Personalized Fitness Assistance Using WiFi

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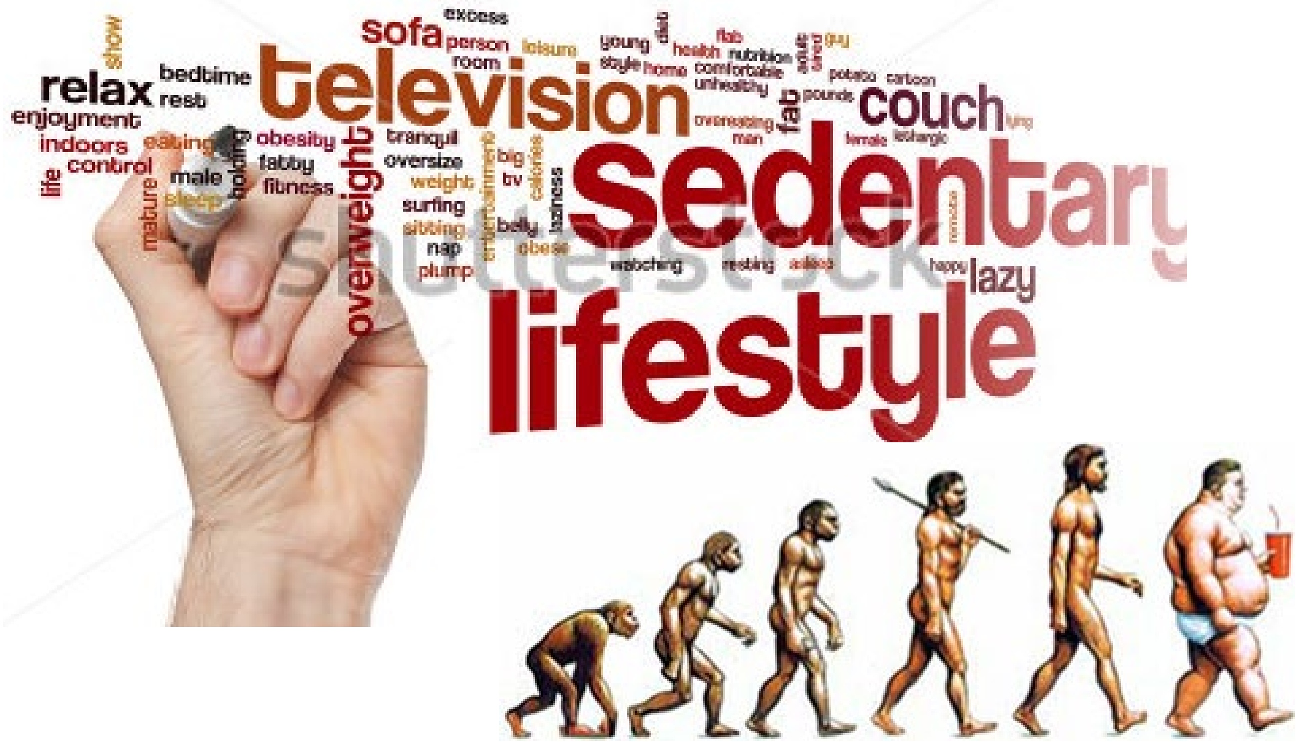
Why Exercise?

- Accelerated pace of life has resulted in many of us adapting to a sedentary lifestyle
- People are required to have regular exercise to stay healthy

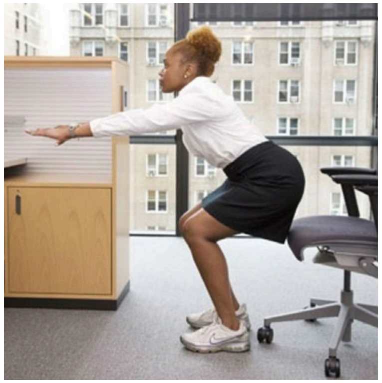


Motivation

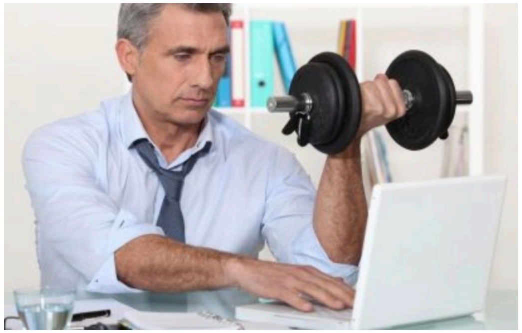
- Work-at-home people/office workers can barely squeeze in time to go to dedicated exercise places.

Motivation

- There is a trend for people to perform regular workout in home/office environments!



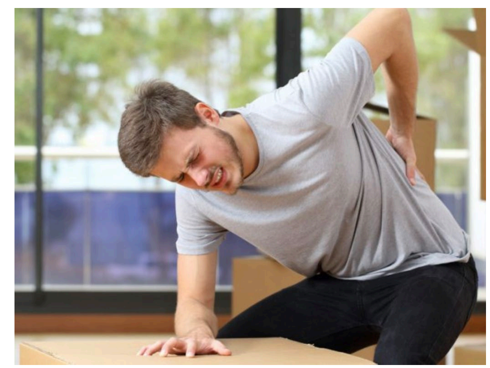
No space and time constraint!



Why Exercise Monitoring?

Did I follow my plan?

Is my movement correct?



Keeping track of your workouts

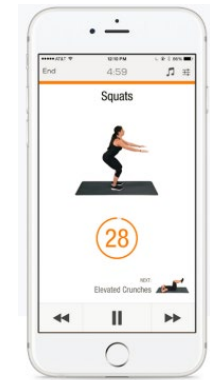
Avoid inefficient training or even accidental injuries

Traditional Fitness Assistants

Personal coach

Video

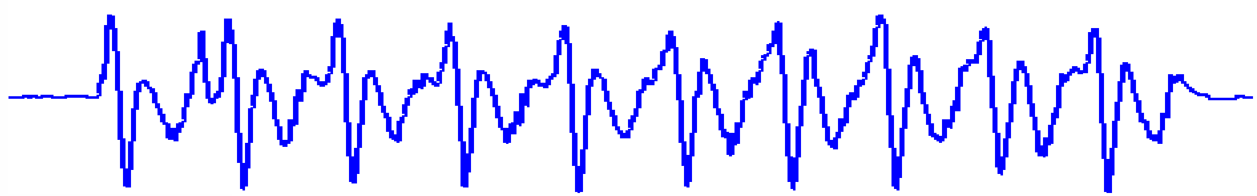
App instruction



- **Desirable system:**
  - Workout statistic & workout assessment
  - Doesn’t require any attached sensors
  - Incurs minimum involvement (e.g., w/o coach)

Our Previous Work: Virtual Fitness Coach Empowered by Wearable Mobile Devices

- Basic idea
  - Recording the sensor readings on wearable mobile devices
  - Exploring their capability of deriving fine-grained exercise information
  - Assessing dynamic postures (movement patterns & positions) automatically during workout
- Intuition

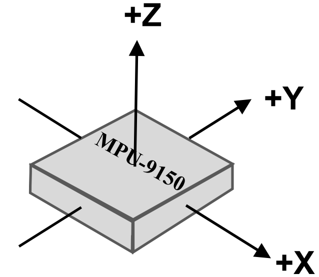


Our Previous Work: Virtual Fitness Coach Empowered by Wearable Mobile Devices

Integrated accelerometer, gyroscope, magnetometer

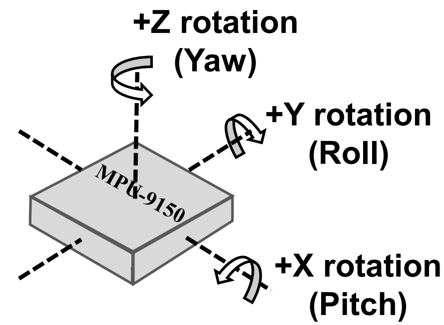
- **Accelerometer**

  Measures the acceleration



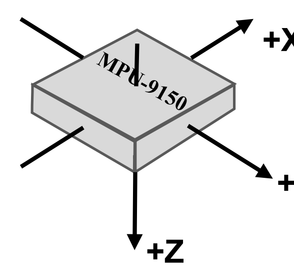
- **Gyroscope**

  Measures the orientation of the axis



- **Magnetometer**

  Measures the magnetic field strength



Our Goal

- Contactless smart fitness assistant

  - Device-free
  - Non-intrusive
  - Reuse of existing WiFi infrastructure

Basic Idea

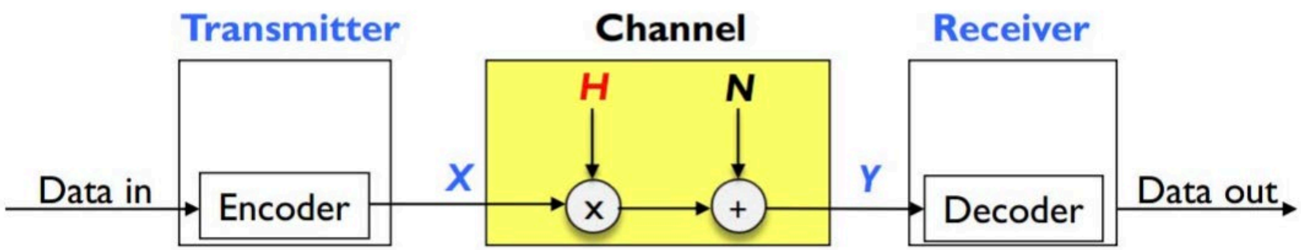
- Different exercises involve different body movements
  - Such movements affect WiFi channels differently

- Leverage WiFi channel information to obtain workout statistic and perform workout assessment

Capture Body Movements Using CSI

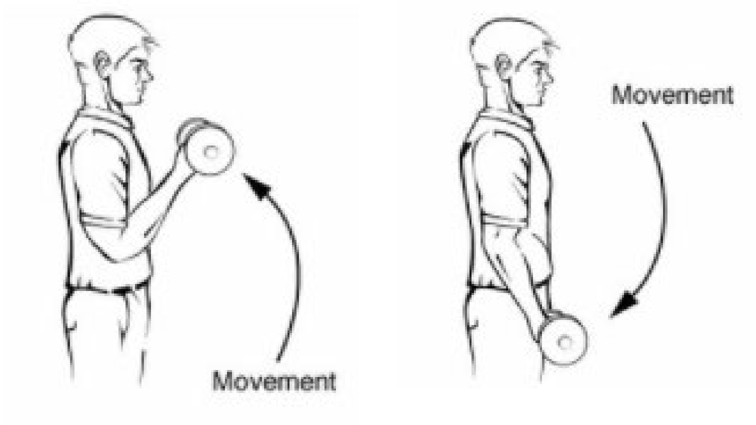
- **Exploit fine-grained CSI (Channel State Information) to detect body movements**

- **In an OFDM system, the received signal over multiple subcarriers is**
  $Y = HX + N$ (X– transmit signal, N– noise)
  - H=Y/X -- Channel State Information (CSI)
  - $H = he^{jw}$ (h: amplitude, w: phase)



Exercise (Reps & Sets)

- Exercises consists of repetitive movements
  - Provide statistic information (e.g., how many sets and reps for a given exercise).

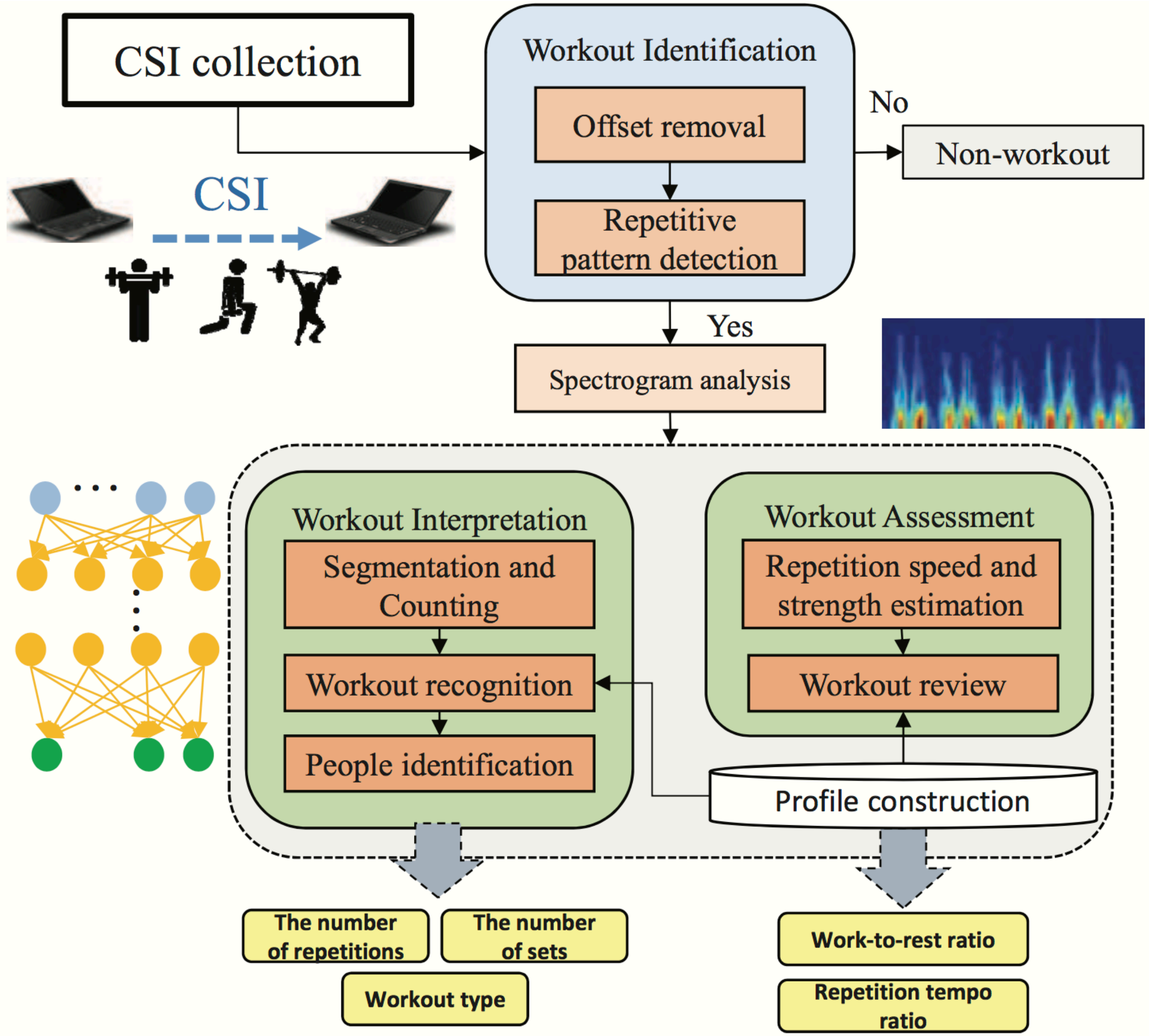


Repetition: one complete motion of an exercise

Set: a group of consecutive repetitions

- Different exercises have distinct impact on CSI
  - Capture unique features of CSI readings to infer exercise type

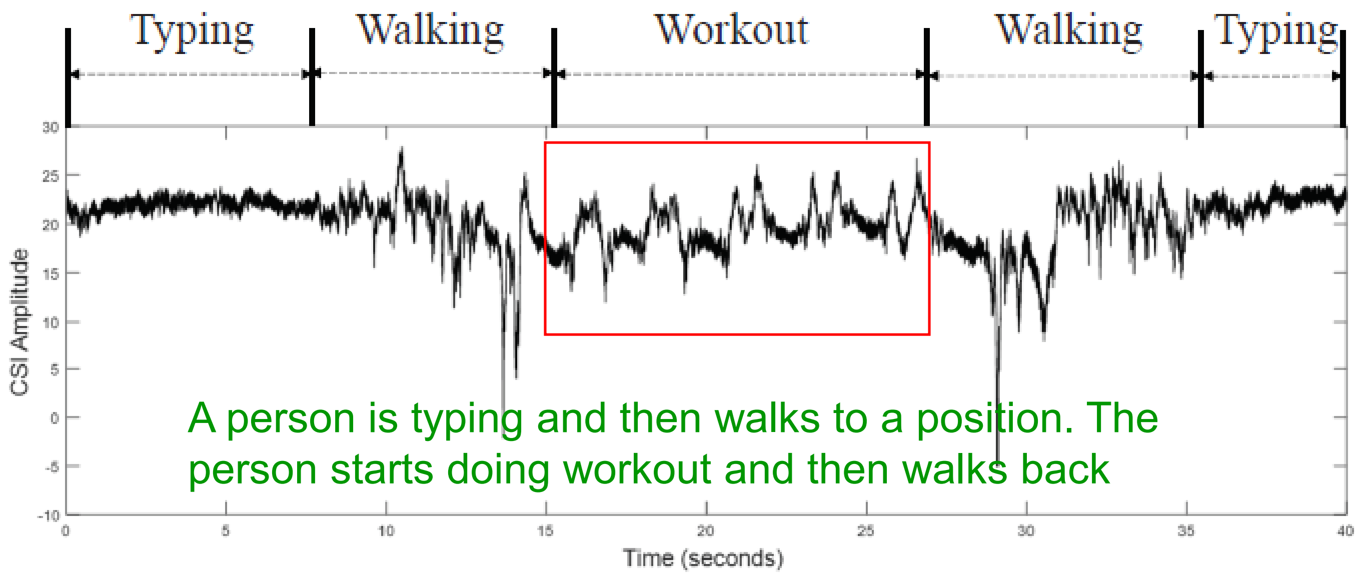
System Design



Workout Detection

❑ Intuition

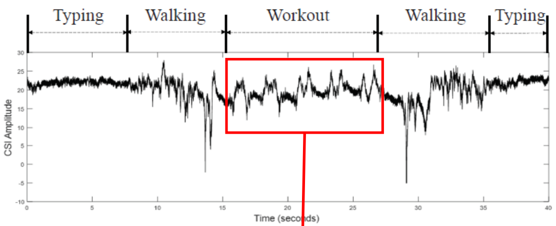
- Repetitive patterns are revealed in CSI readings collected during workout.
- Non-workout activities do not exhibit such characteristic .



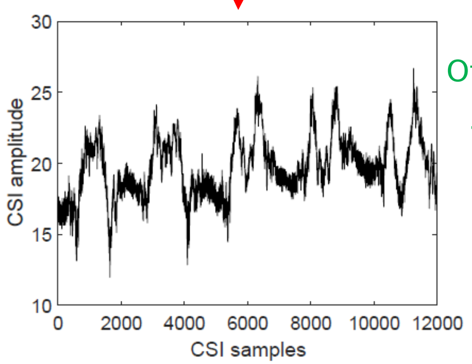
CSI amplitude of one subcarrier with corresponding activity time frame.

Workout Detection (cont.)

- Offset removal
  - Subtract a fitted low-order polynomial and further remove the mean value.
- Repetitive pattern detection
  - Autocorrelation calculation

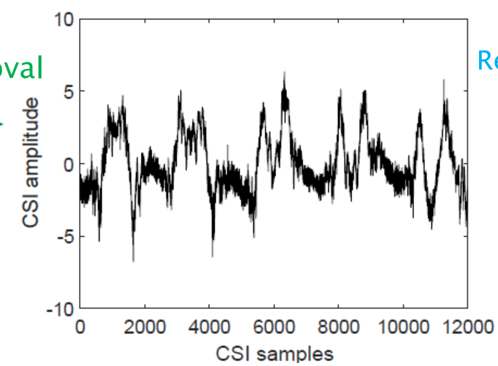


Zoom in



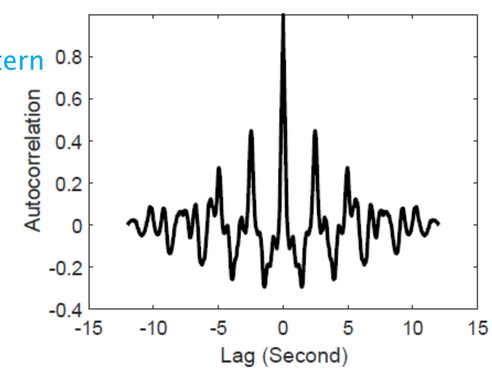
Workout CSI readings

Offset removal



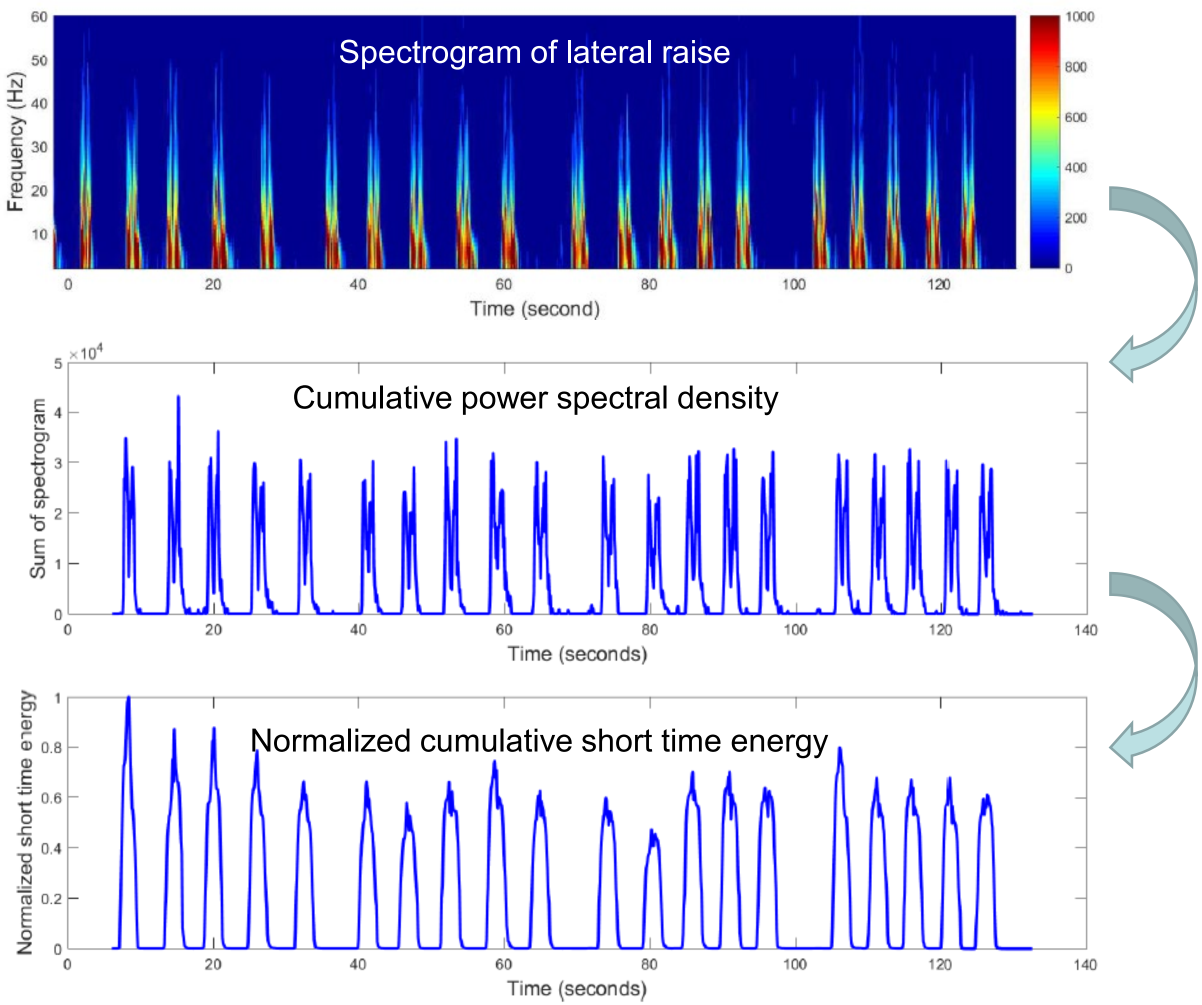
After offset removal

Repetitive pattern detection



Repetitive pattern detection

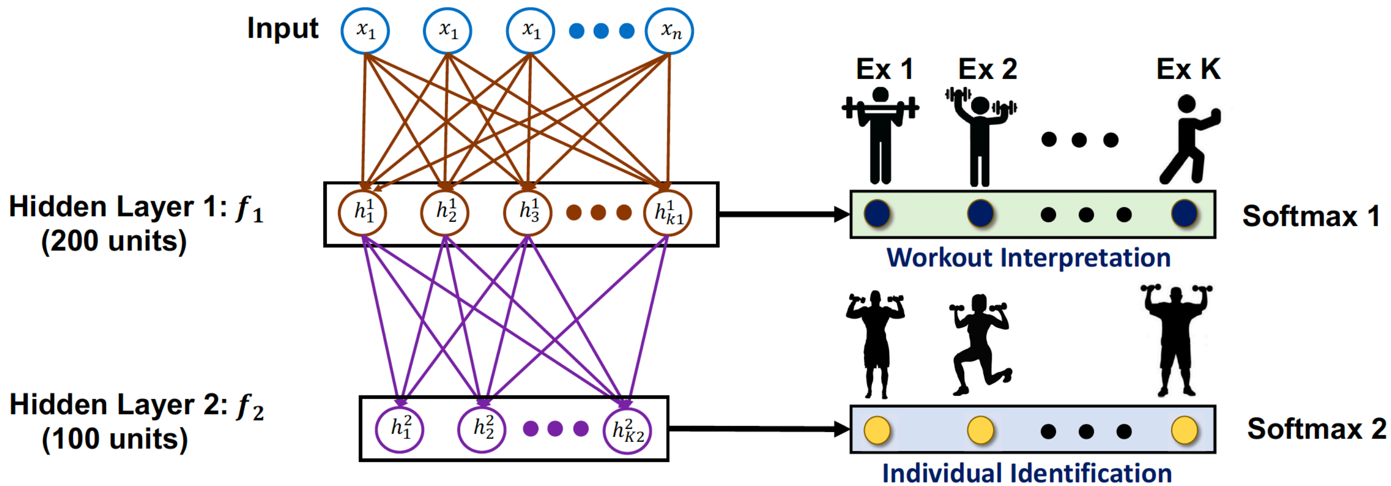
Segmentation and Counting



- Accumulates all power spectral density (PSD) along the frequency dimension of the spectrogram
- Accumulates the energy of the cumulative PSD based on short time energy (STE)

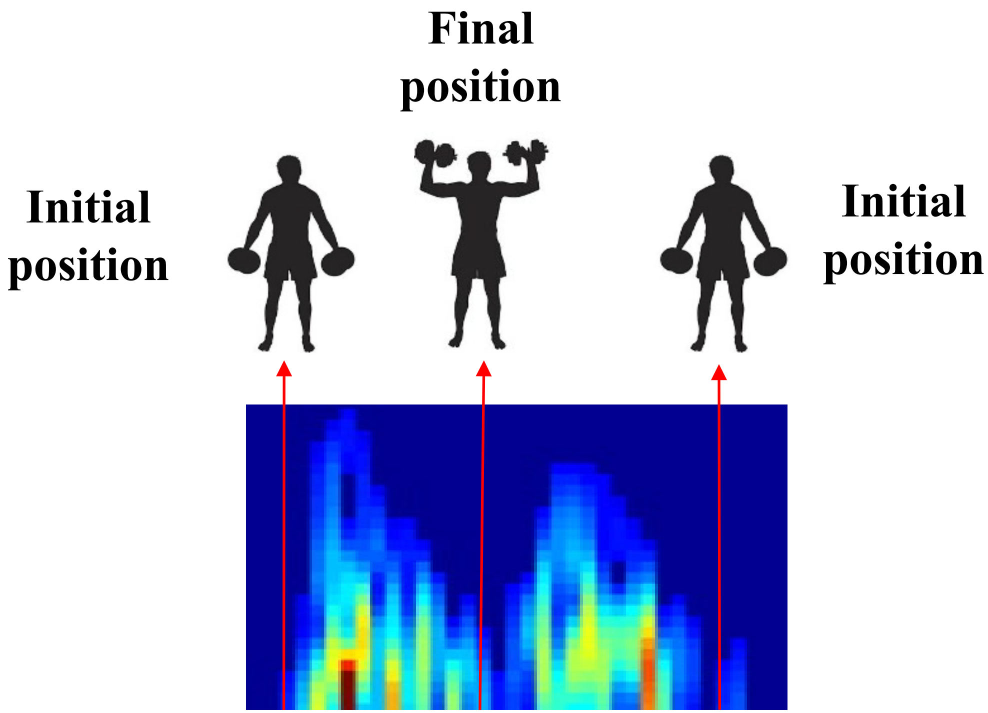
Workout Interpretation (cont.)

- Workout recognition
  - Differentiate individuals as a user may share workout space with other family members or colleagues
- Feature extraction
  - 8 time domain features extracted from each OFDM subcarrier, including *maximum, minimum, mean, kurtosis, skewness, variance, median* and *standard deviation*
- Deep learning-based solution



Workout Assessment

- Anatomy of a repetition
  - A repetition: from an initial position to a final position and then back to the initial position
  - Good exercise repetitions: keep a constant rhythm (i.e., the time ratio between concentric contractions and eccentric contractions)



Workout Assessment (cont.)

- Two metrics
  - Work-to-rest ratio□ measures the ratio between the time of repetition and the following time of rest
  - Repetition tempo ratio: refers to the tempo (or speed) at which a user performs a repetition

Work-to-rest ratio = $$\frac{T_w^{(i)}}{T_r^{(i)}}$$

Repetition tempo ratio = $$\frac{T_{i2f}^{i}}{T_{f2i}^{i}}$$

$T_w^{(i)}$: the time duration for the ith workout

$T_r^{(i)}$: the time duration of the rest followed by the ith workout.

T_{i2f}^{i} : the time duration from an initial position to a final position of the ith repetition

T_{f2i}^{i} : the time duration from the final position back to the initial position of the ith repetition.

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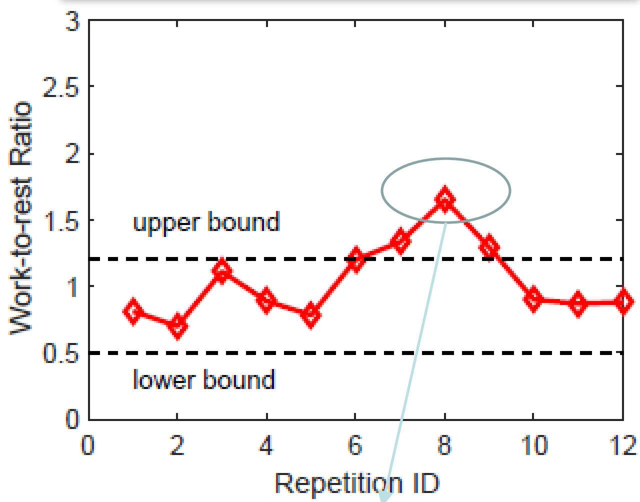
Workout Assessment (cont.)

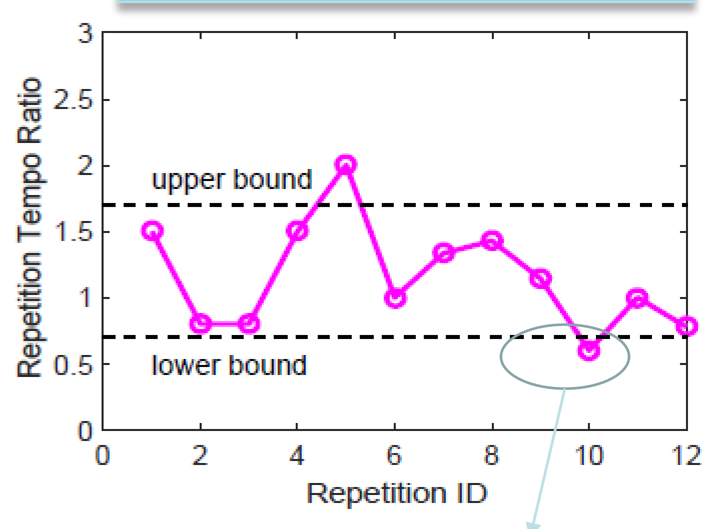
- Perform workout assessment for each repetition based on the two metrics.
- Empirically set an upper and a lower bound so that the users can obtain feedback from the system.

Work-to-rest ratio



Over the upper bound means the user completes the repetition too fast

Repetition tempo ratio



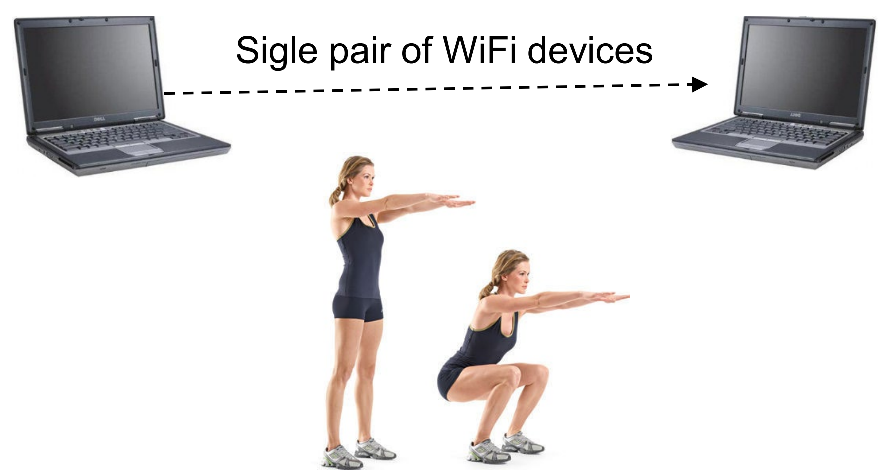
Below the lower bound means the user has a low speed from initial position to final position

Experimental Methodology

- **10 representative exercises**

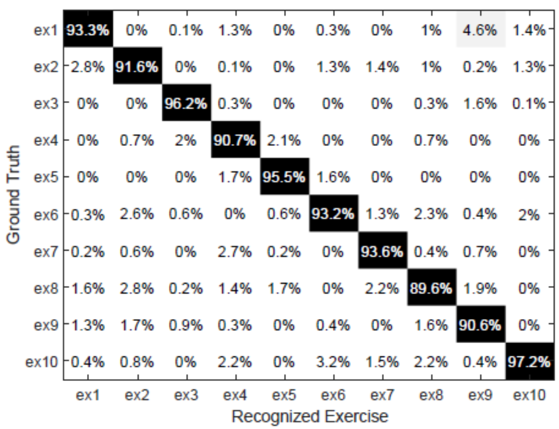
Code	Exercise	Code	Exercise
Ex1	Standing biceps curl	Ex6	Tai Chi
Ex2	Lateral raise	Ex7	Dumbbell curl
Ex3	Leg stretch	Ex8	Pile squat
Ex4	Raise and squat	Ex9	Dumbbell triceps extension
Ex5	Leg press	Ex10	Body extension

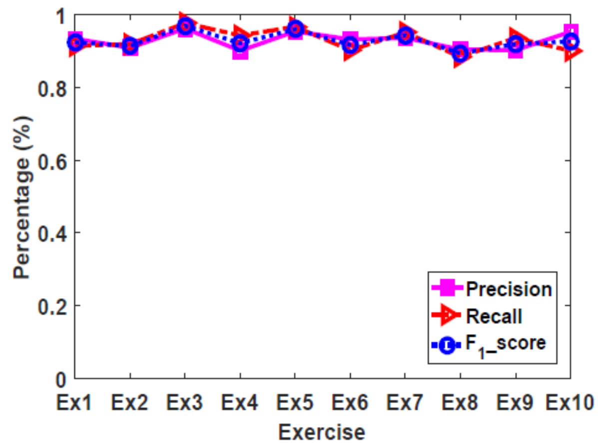
- **Two laptops (Tx-Rx)**
  - Intel 5300 NICs
- **Data collection**
  - 20 volunteers (18 males and 2 females)
  - Three different indoor venues over a 10-month time period
- **Evaluation metrics**
  - Recognition accuracy; Precision; Recall; F-1 Score;

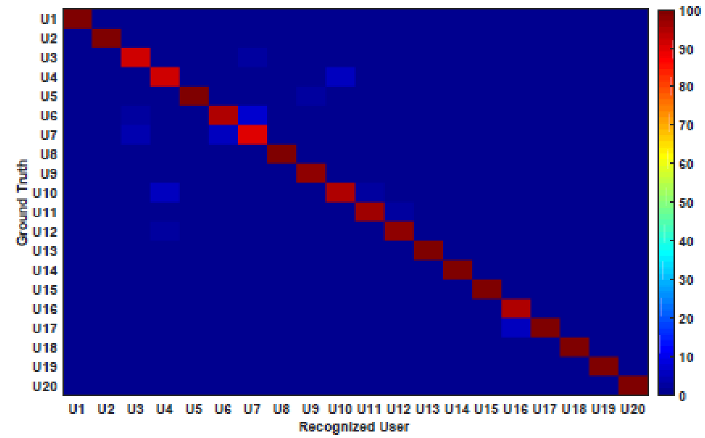


Performance Evaluation

- DNN-based personalized workout recognition







- **Workout recognition** : achieves **93%** recognition accuracy and standard deviation is **2.6%.**
- **Robustness**: corresponding precision, recall and F1 score are all around **93%.**
- **People identification :** achieves **97%** for 20 users.

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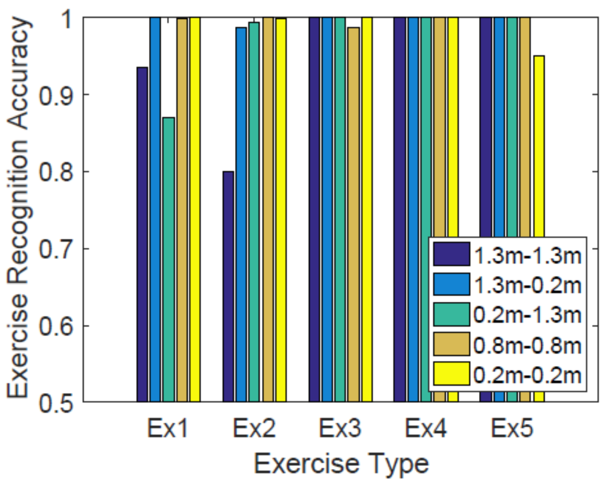
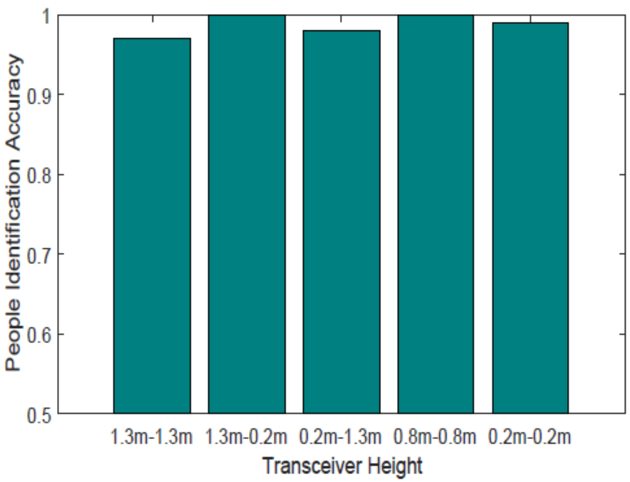
Performance Evaluation (cont.)

- Impact of different heights of device placement (e.g., on the floor, table, furniture)





- **Exercise recognition:** Three height combinations (i.e., 1.3m − 0.2m, 0.8m − 0.8m, and 0.2m − 0.2m) achieve over **94%** accuracy for all five exercises.

- **People identification:** All heights achieves **97%** for 20 users**.**

Conclusion

- Using ubiquitous WiFi signals can help users to achieve effective in-home/office workout.

- The DNN-based system can differentiate individuals on top of fine-grained workout recognition.

- Offering personalized fine-grained workout statistics including workout type, the number of sets, the number of repetitions and the user identity.

- Extensive experiments involving 20 participants demonstrate that the proposed system can achieve over 93% and 97% accuracy to identify the type of performed exercises and the user.

Thank You

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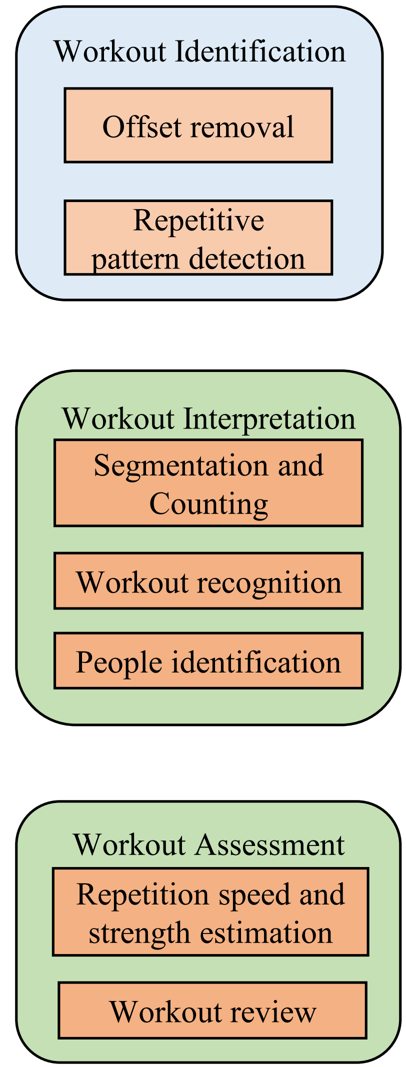
Methodology

- **Workout detection**
  - Detect the CSI segment that is related to workout activities
- **Workout interpretation**
  - Provide personalized information about the workout type with statistic information (e.g., how many sets and how many repetitions)
- **Workout assessment**
  - Assess workout in repetition level and provide feedback to users so as to help users correct their gestures



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