Demonstrating ProxiFit: Proximal Magnetic Sensing using a Single Commodity Mobile toward Holistic Weight Exercise Monitoring

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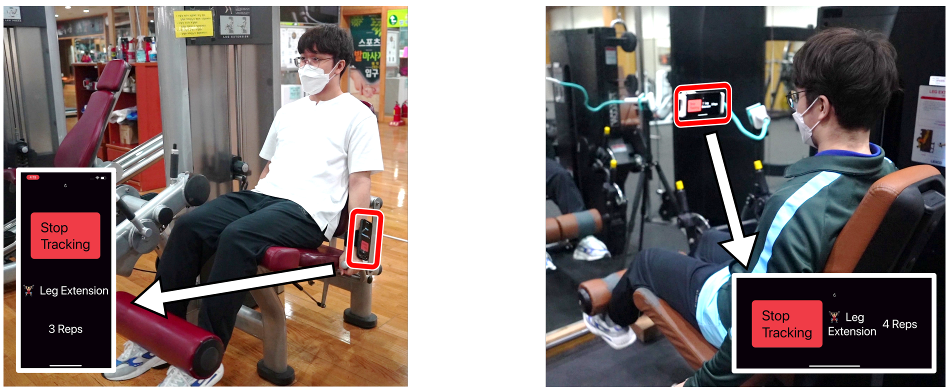

Figure 1: Demonstration of ProxiFit monitoring exercises in real-world gyms. ProxiFit can either be deployed in *wearable* mode (left) or in *signage* mode (right). Both modes deliver pervasive exercise classification and repetition counting. For *wearable* mode, *either* a smartwatch or a smartphone is worn on the user's wrist. For *signage* mode, a smartphone is mounted to the holder in front of the user with line-of-sight visibility.

ABSTRACT

Although many works bring exercise monitoring to smartphones and smartwatches, inertial sensors used in such systems require the device to be in motion to detect exercises. We demonstrate our full paper ProxiFit, a practical on-device exercise monitoring system capable of classifying and counting exercises despite the device being still. ProxiFit remotely detects adjacent exercises with magnetic field fluctuations induced by the motions of ferrous exercise equipment. Novel proximal sensing nature of ProxiFit (1) extends coverage of wearable exercise monitoring to exercises that do not involve device motion such as lower-body machine exercise, and (2) brings a new off-body exercise monitoring mode with line-of-sight screen visibility, namely *signage* mode, to a smartphone mounted in front of the user.

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CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous computing**; *Interactive systems and tools*; • **Hardware** → **Sensor applications and deployments**.

KEYWORDS

Exercise Monitoring; Magnetic Sensing; Wearable; Proximity Sensing

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1 INTRODUCTION

Prior researches report that manual logging of health data is burdensome [1] and thus pervasive fitness tracking should be adopted [35, 50], and gym-goers' preference are in line with the claim [2, 52, 53]. Extensive efforts have been put into the pervasive tracking of gym exercises. Among various approaches, systems based on personal commodity mobile/wearable such as smartphones or smartwatches have unique merits of zero hardware investment, gym-independent applicability, and keeping gym-goers' privacy from third-parties.

However, the main sensing modality of exercise monitoring systems on commodity mobile/wearable is inertial features from accelerometer and gyroscope [14, 15, 33, 34, 46], which requires the device to be in motion to detect exercises. This limitation prevents monitoring exercises that do not involve device motion, such as lower-body machine exercises and free-weight exercises on the non-device-worn arm. In addition, smartphones lose screen visibility, which is their main interface, as they must be put in motion by being worn on the user's body to monitor exercises.

We present ProxiFit, a practical on-device exercise monitoring system capable of classifying and counting exercises without the motion of the device itself. Unlike prior works that use inertial features, ProxiFit exploits the built-in magnetometer of smartwatches and smartphones to enable proximity sensing of exercise equipment.

Weight exercise equipment is often made of ferrous metal, and thus have faint self-magnetism. When the equipment is in motion, its self-magnetism influences the surrounding magnetic field. However, the magnetic disturbances around unmagnetized iron are extremely weak [12, 37], and the magnetic signature of each piece of equipment is determined at its annealing process [5, 13, 17]. These constraints mandate a robust yet data-efficient classifier as the model should be trained per-instance manner. ProxiFit devises a simple yet efficient classifier that overcomes both constraints to successfully detect, classify, and count adjacent exercises remotely.

With new proximity magnetic sensing modality, ProxiFit implements two modes, namely *wearable* and *signage* modes. *Wearable* mode targets wrist-worn wearables such as a smartwatch, where ProxiFit newly brings the capabilities to monitor a new category of exercises without device motion such as lower-body machine exercises or free-weight exercises done on the non-device-worn arm. *Signage* mode is a new off-body exercise monitoring setup for smartphones featuring line-of-sight screen visibility, where a smartphone is mounted in front of the user during exercise. The user may watch a video player or a self-monitoring & guidance app [32]. Both modes provide real-time exercise classification and repetition counting via auditory feedback [27, 28, 49]. Refer to Figure 1 for the real-world demonstration of ProxiFit in both modes.

2 RELATED WORKS

Exercise monitoring on mobile. There have been other approaches to overcome coverage limitations of inertial exercise monitoring on commodity mobile devices.

A most straightforward approach is to introduce more devices so that they can sense the inertial movements of different limbs [7, 25, 42, 56] or even dumbbells [49, 53] and various equipment [26, 45, 47]. While this is the most intuitive solution, it requires users to buy

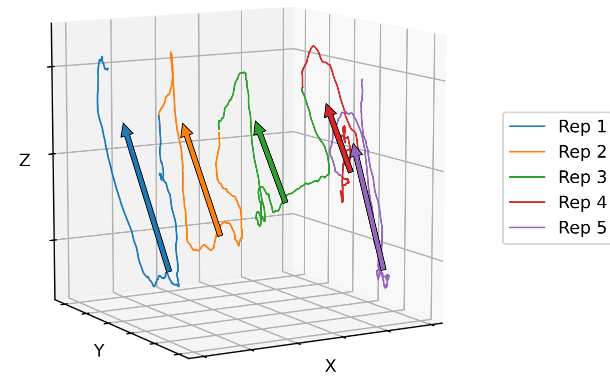


Figure 2: Exemplary trajectories and their primary component vectors of hip abduction repetitions. There exist noticeable drift and deviation between repetitions. However, the primary component vector of each repetition is consistent.

and wear extra devices. Detachable smartwatch [29] avoids the burden of equipping extra devices by allowing the smartwatch to be relocated on-demand. However, it poses practicality concerns where users need to frequently change the device position during workouts.

Fu et al. [20, 21] suggests acoustic Doppler sensing to detect nearby activities. While it is capable of detecting exercise without device motion, susceptibility to multi-paths and ambient noise in crowded gyms would limit its deployment [55].

Bian et al. [6] proposes a wearable capacitive coupling sensor to detect the motions of body parts apart from the limb where the sensor is worn. However, such a sensor is not yet available on commodity mobile devices, and its accuracy needs refinement for practical deployment.

Magnetic sensing. Ambient magnetic field sensing based on a commodity mobile device has been studied for real-life problems, e.g., indoor localization [3, 16, 18, 19, 38, 48, 51, 54], NFC [43], and daily hygiene [24]. Other side of works track magnetic fields to discover cyber-physical vulnerabilities [12, 37], driver monitoring [23], natural user interfaces [4, 8–10, 22, 39–41, 44], and mode of transport [11].

ProxiFit is the first exercise monitoring system that satisfies the following constraints towards high practicality; (1) supports exercises without device motion, (2) only requires a single commercial off-the-shelf (COTS) smartwatch or smartphone, (3) preserves intended use of the device (i.e., the smartwatch is worn on wrist/smartphone screen is visible to the user), and (4) assumes no external instrumentation.

3 METHODS

Following is a brief description of ProxiFit architecture. Further details can be found in the full paper [30].

While magnetic sensing enables detecting exercise equipment without device motion, its faint signal poses a challenge for accurate exercise classification and repetition counting. Signal-to-noise ratio

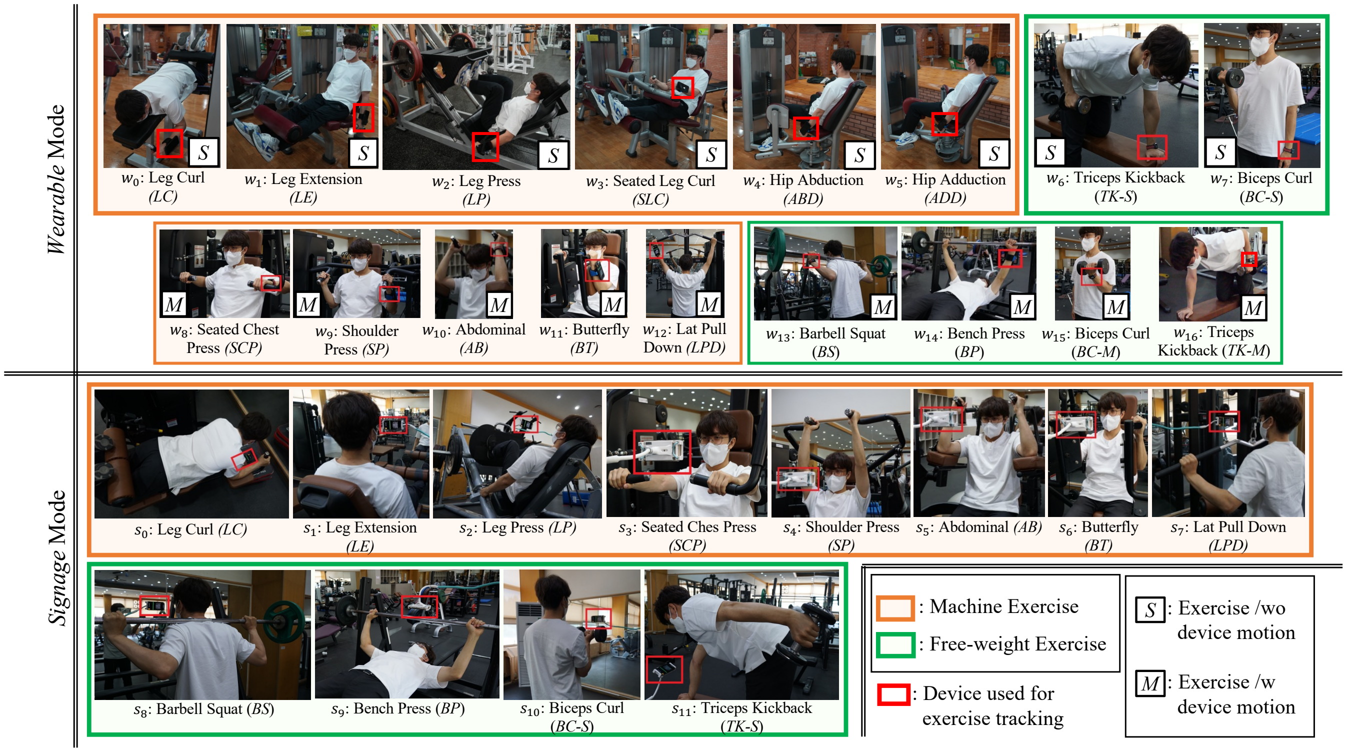


Figure 3: Exercises tested on each mode of ProxiFit.

measurements on 6 classes of equipment range from 2.5 to 15.3 dB. Extracting useful information from such noisy magnetic field signals requires careful feature crafting based on the characteristics of weight exercises – repetitive motion and consistent directionality of motion.

Figure 2 represents five continuous repetitions of the hip abduction exercise. Even though each repetition is executed right after one another, there exist prominent drift and deviations between repetitions. Therefore, bespoke methods are to be devised to ensure robustness.

3.1 Sampling Data

ProxiFit collects accelerometer, gyroscope, and magnetometer data at 100 Hz. IMUs (i.e., accelerometer and gyroscope) are solely used for efficient exercise detection and frame normalization, while exercise classification and counting are performed with magnetometer data. Data is bundled into 3-second windows with 2.5-second overlap to contain at least a single repetition of exercise without too much processing delay.

3.2 Exercise Detection

We employ a light-weight exercise detector in favor of efficiency. The detector adopts low-acceleration thresholding to find *wearable* mode exercises, based on the observation that a user's wrist is unnaturally still during target exercises. For *signage* mode, autocorrelation is alternatively used to detect the periodic motion of exercise equipment.

3.3 Frame Normalization

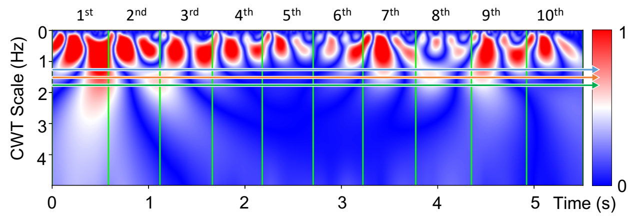
In *wearable* mode, the orientation of the device varies by users' physiques, how users wear the device, and slight instance-wise differences in grips to hold exercise equipment. The frame normalizer negates such rotational deviations by transforming each sample according to its frame of reference.

3.4 Exercise Classification

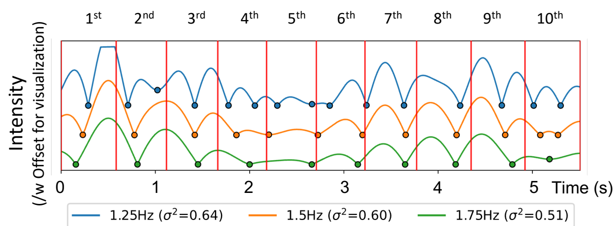
The *wearable* and *signage* modes both utilize the same classifier architecture, as the fundamental concept of magnetic sensing is applicable to both modes. We handcrafted the features by carefully observing the magnetic trajectories of repeated exercises. Despite the trajectories represented in Figure 2 appearing erratic, we observe that the primary component vector of the magnetic trace is consistent for each repetition, as illustrated by the arrows. Therefore, we apply principal component analysis to extract the primary component vector of the given window. Features are then heuristically constructed with the primary component vector of the raw signal, which is then fed into a support vector machine (SVM) for classification. Due to the instance-specific nature of each weight machine's magnetic signature, we train a separate model for each gym. Loading the model for the current gym is straightforwardly done by PoI-level localization techniques [31, 36].

3.5 Repetition Counting

Exercise monitoring systems often look for peaks on the target signal to count repetitions. However, naïve peak counting is not



(a) Continuous wavelet transform of an exercise session



(b) Peak counting results alongside varying scales of CWT

Figure 4: Visualization of continuous wavelet transform and ProxiFit's automatic scale finding algorithm

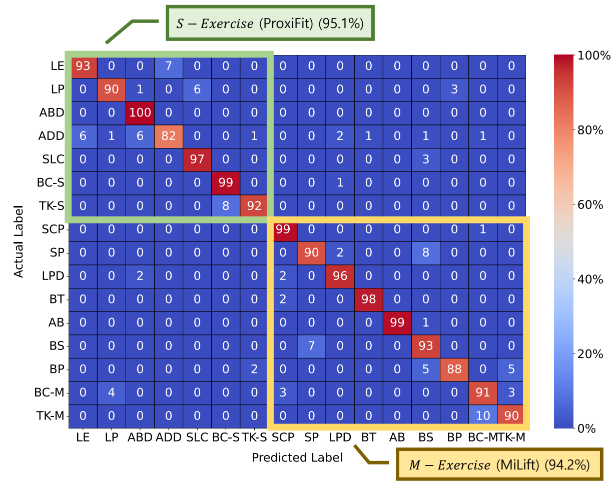


Figure 5: Confusion matrix of end-to-end evaluation on *wearable* mode ProxiFit. MiLift is integrated to cover exercises that involve device motion. (Average accuracy 93.1%)

applicable to magnetic sensing due to the noisy nature of the magnetic field. Instead, continuous wavelet transform (CWT) is applied to better extract periodic features. Figure 4 showcases the result of the continuous wavelet transform. To count repetitions, peak counting is applied alongside a horizontal line (or a scale) of CWT. Figure 4b plots each line and its peaks on three scales, which are also annotated as arrows in Figure 4a.

Despite observable periodicity, noise introduces false peaks on the 1.25 Hz and 1.5 Hz scales. ProxiFit automatically counts peaks alongside multiple scales and chooses the one with the least interval variance between peaks, which is 1.75 Hz in this case.

4 EVALUATION

ProxiFit is tested on both *wearable* and *signage* modes for exercise classification and repetition counting. Figure 3 shows exercises that ProxiFit is tested on. Note that, exercises both with and without device motion are tested for *wearable* mode.

We test the end-to-end performance of *wearable* mode ProxiFit under a real-life gym workout scenario. MiLift [52], an IMU-based exercise monitoring system, is integrated to support exercises with device motion, as a realistic exercise routine would include both categories of exercises. Subjects are asked to freely perform workouts in a gym with ProxiFit running on a wrist-worn smartphone, mimicking a smartwatch. In 11.6 hours of end-to-end sessions, ProxiFit achieved 93.1% classification accuracy as seen in Figure 5, with an average counting error of 0.77 reps per 10-rep session.

We also test classification and repetition counting accuracy in *signage* mode. Average classification accuracy was 97.7% when left and right arm free weights are seen as discrete exercise classes, and was 100% under side-agnostic evaluation. The average counting error was 0.69 reps per 10-rep session.

ProxiFit is also tested against longitudinal aging, displacement, interference from adjacent machines, weather variances, and user diversity. There was no significant impact on accuracy. For more information, please refer to the full paper [30].

5 DEMONSTRATION

ProxiFit employs both *wearable* and *signage* modes, which of each supports both machine exercises and free-weight exercises. At the demo venue, we will showcase the *signage* mode as it allows users to quickly participate without wearing/taking off a device. Also, we focus on free-weight exercises, as such exercises involve portable equipment that can be brought to the demonstration venue.

We will prepare free-weight exercise equipment and install an iPhone running *signage* mode of ProxiFit on a holder. Participants can come by to pick up a dumbbell and perform simple weight exercises in front of it. ProxiFit will automatically detect ongoing exercise and count repetitions. While the main work of ProxiFit includes two dumbbell exercises, the demonstration variant of ProxiFit is tailored towards demo-friendly free-weight exercises including, but not limited to, biceps curl and other dumbbell exercises that can be performed while standing, along with kettlebell exercises.

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