Demo: WiFit—A Bodyweight Exercise Monitoring System with Commodity Wi-Fi

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Abstract
Bodyweight exercises, such as push-up, sit-up, and squat, are effective forms of strength training to maintain good health. In order to improve people's exercise experience and provide feedback, lots of work has been done to monitor the bodyweight exercise by requiring people to wear special sensors on body. Different from traditional ways, a non-intrusive system WiFit is shown in this demo which uses surrounding Wi-Fi signals to monitor the bodyweight exercises without any attachment requirements. It not only could recognize the exercise type but also count the repetition number of exercise for diverse population even in different environments.

Author Keywords
Wi-Fi, Ubiquitous, Bodyweight exercise, CSI

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous;

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. In order to monitor people's bodyweight exercises and provide feedback, various techniques 12417 exist in the literature. However, these techniques either raise

privacy concern or require body attachment to the devices.

With the ubiquitous availability of Wi-Fi devices, a number of Wi-Fi based and device-free sensing systems have been proposed. They focus mainly on monitoring human physiological features10 121516, detecting human motion and location information5-[9], or recognizing human daily activities 111314. Unlike existing works, in this work, we develop a bodyweight exercise monitoring system that not only could detect the occurrence of each type exercise, but also provide the fine-grained information such as number of repetitions in each exercise set.

To achieve the bodyweight exercise monitoring goal, WiFit utilizes the basic physical phenomena called Doppler Effect. Given a pair of Wi-Fi transmitter (TX) and receiver (RX) as shown in Figure 1, the Wi-Fi signal propagates from the transmitter to the receiver via a direct path, or via paths reflected by human body, wall and other objects. Human motion would 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 Wi-Fi signal, v_{path} is the speed of path length change, and c is light speed. As Wi-Fi Channel State Information (CSI) characterizes both the amplitude attenuation and phase change when a signal propagates from the transmitter to the receiver, it also contains Doppler frequency shift information. We obtain this Doppler frequency shift from Wi-Fi CSI. Then based on the Doppler frequency shift, effective features are extracted and a novel scheme is also developed to recognize the exercise type and count the repetition number of exercise.

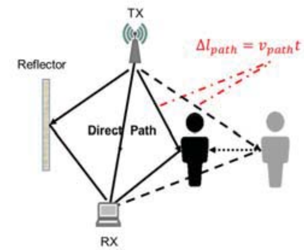

Figure 1: Doppler Effect on Wi-Fi signal

Demonstration Set-up

The demonstration set-up consists of a pair of Wi-Fi devices (i.e. GIGABYTE miniPCs) and an ordinary fitness cushion as shown in Figure 2. One Wi-Fi device is applied as a transmitter and the other serves as a receiver. Both devices are equipped with CSI Tool3 to collect CSI information. The transmitter communicates with the receiver on commodity 5.56GHz channel.

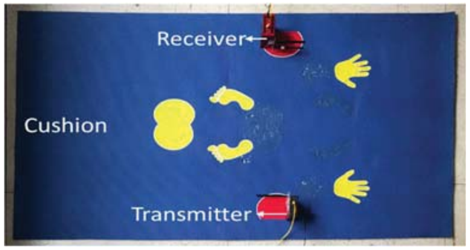

Figure 2: System set-up

Demonstration Process

With a pair of Wi-Fi devices placed on both sides of the cushion, the exerciser starts the exercise monitoring application and walks towards marked locations of the cushion to conduct corresponding exercises. The monitoring system will recognize the exercise type and count the repetition number of exercises in real-time. The designed user interface is shown in Figure 3.

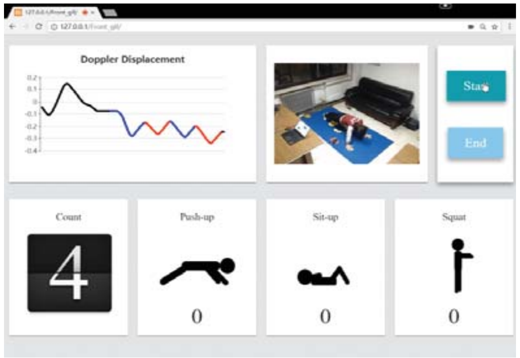

Figure 3: User interface

Contributions

1) WiFit achieves contactless bodyweight exercise monitoring by utilizing the Wi-Fi signals in the environment.
2) WiFit could automatically recognize the exercise type and count the repetition number of exercise by coupling the exercise patterns with detailed Doppler frequency shift on Wi-Fi signal.
3) WiFit maintains good performance for the diverse population even in different environments with an accuracy of 95.8% in exercise recognition and 99% in repetition counting.

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