *SIGCOMM Comput. Commun. Rev.*, vol. 41, no. 1, pp. 53–53, Jan. 2011.

Authorized licensed use limited to: Peking University. Downloaded on May 13,2021 at 06:17:21 UTC from IEEE Xplore. Restrictions apply.