SeamFit: Towards Practical Smart Clothing for Automatic Exercise Logging

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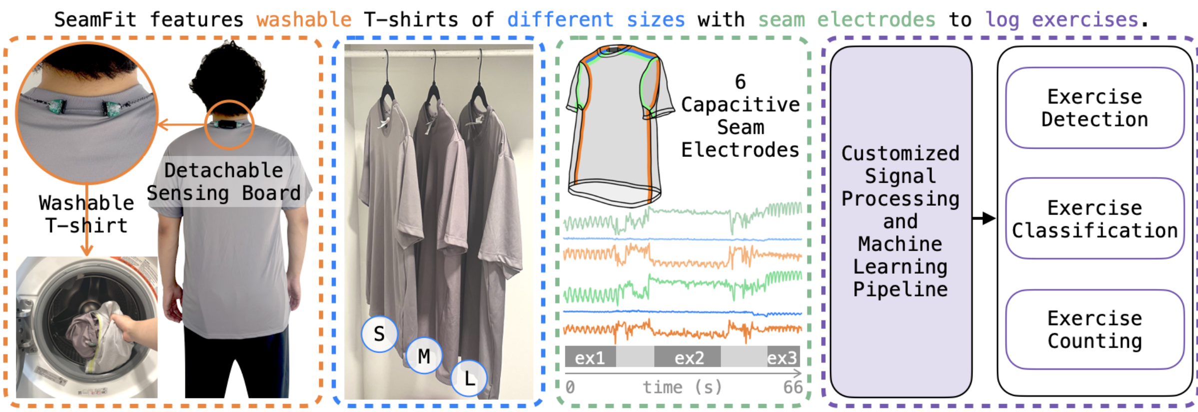

Fig. 1. SeamFit features washable T-shirts of different sizes with seam electrodes to log exercises.

Smart clothing has exhibited impressive body pose/movement tracking capabilities while preserving the soft, comfortable, and familiar nature of clothing. For practical everyday use, smart clothing should (1) be available in a range of sizes to accommodate different fit preferences, and (2) be washable to allow repeated use. In SeamFit, we demonstrate washable T-shirts, embedded with capacitive seam electrodes, available in three different sizes, for exercise logging. Our T-shirt design,

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customized signal processing & machine learning pipeline allow the SeamFit system to generalize across users, fits, and wash cycles. Prior wearable exercise logging solutions, which often attach a miniaturized sensor to a body location, struggle to track exercises that mainly involve other body parts. SeamFit T-shirt naturally covers a large area of the body and still tracks exercises that mainly involve uncovered joints (*e.g.*, elbows and the lower body). In a user study with 15 participants performing 14 exercises, SeamFit detects exercises with an accuracy of 89%, classifies exercises with an accuracy of 93.4%, and counts exercises with an error of 0.9 counts, on average. SeamFit is a step towards practical smart clothing for everyday uses.

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1 INTRODUCTION

Integrating conductive/functional fibers and miniaturized electronics seamlessly augments clothing with exciting sensing opportunities [27], while preserving the soft and comfortable nature of this ubiquitous wearable form factor. Recent research efforts in material innovation, hardware miniaturization, and machine learning algorithms have enabled unobtrusive smart clothing for physiological sensing [34, 39], body movement tracking [5, 9], gestural interaction [2, 30], etc., demonstrating a plethora of opportunities for all-textile (i.e., the sensors are made of textiles instead of rigid electronics) sensing systems.

More recently, researchers exploited the fact that clothing covers a large area of the human body to track body poses with loose-fitting clothing that affords longer and more comfortable wears [41, 44]. Towards the widespread adoption of everyday smart clothing for body movement tracking, ideally, these sensing systems should be very similar to conventional clothing: the wearer chooses the fit/size based on their personal preferences and the smart clothing can be conveniently washed after wearing for reuse. However, some practical challenges are almost always ignored in research projects:

- Challenge #1, **Generalizability across Clothing Fits**: A single one-size-fits-all prototype is sufficient to demonstrate the feasibility of a sensing principle, but for practical uses, the sizes/fits of the clothing are the choices of users [1]. For example, sleeve lengths and tightness differ for different sizes and fits. A conductive thread sensor along the sleeve of a small shirt is shorter than that in a large shirt. Loose-fitting clothing poses significantly more sensing challenges than tight-fitting clothing does, as the fabrics do not perfectly conform to the body [41, 44, 46]. Such challenges are further amplified when there are multiple sizes for a broader range of fits.
- Challenge #2, **Washing Durability of the End-to-End Sensing System**: First of all, conventional electronic components and some soft-to-rigid electrical connections stop functioning after a single wash [27, 40]. For conductive textile components that remain functional after washes, their durability (e.g., thread breakage) [38] and electrical properties (e.g., resistances, and responses to stimuli like pressure) [22, 28] change over time. Even for normal clothing, shrinkage commonly occurs in washing-drying cycles. Washing durability of the end-to-end smart clothing sensing system, including the data pipeline, is a key consideration for practical everyday uses [45] because sensor reading changes caused by washings pose challenges for both heuristic- and data-driven algorithms.

In this paper, we aim to investigate and address these challenges by prototyping different sizes (Challenge #1) of washable (Challenge #2) smart clothing that tracks body movements in a way that can be generalized across fits and washing cycles. We focus on an all-textile smart clothing system for automatic exercise logging, a sensing task that involves:

(1) detecting exercises (accuracy = 89%),
(2) classifying exercises (accuracy = 93.4%), and

(3) counting exercises (±0.9 counts).

We choose the exercise logging task because (a) clothing comfort is important for exercising (Challenge #1); (b) sweating is inevitable during exercises and requires frequent washes (Challenge #2); and (c) smart clothing that monitors physiological signals for fitness has a large market share in commercial smart clothing [27], and the exercise recording capability will extend the functions of smart clothing for fitness.

Automatic exercise logging promotes healthier lifestyles and improves general well-being by reducing the burden of manually logging the exercises [3, 15, 24, 31]. Existing portable and wearable solutions mainly center on IMUs, which only sense the movements of instrumentation points (*e.g.*, one wrist), failing to track exercises that involve isolated movements of other body parts (*e.g.*, dumbbell row with the side without the IMU). Consider the following envisioned scenario:

> Kate is about to exercise at home, so she changes into a smart T-shirt of her desired fit and attaches the processing unit to it. She wears the smart T-shirt just like a conventional workout T-shirt and finishes the workout. The smart T-shirt logged her workout, including what exercises she did and how many repetitions each, so Kate could maintain an exercise log. Finally, she detaches the processing unit and puts her sweaty and dirty smart T-shirt into the laundry machine. Kate can wear the clean smart T-shirt again, the next time she works out.

To realize the above scenario, we present SeamFit, illustrated in Fig. 1, a washable all-textile T-shirt sensing system of different sizes that logs exercises. Compared with long-sleeve shirts, T-shirts are more commonly worn for exercises but complicate the sensing task as the elbow, an important joint, cannot be directly sensed. With SeamFit, the research questions we aim to answer are: (1) **Can an all-textile (i.e., no rigid sensors attached) T-shirt log exercises?**, and (2) **Can the smart T-shirt sensing system generalize across fits and washes?**

To this end, we use the sensing principle of body pose&movement tracking with capacitive sensing seams, repurposed from clothing seams, areas of overlap fabric formed when two pieces of fabric are joined, by attaching conductive threads over existing seams [41]. The minimal instrumentation that does not alter the clothing surface, compared with using pieces of conductive fabrics, reduces the sensor inconsistencies (*e.g.*, sizes and placements) across different prototypes. The sensing seams are connected to a detachable sensing board when in use. The measured seam signals are processed by a customized signal processing machine learning pipeline that generalizes across fits and washes. To evaluate SeamFit, we conducted a user study with 15 participants: 5 participants for each size. The prototype is machine-washed and -dried before each participant wears it.

To the best of our knowledge, SeamFit is the **first to demonstrate exercise logging with smart clothing** (loose-fitting or not). Though prior works have shown body pose-tracking capabilities [41, 44], applying the sensed signals for the exercise logging is not trivial, as skeleton-based exercise logging is still an open research problem. Further, SeamFit T-shirt **does not cover all the moving joints involved in the exercises**, probing the possibilities of a wide range of clothing choices for exercise logging. Finally, SeamFit T-shirts are **washable prototypes of different sizes**, allowing us to explore and evaluate the generalizability across fits and washings.

2 RELATED WORK

SeamFit aims to solve the sensing task of logging exercises with a T-shirt embedded with capacitive seam sensors. Exercise tracking/logging alleviates the burden of manually logging exercises and encourages more active lifestyles that benefit general well-being and reduce the risk of diseases [3, 15, 24, 31]. Numerous efforts in recognizing different exercise or tracking body movements during exercise in solutions that are skeleton based [21, 29], optical flow based [16], environmental sensor based (e.g., WiFi) [12, 18], wearables based (acoustics [23], egocentric camera [19]), etc. Compared with other approaches, wearables are more personal, portable, and privacy-sensitive.

In this section, we focus on discussing prior work that is closely related to SeamFit: (1) exercise tracking with wearables, and (2) smart clothing for body movement sensing.

2.1 Exercise Tracking with Wearables

Commercial fitness trackers (*e.g.*, smartwatches) can recognize long-period cardiovascular exercise activities, such as jogging, running, and swimming, and even distinguish swim strokes [4]. However, they are not capable of recognizing/logging shorter or fine-grained exercises like weight training and home workouts. Inertial measurement units (IMUs) have a long history and are the most prevalent for wearable motion sensing owing to their high sensitivity to motions and robustness to different environments. RecoFit uses a 6-axis IMU on an armband placed on the right forearm and leverages the repetitive nature of exercises to segment, recognize, and count exercises [25]. Since then, there have been many attempts with single IMUs on wrists/arms for exercise logging [20, 35]. One significant and inherent drawback of IMUs is that they only sense the movements of the instrumentation points, so single-IMU approaches excel in symmetric exercises but fail in asymmetric exercises (*e.g.*, right and left bicep curls). To address this limitation, researchers have instrumented more IMUs across the body [37] or sensed the magnetic changes caused by moving iron masses of the equipment [17]. However, these approaches rely on more than one device instrumentation, which is tedious, or requires gym equipment that is not available for home workouts. In this work, we demonstrate a smart T-shirt, a single wearable device that does not cover all moving joints during exercises, yet sufficiently recognizes a mixture of upper-/lower-/full-body and symmetric/asymmetric exercises.

2.2 Smart Clothing for Body Movement Sensing

Clothing, inherently covering a large portion of the body, is an exciting form factor for wearable body movement sensing by integrating miniaturized electronics (*e.g.*, IMUs and flex sensors) [8, 13, 26] and/or conductive fibers/threads/textiles [9, 33, 41, 44]. Early smart clothing that tracks body movements uses tight-fitting garments embedded with sensors that tightly couple with joints or body part locations [8, 9, 13], but such smart clothing are not as comfortable as everyday clothing, at the trade-off between performance and comfort.

Recently, advancements in textile sensor designs and machine learning enabled all-textile loose-fitting garments to efficiently track body movements [5, 41, 44]. Without any rigid electronics (excluding the sensor board that acquires and transmits the signals) on the clothing surface, these smart clothing systems pave the way for smart clothing that wears and looks like conventional clothing. Loose-fitting systems eliminate the comfort vs. performance trade-off and offer options (*e.g.*, some prefer tight clothing for exercise while others prefer loose ones.) for the user. MoCapaci, a loose-fitting blazer embedded with 4 capacitive antennas, first demonstrated body gesture recognition [5]. MoCaPose [44] and SeamPose [41], utilizing capacitive sensing, continuously track upper-body poses with promising user-independent performances, utilizing 16 patches of conductive fabric in a jacket and 8 conductive seam electrodes in a shirt, respectively.

Our SeamFit T-shirt implementation falls under the clothing-seam-based sensing approaches [32, 33, 41]: we attach conductive threads to repurpose existing clothing seams into sensing seams. Seams originally are inside of the shirt, so they are invisible when worn. Repurposing seams does not alter the visual and material (e.g., breathability, which is essential for exercising) characteristics of the clothing surface. Though the changes are minimal, seams placements highly correlate with body joints and thus enable fine-grained tracking [41]. Exercise logging with sensor signals that could track body poses is not trivial because (a) exercise logging with skeletons/poses is still an open research problem [37] and (b) even with a "perfect" skeleton-to-exercise model, a single wrong joint location prediction by an imperfect wearable pose tracking solution will yield incorrect exercise predictions. Finally, although washability for textile-based sensors has been investigated [14, 22, 28, 34, 38, 40] to different extents, no prior works on smart clothing for body movement sensing have investigated the overall system performance across washes and fits, which are essential for real-world uses.

3 SEAMFIT IMPLEMENTATION

SeamFit features washable T-shirts of different sizes (Sec. 3.1), embedded with conductive-thread-repurposed seam electrodes (Sec. 3.2). The detachable sensing board acquires the capacitance measurements of the seam electrodes (Sec. 3.3), whose capacitances change as a result of the wearer's movements (Sec. 3.4). The capacitive readings allow SeamFit to log exercises with a customized signal processing and machine learning pipeline (Sec. 3.5).

3.1 Clothing, Seam Electrode Layout, Seam Electrode Thread Selection

Towards practical smart clothing for exercise logging, the designed garment should (a) preserve the breathability and stretchability of the clothing, (b) resemble conventional exercise clothing in terms of form and fit, and (c) be durable for extensive movements and washings. To meet these design goals while achieving promising sensing performance, we carefully selected the clothing type, the seam electrode layout, and the seam electrode thread.

3.1.1 Clothing Selection: Loose Polyester T-shirt of Sizes S/M/L. People's preferences for exercise clothing span a broad range, we consider these factors together with their implications on the information gain that we can obtain from different choices:

- Material: Polyester is a popular material for exercise clothing because it is lightweight, quick-drying, durable, odor-resistant, etc. As demonstrated in prior works [33, 41], clothing-seam sensors provide motion-sensing capabilities without altering the clothing surface, and thus preserving the desired qualities of the materials without attaching patches of conductive fabrics [9, 44].
- Sleeve Length: Long-, short-, and no-sleeve tops directly instrument (i.e. the fabric covers) shoulders&elbows, shoulders, and shoulders partially, respectively. From the sensing perspective, intuitively, the more covered joints provide more information for motion tracking. In SeamPose, Yu et al. found that even without [41] the sleeve electrode in a long-sleeve shirt, the shirt still sufficiently tracks upper-body poses with only electrodes around the shoulder, but it is unclear how sleeveless shirts perform. Thus, for better generalizability, we select a short-sleeve T-shirt.
- Fit: When exercising, some prefer form/tight-fitting ones, while others prefer relaxed/loose-fitting ones. As discussed in the related work, loose-fitting clothing poses more challenges to the motion-tracking task because the sensors are not tightly coupled with the moving joints. In addition to the fit design of T-shirts, T-shirts come in many sizes, so the wearer has the option to choose different fits of the same T-shirt design. Thus, we chose to fabricate three prototypes of sizes small, medium, and large, allowing wearers to choose their preferred size.

In summary, although a long-sleeve tight-fitting shirt is expected to have the highest information gain, to push for the practicability of smart clothing for exercise logging, we opt to open up the options for the users: we implement SeamFit by repurposing seams in polyester T-shirts (Hanes Men's Cool Dri Moisture-wicking Performance Tee) of 3 different sizes (small, medium, and large). With clothing seam sensors that do not alter the clothing surface, the smart T-shirt has the same material qualities as conventional T-shirts.

3.1.2 Seam Electrode Layout Selection: 6 Electrodes Around the Shoulders, Along the Sleeves, on the Sides of the Torso. In garment manufacturing, *patterns* represent the shapes and sizes of the fabric pieces required to construct a specific garment. Seams, areas of overlapping fabric, are formed when stitching the patterned fabrics together. In other words, the number and the placements of the seams are determined by the *patterns*. For a basic T-shirt pattern, like the one we repurpose, there are seams above the shoulders, around the shoulders, and along the

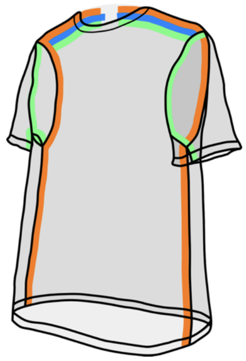

Fig. 2. There are 6 seam electrodes in a SeamFit T-shirt prototype, three on each left/right side.

sleeves. Following SeamPose [41], we only repurpose existing seams and do not strategically add more seams for minimal alterations. More complex patterns have more seams which provide more sensed information. We choose a basic pattern for greater generalizability. After preliminary investigations of the exact sensing seam layouts based on the existing conventional seam layouts based on fabrication ease and information gain, we choose these 3 sensing seams on each left/right side (6 in total, symmetrically as illustrated in Fig. 2):

- Top Electrode (TE, colored in blue): from the back of the neck to the end of one shoulder;
- Top-Back-Torso Electrode (TBTE, colored in orange): from the back of the neck to the end of one shoulder, through the back of the arm, and down the side of the body; and
- Top-Front-Sleeve Electrode (TFSE, colored in green): from the back of the neck to the end of the shoulder, through the front of the arm, and down the sleeve seam.

Both SeamPose [41] and our preliminary investigations suggest even though the sensors overlap spatially (*e.g.*, all electrodes run between the back of the neck to the end of the shoulder), they still individually perform sensing information. The key is for the sensing electrodes to cover the moving body parts.

3.1.3 Seam Electrode Thread Selection: TPU-Coated Silver-Nylon Thread. Recent successes with capacitive thread/fabric sensors for wearable body movement sensing use insulated sensors for durability and undesired shorting caused by movements [41, 44]. We explored two different off-the-shelf insulated conductive threads: (1) a TPU-coated 2-ply silver-plated nylon thread (<300Ω/m, Shieldex 117/17 x2 HCB TPU) and (2) a litz wire wrapped with nylon yarn (~30Ω/m, 0.04mm x 8 strands, 8/46). Although the nylon-wrapped litz wire is more conductive, we experienced thread breakages during both the fabrication and wearing stages. On the other hand, the TPU-coated conductive thread never breaks due to its strong mechanical properties (21% ± 5 elongation[1]). Thus, we choose the TPU-coated conductive thread. Further, the 2-ply silver-plated nylon conductive core has an additional nitrile rubber protective coating, allowing the thread to be more resilient to abrasions and washing.

3.2 Couched Seam Electrodes

3.2.1 The Couching Technique. To augment conventional seams into sensing seams, we couch the insulated conductive seams over the existing seams. Couching is a sewing technique traditionally used to attach thread/chord (or a group of threads/chords) when they cannot directly form stitches themselves because they are too fragile or thick. In the couching process, the couched thread(s) are attached to the fabric by stitching another thread around it. The couching technique has been applied for embedding thick sensors [7] or actuators [42] and insulation [6, 11]

[1]https://www.shieldex.de/wp-content/uploads/2021/05/Y-VTT-Datasheet-Shieldex-117-17-x2-HCB-TPU-V4.pdf

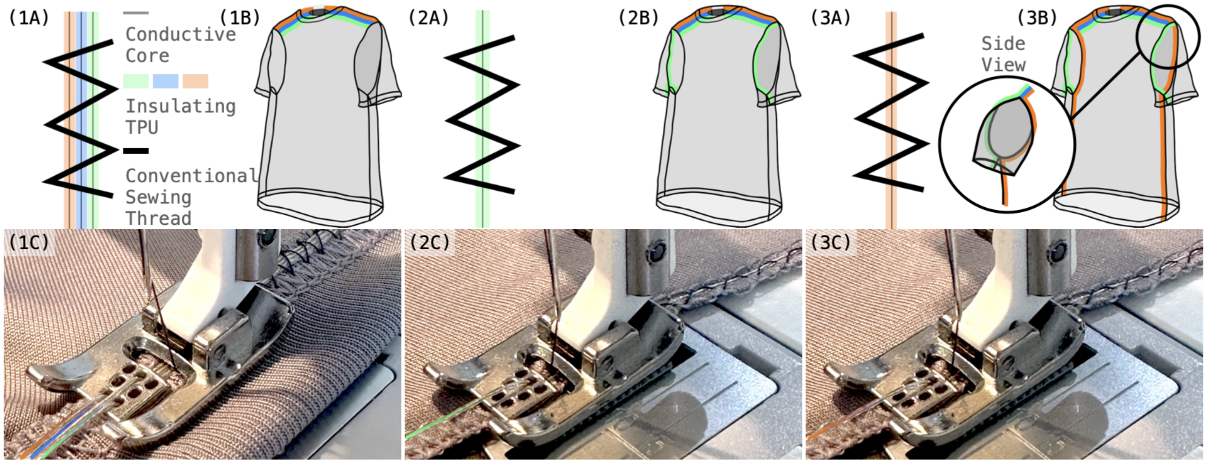

Fig. 3. Machine-Sewing Steps. For each side, we use the chording presser foot to first couch the three electrodes from the back of the neck to the tip of the shoulder (1A-C), then couch the top-front-sleeve electrode (TFSE, 2A-C) and top-back-torso electrode (TBTE, 3A-C), individually.

purposes. We apply the couching technique with a multi-strand cording footer to secure conductive threads in parallel. Compared with stitching multiple insulated conductive threads one by one with the conventional methods [41], the couching approach is (1) faster as it secures all parallel threads in one pass, and (2) more space-conservative, resulting in a slimmer sensing seam, as the threads can be tightly secured without accidental shorting caused by penetrating through other conductive threads.

3.2.2 Seam Electrode Fabrication. To couch the seam electrodes, we use a home sewing machine (Husqvarna Viking Platinum 950 E) with a 7-hole chording presser foot (HONEYSEW Cording Foot (7G)), as shown in Fig. 3(1-3C). As discussed in Sec. 3.1.2, there are 3 electrodes on each side: the top electrode (TE), the top-back-torso electrode (TBTE), and the top-front-sleeve electrode (TFSE). With the T-shirt facing inside out, for each side, we first thread the 3 conductive threads through their corresponding holes: TE through the center one of the first row of holes and TBTE and TFSE through the side ones of the second row of holes. The conductive threads are laid flat, aligned in parallel, and secured with a zigzag stitch (stitch length: 3.5, stitch width: 4) formed by conventional polyester sewing threads as the top and bottom threads. Firstly, all TE, TBTE, and TFSE are couched together from the back of the neck to the edge of the shoulder. Then TE is cut as its end is reached. Then, we pull one of TBTE and TFSE out of the cording presser hole and cord the other one. Similarly, when the end is reached, cut the conductive thread, and then rethread the electrode that was earlier pulled out and couch the other electrode. Finally, we additionally secure the ends of the conductive threads to prevent loosenings caused by the machine washing and drying cycles (observed in the early testings): we bend the end of conductive threads into U-shapes and couch over.

3.2.3 Connectors. Robust and washable connections between the textile sensors and the sensing board are still an open research problem [27, 36]. Like most conductive threads, our silver-nylon conductive core thread is not reliably solderable: the nitrile rubber coating's melting point is below most low melt solder temperatures, and thus insulates the thread which loses the electrical connectivity. To address this challenge, we first connect our thread to DuPont wire-to-wire connectors: we crimp the stripped conductive thread core inside the conductor tab and the entire insulating thread inside the insulation tab. Then we use a low-melt solder paste (CHIPQUIK SMDLTLFP10)

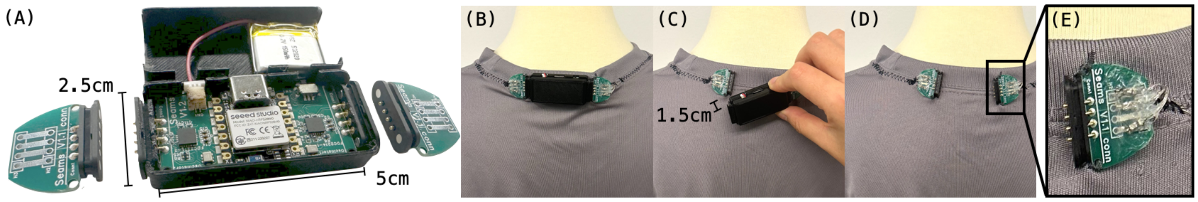

Fig. 4. SeamFit Detachable Sensing Board. The sensing board (A) can be easily detached from the shirt (B-D). The conductive threads are first connected to DuPont connectors which are trimmed and soldered onto our PCB connectors (E).

to solder the trimmed DuPont connectors to our customized PCB connectors that join the detachable sensing board via magnets and pogo pins. The soldered DuPont connectors and the soldered pads are covered with silicone glue (GE Household Silicone).

3.3 Customized Detachable Sensing Board

Washability is essential for smart clothing systems. Oftentimes, after washes, the conductive fabric/thread remains functional but other electronic components (e.g., the microcontroller) do not. A common approach is to make the microcontroller module detachable so that the clothing itself can be washed [27]. As shown in Fig. 4, the detachable sensing board (5 x 2.5 cm, 15.7g including the case) measures the capacitances of the seam electrodes and transmits the readings via Bluetooth Low Energy (BLE) functions, programmed by UART, to a nearby computer. The hub of the sensing board is XIAO nRF52840 (Seeed Studio). The sensing circuit is replicated from the FDC2214 (Texas Instruments) evaluation module[2]. We chain 2 FDC2214s on I2C to provide sensing 8 channels at a configured sample rate of 30Hz. A 3.7V 150mAh Lipo battery powers the board. The mean measured[3] power consumption is 43 mW, which can continuously transmit readings for 13.2 hours, lasting several exercise sessions. The sensing board, housed in a 3D-printed case, can be easily detached from and attached to the T-shirt using the right-angled magnetic pogo pin connectors (Adafruit). The 3D-printed case has hooks on the two sides to prevent detachments during large movements (*e.g.*, jumping jacks).

3.4 Theory of Operation

The core of SeamFit's theory of operation is that the capacitances of the seam electrodes, sewn into the T-shirt, change in correspondence to the wearer's body pose changes [41]. Such changes mainly come from two sources: When the wearer's body pose changes during exercises, (1) the seam electrodes, i.e. the conductive threads, deform and change their self-capacitances; and (2) the coupling between the wearer's body, a large conductor, and the seam electrodes alters. By monitoring the changes in the capacitances, we can infer back the body movements that induce these changes. To open up more options for wearers, SeamFit adopts short-sleeve T-shirts, this creates an additional challenge: some body parts do not have their corresponding seam electrodes to capture their movements:

- Elbows: We found that the elbows can be indirectly tracked by our electrodes. For example, for alternate bicep curls, the forearms move away and towards the torso in close proximity, which can be sensed by the top-back-torso electrode (similar to the sensing principle in Head'n-Shoulder [10]), as shown by the example signals in Fig. 5. Similarly for overhead extensions, the shoulders have subtle movements and deformations caused by the elbow movements, which can be sensed by the electrodes around the shoulder.

[2]https://www.ti.com/tool/FDC2214EVM
[3]https://lowpowerlab.com/guide/currentranger/

Fig. 5. Exercise set in the user study. The set spans full-body, lower-body, upper-body, and elbow-only exercises. 9 of the exercises are symmetric movements (labels colored in blue), and 5 of the exercises are asymmetric movements (labels colored in green). We show selected signals and their corresponding repetitions from two participants: P1 and P6.

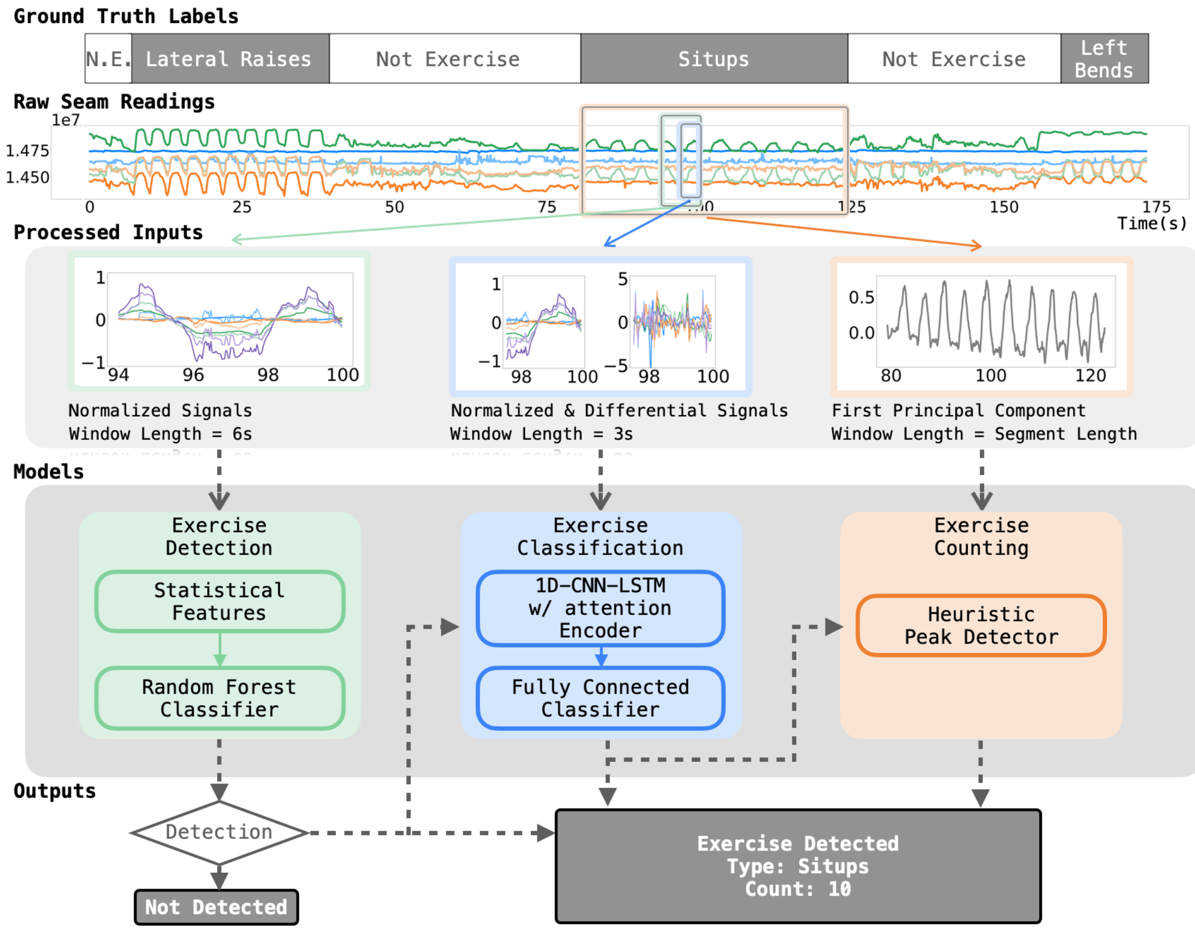

Fig. 6. SeamFit data processsing and machine learning pipeline.

- The Lower Body: Although lower body movements change the coupling between the body and the electrodes, in our experiments, we found isolated leg movements (*e.g.*, bending the knee) cause very small changes in the signals that are not robust to noises. However, during exercises, it is very rare to have truly isolated movements even for exercises that strictly target the lower body as the upper body very frequently moves along. Thus, we observe repeatable signal changes as shown by the example signals of squats and alternate lunges in Fig. 5.

In other words, although some joints are not directly instrumented, in the context of exercise logging, the movements of these joints can still be indirectly tracked.

3.5 Data Processing and Machine Learning

Exercise logging involves three sub-tasks: exercise detection (is the user resting or exercising?), detailed in Sec. 3.5.1; exercise classification (if the user is exercising; what exercise is it?), detailed in Sec. 3.5.2; and exercise counting (how many repetitions have the user performed?), detailed in Sec. 3.5.3. As illustrated in Fig. 6, we have different processed inputs and models for each of the sub-tasks.

3.5.1 Exercise Detection. For exercise detection, we adopt a statistical features approach that heavily relies on autocorrelation features, originally designed to detect/segment exercise or non-exercises with IMU signals recorded from the forearm [25]. The intuition is that exercises are more repetitive than non-exercises, and based on our experiments, this repetitive nature is better recognized by statistical features with ensemble learning methods than by deep learning methods.

Processed Inputs. We denote the raw sensor output values at time t from 6 channels, plus the sum of 3 left channels and the sum of 3 right channels, denoted as $r^t = (r_1^t, r_2^t, r_3^t, r_4^t, r_5^t, r_6^t, r_1^t + r_2^t + r_3^t, r_4^t + r_5^t + r_6^t)$. The 2 extra channels are colored in purples in Fig. 6 processed inputs. They are added to further capture asymmetries. We process the inputs on a *sample window* length $T = 6s$ with a stride $\tau = 0.2s$. For a *sample window* ending at t, it is denoted as $R_t = (r^{t-\frac{N-1}{f_s}}, r^{t-\frac{N-2}{f_s}}, \cdots, r^{t-\frac{1}{f_s}}, r^t)$, where $N = T \times f_s = 180$ is the number of samples in each channel in the window, $f_s = 30$Hz is the sampling rate. We then perform median normalization to obtain $\hat{R}_t$. We further process it to make the values in a more suitable range, and better center the signal around 0 [41], to obtain the processed input $\tilde{R}_t = 100(\hat{R}_t - 0.98\bar{\hat{R}}_t)$, where $\bar{\hat{R}}_t$ is the channel-wise mean for each channel in $\hat{R}_t$.

Featurization. Although SeamFit's seam-based sensing principle is very different from IMU-based approaches such as RecoFit [25], the repetitive signal patterns caused by the repetitive exercises are very similar. For each *sample window* of processed input $\tilde{R}_t$ ending at time t, we calculate the following features: **First**, following RecoFit, we compute the autocorrelation of each processed input channel in $\tilde{R}_t$ and calculate these 5 autocorrelation-based features: number of autocorrelation peaks[4], number of prominent autocorrelation peaks[5], number of weak autocorrelation peaks[6], maximum autocorrelation value, and height of the first autocorrelation peak after a zero crossing. The exact parameters for prominent and weak peaks are tuned on the basis of seam signal characteristics. **Then**, for each channel, we compute non-autocorrelation-related features: root mean square (RMS), Power bands (power spectrum in 10 bands spaced linearly from 0.1-25Hz, resulting in 10 features), mean, standard deviation (SD), variance, and integrated RMS. In addition, RMS, mean, SD, and variance are computed for the first and second halves of the windows, for smoother transitions between boundaries [25]. In total, there are 28 features × 8 channels = 224 features. We denote the featurized input of window $\tilde{R}_t$ as $X_t \in \mathbb{R}_{224 \times N}$, where $N = 180$ is the number of samples in each channel in each window.

Prediction Smoothing. Then, for each *sample window* ending at time t, the features X_t are aggregated into a random forest classifier[7] to obtain prediction p_t, which indicates the predicted status (1: exercise, 0: not-exercise) at time t. However, window-based predictions frequently have short periods of misclassification. To filter out such misclassifications, we further perform two rounds of prediction smoothing. For the first round, for each prediction, p_t, we take a 6-second *prediction window* of predictions $\{p_{t-3}, p_{t-3+\tau}, \cdots, p_{t-\tau}, p_t, p_{t+\tau}, \cdots, p_{t+3}\}$ centered at p_t, and adjust p_t by the 50% majority vote of the window. Then, to bias detections of exercises [16], we repeat this process, except that the threshold is increased to 80%: the window is considered "not exercise" only when more than 80% of the predictions in the window are "not exercise"s. Finally, we filter out exercise segments that are shorter than 3 seconds.

3.5.2 Exercise Classification. For exercise classification, we design a deep-learning model that learns movement and pose information from the seam signals.

[4] ScipPy.Signal v1.11.4 find_peaks(prominence=0.05, distance=0.33s)
[5] ScipPy.Signal v1.11.4 find_peaks(prominence=0.35, distance=0.66s)
[6] ScipPy.Signal v1.11.4 find_peaks(prominence=(0.05, 0.15), distance=0.33s)
[7] Default scikit-learn (v1.2.2) parameters

Processed Inputs. We take a 3-second *sample window*, with a stride of 0.33 seconds. We first process the inputs similar to that described in Sec. 3.5.1, except that the window mean is calculated with a larger 6-second *sample window*, aligned by the last frame of the windows, for more consistencies in the presence of large movements. Additionally, we calculate differential signals, the 1st discrete difference, for each channel, to amplify the movements from the seam signals which are measurements of body poses. In total, there are 16 processed input channels: 8 normalized signals and 8 corresponding differential signals.

Model Architecture. The customized deep-learning network has a 1D-CNN-LSTM encoder with attention mechanisms and a fully connected classifier. The [89x16] processed inputs first go through a series of 3 one-dimensional convolution layers (kernel size = 3; depths = 64, 128, 256; LeakyReLU activation; output dimensions = [89x64], [89x128], [44x256]). Each layer is followed by a batch normalization, and the last two layers have dropouts (p=0.2) and are followed by maxpool (kernel size = 2). After the 1D-CNN layers, the [22x256] embeddings go through a 2-layer bidirectional LSTM (hidden dimension = 512; dropout=0.1). Then the [22x1024] embeddings pass through a temporal attention block and output [1024] features. Finally, we apply 2 fully connected layers (dropout=0.8; dimension=256, # of output classes). The first and second layers are activated with LeakyReLU and SoftMax, respectively.

Training. The models are implemented in PyTorch and trained on an NVIDIA GeForce RTX 2080 Ti. We use the cross entropy loss function and the Adam Optimizer with a cosine learning rate scheduler starting at 0.001. The model is trained with 150 epochs with a batch size of 256.

Prediction Smoothing. Similar to that in the detection pipeline, we smooth the outputs to exclude short periods of misclassification. For each prediction, p_i, we take a 5-second *prediction window* of predictions centered at p_i, and change its label to the majority vote of the window.

Data Augmentation. For a model that better generalizes across users, sizes, and washes, we apply data augmentation techniques: (1) at 50% chance, we apply linear stretching to change the movement speed, with the scaling factor in the range of $[0.7, 1.3]$, of exercise movements; and (2) to introduce randomness, at 50% chance, we scale normalized individual reading with factor in the range of $[0.97, 1.03]$.

3.5.3 Exercise Counting. After analyzing the signals, we observed that the repetitive patterns of each repetition of the exercise will involve at least a peak (Fig. 5). This is similar to that of signals from IMU methods. As a result, we developed a counting algorithm based on previous work regarding IMU-based exercise counting [25, 37].

Processed Inputs. Exercise counting assumes the aforementioned models have already segmented and classified the exercise types, so the input is a window of segmented exercises with a known label, as shown in Fig. 6. To simplify the signal processing while maintaining the information of the six signals, we apply principle component analysis (PCA) to the eight channels of normalized (in the same manner as input processing for exercise detection) signals. With PCA, the eight signals will be projected onto the first principle component resulting in just one channel of signals.

Heuristic Peak Detection. Although peak finding for counting sounds straightforward, the reality is that each repetition may involve more than one peak. To identify the most representative peak in each repetition, we first find the local peaks and calculate their corresponding prominences. Then, we remove the peaks that are too close to their neighbors and have a smaller prominence. Since the time needed to perform the exercise varies among the exercises and the users, the definition of "too close" is based on the estimated period of each labeled chunk. We estimate the averaged period (*estAvgPeriod*) with the duration of the chunk and the peaks of autocorrelation results. All peaks that are less than $0.7 \times estAvgPeriod$ apart from their neighbors are considered "too close."

Table 1. Anthropometric data of participants. "SD" stands for standard deviation.

	Height (cm)	Weight (kg)	Arm Length (cm)	Upper Arm Circumference (cm)	Bust (cm)	Waist (cm)
All Participants Mean	170	66	55.3	28.5	88.4	75.9
All Participants SD	9.1	12.2	5.0	3.4	6.9	8.1
S-size Participants Mean	167	61	53.8	27.2	85.4	72.6
S-size Participants SD	8	4.2	3.1	1.3	5.8	4.6
M-size Participants Mean	164	56	55.0	26.2	83.6	69.8
M-size Participants SD	7.5	7.7	8.1	2.4	2.5	5.1
L-size Participants Mean	178	79	57.2	32.2	96.2	85.2
L-size Participants SD	4.9	8.3	2.4	2.9	3.0	4.0

Next, we filter the peaks based on autocorrelation within a window centered at each peak, considering lags between the minimum and maximum expected durations. The corresponding estimated period of the peak ($estLocalPeriod$) is retrieved based on the largest autocorrelation value. All the peaks that are less than $0.75 \times estLocalPeriod$ apart from their neighbors and have a smaller prominence are removed.

The remaining peaks are considered the representative peaks of each repetition, and we count the number of them as the number of repetitions.

4 DATA COLLECTION

To evaluate the performance of SeamFit exercise log and explore its generalizability across users, washes, and sizes, we conducted a user study, approved by the Institutional Review Board (IRB).

4.1 Exercise Set

We chose a set of 14 common home exercises, informed by prior works [16, 25, 37]: squats, alternate lunges, jumping jacks, situps, pushups, Russian twists, alternate bicep curls, dumbbell shoulder presses, dumbbell lateral raise, overhead tricep extensions, left dumbbell rows, right dumbbell rows, left side bends, and right side bends. As denoted in Fig. 5, these 14 exercises span upper- (N=8), lower- (N=2), and full-body exercises (N=4) with (N=8) or without (N=6) dumbbells of symmetric (N=9) and asymmetric (N=5) movements. Note that we intentionally selected some exercises that are challenging for the T-shirt, as discussed in Sec. 3.4. For example, alternate bicep curls and overhead tricep extensions are mainly composed of movements of the elbows that are not instrumented by the T-shirt. Squats and lunges are lower-body movements composed of movements of the legs which also are not covered by the T-shirt. Including such exercises allows us to understand of limitations of the T-shirt form factor. During data collection, we noticed that pushups and situps have the most form variations among the users because they require more physical effort. Thus, many participants performed variations (*e.g.*, knee pushups and situps with arm assitances) of the 2 exercises.

4.2 User Study Procedure

We recruited 15 participants (8 self-identified as female, 7 as male, mean age=24.6, std age=4.6): 5 participants for each size (S/M/L). We experienced hardware malfunctioning (further discussed in Sec. 5.5.1) in 2 studies and we invited 1 participant back for the study and recruited another participant. We asked the participants to select the sizes SeamFit T-shirt they usually wear for exercise instead of assigning sizes to them, adhering to our design goal of resembling conventional exercise clothing at the user level. The participants have a variety of body sizes.

Table 2. Average time per repetition and average repetition per segment in the collected dataset. The abbreviated exercise names are squat (SQ), lunge (LG), situp (SU), pushup (PU), Russian twist (RT), jumping jack (JJ), overhead press (OP), lateral raise (LR), left dumbbell row (LDR), right dumbbell row (RDR), left side bend (LSB), right side bend (RSB), overhead extension (OE), and alternate bicep curls (BC).

	SQ	LG	SU	PU	RT	JJ	OP	LR	LDR	RDR	LSB	RSB	OE	BC	**All**
Average Time (s)	2.2	5.0	3.0	1.8	1.7	1.0	2.1	2.2	1.8	1.7	2.2	2.2	2.2	3.6	**2.3**
Average Repetitions	10.6	10.0	10.5	10.1	11.5	10.7	10.3	10.4	10.4	10.1	10.7	10.8	10.2	10.5	**10.5**

Please see Table. 1 for the summary of anthropometric data. Each study lasted about 1 hour in an experiment room (see Fig. 5 for the setup) on a university campus and compensated US$15 worth in local currency.

At the beginning of each study, the experimenter explained the data collection interface, displayed on a laptop (Apple Macbook Air, 2022) placed in a corner of the room. The laptop (1) displayed imagery and textual stimuli for the exercise, (2) recorded seam electrode signals from SeamFit T-shirts, and (3) recorded ground truth videos for annotations. As the experimenter explained the collection interface, the participant did one repetition of each exercise to get familiarized. The main data collection portion consisted of 3 sessions of 14 exercises in randomized order. The participants were instructed to do 10 repetitions per exercise, but the experimenter did not correct the repetitions or the speed. Between each exercise, the participant walked up the the laptop to switch to the next exercise by hitting a keyboard. We designed so to encourage walking and movements in between the exercises. Participants were also instructed to take breaks, at any time if they wanted to drink water, check their phones, etc., during the session for a more naturalistic data set. For all exercises that involved dumbbells, there were 2 sets of dumbbells of 10lbs and 15lbs of each for the participants to choose, and they did not need to stay consistent with the chosen dumbbells.

Between each session, the T-shirt was remounted. At the end of each study, participants completed a questionnaire about their demographic, body sizes (measured by the experimenter), and the wearability of the prototype. In total, we collected an average of 26 minutes of data (standard deviation = 9 min) from each participant as the time varies for different exercise speeds/reps (detailed in Table. 2) and rest times. Among which, on average, 17 minutes are "exercise" data (standard deviation = 6 min), and 9 minutes are "not exercise data" (standard deviation = 3 min). From all 12 participants combined, we collected 6.6 hours of data.

4.3 Washing&Drying Before Each User Study

To explore SeamFit's generalizability across washing-drying cycles, before each study, we cleaned the T-shirt with home washing[8] and drying[9] machines. The washing cycle was 45 minutes long in the delicate mode without detergents, and the drying cycle was about 1 hour long in the delicate mode. For both washing and drying, we put the T-shirt in a washing machine bag, a similar treatment as those for delicate clothing. Each shirt prototype was washed 7 times, throughout pilot studies and user studies.

4.4 Ground Truth Annotation

The dataset was manually annotated by watching the videos: the start time, the end time, and repetitions of each exercise segment, using Vidat [43]. Two annotators annotated independently and followed the manner of MM-Fit [37] to address ambiguities.

[8]a standard home washing machine, Samsung SuperSpeed Stream VRT
[9]a standard home drying machine, Samsung MoistureSesnosr

5 RESULTS

Many data-driven sensing systems require training data from each new user or even new session, which can be challenging in real-world settings. Therefore, to evaluate how our system works across different participants without collecting training data from a new user, we adopt a leave-one-participant-out (LOPO) cross-validation to evaluate the performance of the detection and classification models. The counting model does not require any training data as it is fully heuristic-based. For the LOPO cross-validation, we train the model with data (around 497 min for segmentation, 311 min for classification) from the other 14 participants (around 371 min for segmentation, 242 min for classification) and 3 researchers (126 min for segmentation, 69 min for classification), and test the model on the evaluated participant. All the numbers we report below are user-independent. In addition, the 15 users wore 3 different sizes of T-shirts, and the T-shirts were washed before each study to investigate the generalizability across fits and washes. We first report the performance of our exercise detection, classification, and counting models. Then, we discuss the fit generalizability and washing durability of our system.

5.1 Exercise Detection

Evaluation Metric. Exercise detection is essentially a binary classification task: whether the user is exercising or not. We report the accuracy, precision, and recall of our detection model.

The accuracy, precision, and recall for detecting 14 exercises are 89.0%, 88.4%, and 96.2% respectively. As detailed in our implementation, we bias detections of exercises, at the cost of a slightly lower precision. Many classifications are caused by the confusion between exercises that mainly involve joints that are not directly instrumented by the T-shirt and other periodic non-exercise movements. For example, some participants re-tied up their hair during the non-exercise periods, and the extracted features are very similar to those with overhead extensions, causing the hair-tieing movements to be consistently misclassified.

Takeaways. SeamFit exercise detections favor exercises that involve joints that are directly instrumented by the T-shirts.

5.2 Exercise Classification

Evaluation Metric. Informed by prior works [16, 17, 25, 35], we use the accuracy, the ratio of correctly predicted exercises over all samples, as our evaluation metric.

The accuracy for classifying 14 exercises is 93.4%. As shown in the confusion matrix in Fig. 7(A), misclassifications mainly occur for squats, situps, and pushups. Pushups and situps are the two exercises with many form variations during data collection because they require more physical effort. The form variations introduce additional challenges to the classification model.

Takeaways. SeamFit's classification model efficiently distinguishes different exercises, both symmetric and asymmetric, based on the sensed body pose and movement information, in a user-independent manner. A larger dataset with more form variations will potentially improve the classification performance.

5.3 Exercise Counting

Evaluation Metric. Informed by prior works [16, 17, 25, 37], we adopt the absolute error between sets as the evaluation metric and analyze the percentages of errors that are exact matches or within a threshold.

Given an exercise segment with the exercise type label, the mean counting error of all 14 exercises is 0.90. The percentage of exact, within 1, and within 2 counts are 54%, 83%, and 91%. Table 3 details the counting result with exercise type breakdown. Alternate bicep curls, alternate lunges, and Russian twists have the largest errors. The set largely overlaps with the worst exercises for the detection model. Bicep curls and lunges do not have the

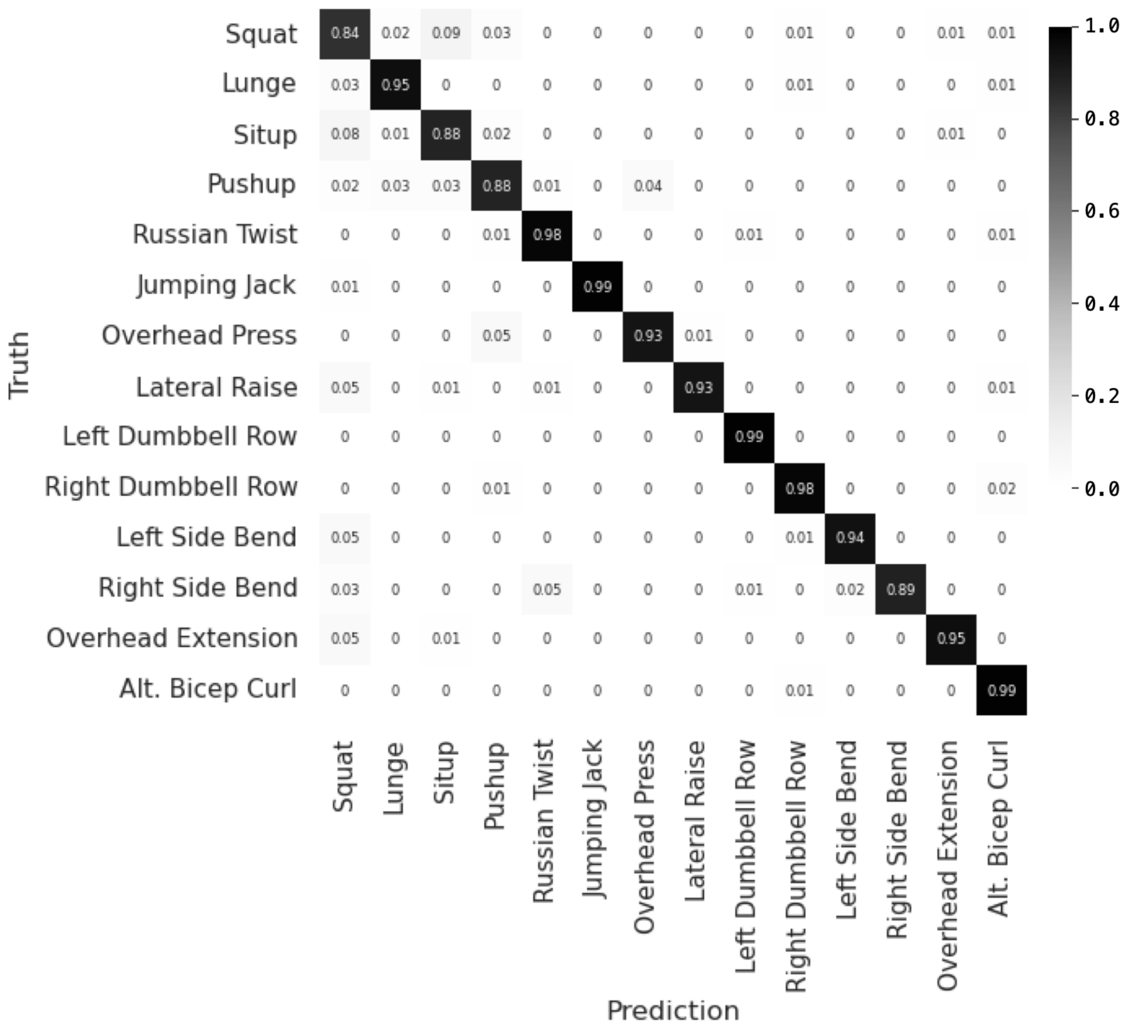

Fig. 7. Exercise classification confusion matrix.

T-shirt cover the key moving joints. As for Russian twists, we believe the large error is attributed to a single repetition having too many peaks, by manually inspecting the signals and identifying peaks.

Takeaways. Similar to the performance of exercise detection, SeamFit exercise counting favors exercises that involve joints that are directly instrumented.

5.4 Performance Analysis Based on Fit

The freedom of choosing clothing fit is one of the critical factors towards practical smart clothing. In our user study, we did not assign sizes to the participants based on their anthropometrics, instead, we asked the participants to pick the sizes they usually wear for exercises. We calculate body mass indices (BMIs) based on their heights and weights, reported in the questionnaire. The scatter plot in Fig. 8(A) shows SeamFit's user-independent

Table 3. Counting results with exercise type breakdown. The "Mean" row refers to the mean absolute counting error across sets. The "Exact" or "Within 1" row refers to the percentage of segments that are counted exactly or within 1. The abbreviated exercise names are squat (SQ), lunge (LG), situp (SU), pushup (PU), Russian twist (RT), jumping jack (JJ), overhead press (OP), lateral raise (LR), left dumbbell row (LDR), right dumbbell row (RDR), left side bend (LSB), right side bend (RSB), overhead extension (OE), and alternate bicep curls (BC).

	SQ	LG	SU	PU	RT	JJ	OP	LR	LDR	RDR	LSB	RSB	OE	BC	**All**
Mean	0.76	1.49	0.74	0.96	1.24	0.43	0.89	0.27	0.93	0.88	0.40	0.36	0.89	2.40	**0.90**
Exact	58%	33%	48%	49%	49%	59%	56%	80%	53%	46%	64%	64%	51%	27%	**53%**
Within 1	87%	62%	84%	80%	76%	98%	84%	96%	82%	84%	98%	100%	80%	53%	**83%**
Within 2	93%	80%	93%	91%	84%	100%	93%	98%	96%	91%	98%	100%	93%	64%	**91%**

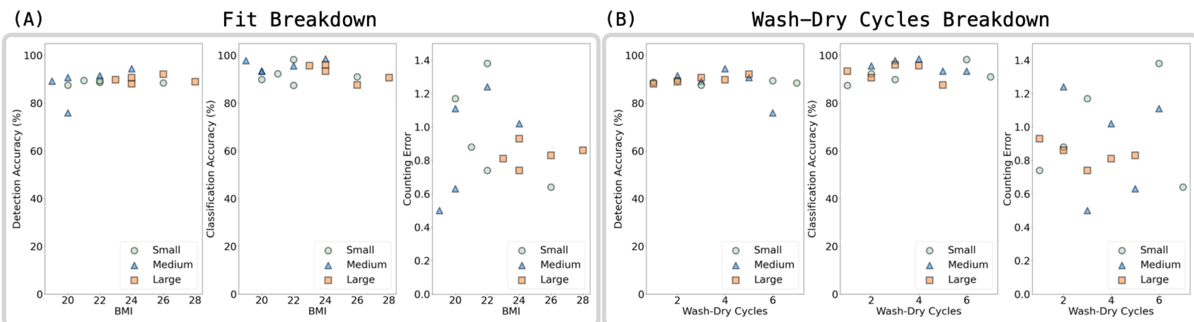

Fig. 8. SeamFit performance breakdown by fit and number of wash-dry cycles. We use BMI as an indicator of body size.

performance breakdown based on the fit. Although our sample size is too small for meaningful statistical analysis, we do not observe obvious trends correlated to the fit. Intuitively, more form-fitting of the T-shirt yields higher information gain. It remains important for future work to conduct large-scale studies to understand the effects caused by fit.

5.5 Washing Durability

Washability and washing durability are key to the practical reuse of smart clothing. We analyze and discuss SeamFit's washing durability in two aspects: (1) mechanical&electical durability, and (2) the generealibility of the system's recognition performance involving signal processing and machine learning, across washes.

5.5.1 Mechanical&Electrical Durabilities. Each T-shirt prototype has 6 connections, and throughout the pilot testing and user studies, each T-shirt has been washed 7 times. SeamFit connections (detailed in Sec. 3.2.3) between the soft threads and the rigid PCBs are through crimping the DuPont connectors with:

- Conductive thread core: when loose connections, as a result of machine washings and drying, occur at the conductive thread core, SeamFit suffers from unreliable sensor readings as the thread is occasionally fully connected, partially connected (i.e. some parts of the threads are still in contact with the connector), and fully disconnected from the sensing board. These electrical unreliable issues occurred 2/42 times for the small prototype, 0/42 times for the medium prototype, and 1/42 for the large prototype. In total, the error rate is 3/126=2.3%. Because such errors are not visible and cannot always be detected due to inconsistent loose connections, we redid 2 user studies after discovering the issues and reconnecting the connections.

Table 4. Situating SeamFit's performance in the literature. All are evaluated in user-independent settings.

	Tracking Device(s)	# of Exercises	Segmentation or Detection	Classification Accuracy	Counting Error
RecoFit [25] 2014	1 inertial sensor on the arm	4	Precision: 99.1% Recall: 98.3%	99.3%	0.26
GymCam [16] 2018	1 grounded camera in the environment	17	Accuracy: 99.86% Precision: 23.0%	80.6%	1.7
MM-Fit [37] 2020	1 inertial sensor in a smartwatch	10	included in classification	91.9%	0.34
ProxiFit [17] 2023	1 magnetometer and 1 IMU in a smartwatch or a smartphone	14	Accuracy: 93.8%	93.1%	0.77
SeamFit	6 conductive seams on a loose-fitting T-shirt	14	Accuracy: 89.0% Precision: 88.4% Recall: 96.2%	93.4%	0.90

- Insulating TPU-coated thread: the benefit of crimping the TPU is to alleviate mechanical strain on the conductive thread core and prevent thread breakage. Indeed, we did not observe any thread breakage throughout our experiment. However, the TPU did slip off from the crimped connectors 1/42 times for the small prototype, 0/42 times for the medium prototype, and 1/42 times for the large prototype. In total, the error rate is 2/126=1.5%. TPU slipping is visible when occurred, so we reconnect the connections after the washing-drying cycle to prevent further damage.

Although we covered the connections with silicone glue to alleviate the damages caused by washing and drying, malfunctioning still occurred. In the future, we will look for or create conductive threads (*e.g.*, aramid core with litz-wire wrapped) that are mechanically strong, electrically conductive, insulated, and solderable, to avoid issues caused by the mechanical connections.

5.5.2 Genaralizability of the Prediction Pipeline. In addition to the robustness of the connectors, washing changes the electrical properties of the conductive thread seam electrodes. Thus, the prediction pipeline needs to be generalized across washes for practical uses. Because we wash the prototype before each study, our user-independent model is also washing-independent. In the scatter plot in Fig. 8(B), we show SeamFit's performance breakdown by the number of wash-dry cycles. Again, we do not observe obvious trends correlated to the number of cycles. Thus, we conclude that our prediction pipeline indeed generalizes across washes with clear water.

Future work should also evaluate the chemical effects of detergents and increase the number of washes to observe long-term effects.

5.6 Performance Comparisons with Prior Works

We situate SeamFit's performance in the literature, in comparison with other wearable [25, 37], environmental [16], and mixed [17] approaches. Although direct performance comparison is difficult because the data sets vary in the amount of training data, the data collection setting, the types and number of exercises, etc., the comparison helps to situate SeamFit, the first smart clothing solution, among other exercise logging solutions. Our classification performance is comparable with other solutions, but the detection and counting performance has room for improvement. What is not shown in this table is that compared to other approaches with a single point of wearable instrumentation [17, 25, 37], SeamFit is able to track asymmetric movements (*e.g.*, left/right dumbbell rows).

5.7 Perceived Comfort and Familiarity

SeamFit aims to preserve the comfort and familiarity of clothing while providing exciting exercise logging capabilities. Based on the questionnaire results, the participants perceived the T-shirts to be very comfortable (Median=5 on the 5-point Likert scale; 1=very uncomfortable, 5=very comfortable) and similar to their everyday clothing (Median=4 on the 5-point Likert scale; 1=very different, 5=not different at all).

6 DISCUSSION

In this paper, we prototyped 3 washable T-shirts of different sizes and a signal processing and machine learning pipeline that generalizes across users, sizes, and washing cycles with a 15-participant user study. However, towards widespread everyday adoption, challenges still lie ahead.

6.1 Improving Sensing Performance

We have demonstrated the feasibility of generalizable exercise logging with SeamFit, but its sensing performance still has room for improvement. One promising direction is integrating IMUs with SeamFit. Adding an IMU to the detachable sensing board does not affect the wearability of the T-shirt and complements the clothing-seam-based sensing approach. SeamFit could work with a smartwatch that better captures the wrist and forearm movements, or shorts/pants versions of SeamFit that directly sense the lower body. Further, SeamFit could benefit from cross-modal learning with other sensing modalities such as inertial sensing and skeletal sensing [37].

Additionally, while this paper focuses on a user-independent pipeline that generalizes across sizes and washes, our user-independent models can be fine-tuned with user-dependent data. Future work on longitudinal studies that evaluate the benefit of user-dependent data over a long period of time would shed more light on the practical use SeamFit: when the user first purchases the T-shirt, they collect some data; as the T-shirt wears and tears, the user may correct some logged exercises, and the system adapts to the new annotated correction data.

It is worth noting that, in modern high-performance sportswear, there are often more seams in front of the chest and around the shoulders. These additional seams will likely increase information gain and sense more fine-grained upper body movements.

6.2 Towards Manufacturing at Scale

For scaled adoption of smart clothing, smart clothing needs to be manufactured at scale. Our proposed approach of couching conductive threads imposes very few mechanical constraints on the conductive thread during the fabrication process, compared with directly machine-sewing with conductive threads. Couching can be applied in serging, the industrial manufacturing method of seaming cut-and-sewn fabric into garments. In that way, seam electrodes can be integrated during the clothing manufacturing process, instead of during the postprocessing/modification stage.

7 CONCLUSION

We present SeamFit, a new solution to wearable exercise logging: washable T-shirts of three different sizes with capacitive seam electrodes that capture body movements. Unlike existing wearable exercise-logging approaches that require sensors on specific body parts and often struggle to track movements elsewhere, the SeamFit T-shirt covers a broader range of body regions and effectively monitors movements in uncovered joints like the elbows and lower body. Our proposed sensing system generalizes across users, fits, and washes. In a 15-participant 14-exercise user study, SeamFit demonstrated an exercise detection accuracy of 89%, exercise classification accuracy of 93.4%, and an average exercise count error of 0.9 counts, independent of users, washes, and fits. SeamFit represents a step towards the prevalent adoption of everyday smart clothing.

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REFERENCES

[1] Mominul Ahsan, Siew Hon Teay, Abu Sadat Muhammad Sayem, and Alhussein Albarbar. 2022. Smart clothing framework for health monitoring applications. *Signals* 3, 1 (2022), 113–145.

[2] Roland Aigner, Andreas Pointner, Thomas Preindl, Rainer Danner, and Michael Haller. 2021. Texyz: Embroidering enameled wires for three degree-of-freedom mutual capacitive sensing. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–12.

[3] Stephanie Alley, Stephanie Schoeppe, Diana Guertler, Cally Jennings, Mitch J Duncan, and Corneel Vandelanotte. 2016. Interest and preferences for using advanced physical activity tracking devices: results of a national cross-sectional survey. *BMJ open* 6, 7 (2016), e011243.

[4] Apple. 2023. Apple Watch Series 9. https://www.apple.com/shop/buy-watch/apple-watch.

[5] Hymalai Bello, Bo Zhou, Sungho Suh, and Paul Lukowicz. 2021. Mocapaci: Posture and gesture detection in loose garments using textile cables as capacitive antennas. In *Proceedings of the 2021 ACM International Symposium on Wearable Computers*. 78–83.

[6] Leah Buechley and Michael Eisenberg. 2009. Fabric PCBs, electronic sequins, and socket buttons: techniques for e-textile craft. *Personal and Ubiquitous Computing* 13 (2009), 133–150.

[7] Steven Ceron, Itai Cohen, Robert F Shepherd, James H Pikul, and Cindy Harnett. 2018. Fiber embroidery of self-sensing soft actuators. *Biomimetics* 3, 3 (2018), 24.

[8] Xiaowei Chen, Xiao Jiang, Lishuang Zhan, Shihui Guo, Qunsheng Ruan, Guoliang Luo, Minghong Liao, and Yipeng Qin. 2023. Full-body human motion reconstruction with sparse joint tracking using flexible sensors. *ACM Transactions on Multimedia Computing, Communications and Applications* 20, 2 (2023), 1–19.

[9] Mohammad Iman Mokhlespour Esfahani and Maury A Nussbaum. 2018. A "smart" undershirt for tracking upper body motions: Task classification and angle estimation. *IEEE sensors Journal* 18, 18 (2018), 7650–7658.

[10] Daniel Geißler, Bo Zhou, Hamraz Javaheri, Esther Friederike Zahn, Emil Woop, Stefan Schaffer, Paul Lukowicz, and Jakob Karolus. 2024. Towards Non-Distracting Smartphone Interaction While Biking Using Capacitive Sensing as Input Device. In *Companion of the 2024 on ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 181–185.

[11] Bruna Goveia da Rocha, Oscar Tomico, Panos Markopoulos, and Daniel Tetteroo. 2020. Crafting research products through digital machine embroidery. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference*. 341–350.

[12] Xiaonan Guo, Jian Liu, Cong Shi, Hongbo Liu, Yingying Chen, and Mooi Choo Chuah. 2018. Device-free personalized fitness assistant using WiFi. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 4 (2018), 1–23.

[13] Holger Harm, Oliver Amft, Daniel Roggen, and Gerhard Tröster. 2010. Smash: A distributed sensing and processing garment for the classification of upper body postures. In *3rd International ICST Conference on Body Area Networks*.

[14] Kunpeng Huang, Ruojia Sun, Ximeng Zhang, Md Tahmidul Islam Molla, Margaret Dunne, Francois Guimbretiere, and Cindy Hsin-Liu Kao. 2021. WovenProbe: probing possibilities for weaving fully-integrated on-skin systems deployable in the field. In *Proceedings of the 2021 ACM Designing Interactive Systems Conference*. 1143–1158.

[15] Ian Janssen and Allana G LeBlanc. 2010. Systematic review of the health benefits of physical activity and fitness in school-aged children and youth. *International journal of behavioral nutrition and physical activity* 7 (2010), 1–16.

[16] Rushil Khurana, Karan Ahuja, Zac Yu, Jennifer Mankoff, Chris Harrison, and Mayank Goel. 2018. GymCam: Detecting, recognizing and tracking simultaneous exercises in unconstrained scenes. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 4 (2018), 1–17.

[17] Jiha Kim, Younho Nam, Jungeun Lee, Young-Joo Suh, and Inseok Hwang. 2023. ProxiFit: Proximity Magnetic Sensing Using a Single Commodity Mobile toward Holistic Weight Exercise Monitoring. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 7, 3 (2023), 1–32.

[18] Shengjie Li, Xiang Li, Qin Lv, Guiyu Tian, and Daqing Zhang. 2018. WiFit: Ubiquitous bodyweight exercise monitoring with commodity wi-fi devices. In *2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*. IEEE, 530–537.

[19] Hyunchul Lim, Yaxuan Li, Matthew Dressa, Fang Hu, Jae Hoon Kim, Ruidong Zhang, and Cheng Zhang. 2022. BodyTrak: Inferring Full-Body Poses from Body Silhouettes Using a Miniature Camera on a Wristband. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 6, 3 (2022), 1–21.

[20] Jongkuk Lim, Youngmin Oh, and Younggeun Choi. 2024. uLift: Adaptive Workout Tracker Using a Single Wrist-Worn Accelerometer. *IEEE Access* (2024).

[21] Ziyu Liu, Hongwen Zhang, Zhenghao Chen, Zhiyong Wang, and Wanli Ouyang. 2020. Disentangling and unifying graph convolutions for skeleton-based action recognition. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 143–152.

[22] Yiyue Luo, Kui Wu, Tomás Palacios, and Wojciech Matusik. 2021. KnitUI: Fabricating interactive and sensing textiles with machine knitting. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–12.

[23] Saif Mahmud, Ke Li, Guilin Hu, Hao Chen, Richard Jin, Ruidong Zhang, François Guimbretière, and Cheng Zhang. 2023. PoseSonic: 3D Upper Body Pose Estimation Through Egocentric Acoustic Sensing on Smartglasses. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 7, 3 (2023), 1–28.

[24] Dafna Merom, Chris Rissel, Philayrath Phongsavan, Ben J Smith, Cathelijne Van Kemenade, Wendy J Brown, and Adrian E Bauman. 2007. Promoting walking with pedometers in the community: the step-by-step trial. *American journal of preventive medicine* 32, 4 (2007), 290–297.

[25] Dan Morris, T Scott Saponas, Andrew Guillory, and Ilya Kelner. 2014. RecoFit: using a wearable sensor to find, recognize, and count repetitive exercises. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 3225–3234.

[26] Movella. 2024. Xsens Products. https://www.movella.com/products/xsens.

[27] Abu Sadat Muhammad Sayem, Siew Hon Teay, Hasan Shahariar, Paula Luise Fink, and Alhussein Albarbar. 2020. Review on smart electro-clothing systems (SeCSs). *Sensors* 20, 3 (2020), 587.

[28] Yuecheng Peng, Danchang Yan, Haotian Chen, Yue Yang, Ye Tao, Weitao Song, Lingyun Sun, and Guanyun Wang. 2024. IntelliTex: Fabricating Low-cost and Washable Functional Textiles using A Double-coating Process. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–18.

[29] Quang-Tien Pham, Duc-Anh Nguyen, Tien-Thanh Nguyen, Thanh Nam Nguyen, Duy-Tung Nguyen, Dinh-Tan Pham, Thanh Hai Tran, Thi-Lan Le, and Hai Vu. 2022. A study on skeleton-based action recognition and its application to physical exercise recognition. In *Proceedings of the 11th International Symposium on Information and Communication Technology*. 239–246.

[30] Ivan Poupyrev, Nan-Wei Gong, Shiho Fukuhara, Mustafa Emre Karagozler, Carsten Schwesig, and Karen E Robinson. 2016. Project Jacquard: interactive digital textiles at scale. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 4216–4227.

[31] Mirana Randriambelonoro, Yu Chen, and Pearl Pu. 2017. Can fitness trackers help diabetic and obese users make and sustain lifestyle changes? *Computer* 50, 3 (2017), 20–29.

[32] Olivia Ruston, Leon Watts, and Mike Fraser. 2021. More than it Seams: Garment Stitching in Wearable e-Textiles. In *Proceedings of the 2021 ACM Designing Interactive Systems Conference*. 1171–1182.

[33] Olivia G Ruston, Adwait Sharma, and Mike Fraser. 2024. SeamSleeve: Robust Arm Movement Sensing through Powered Stitching. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*. 1134–1147.

[34] Qijia Shao, Jiting Liu, Emily Bejerano, Ho Man Colman, Jingping Nie, Xiaofan Jiang, and Xia Zhou. 2024. Joey: Supporting Kangaroo Mother Care with Computational Fabrics. In *Proceedings of the 22nd Annual International Conference on Mobile Systems, Applications and Services*. 237–251.

[35] Chenguang Shen, Bo-Jhang Ho, and Mani Srivastava. 2017. Milift: Efficient smartwatch-based workout tracking using automatic segmentation. *IEEE Transactions on Mobile Computing* 17, 7 (2017), 1609–1622.

[36] Jessica Stanley, John A Hunt, Phil Kunovski, and Yang Wei. 2022. A review of connectors and joining technologies for electronic textiles. *Engineering Reports* 4, 6 (2022), e12491.

[37] David Strömbäck, Sangxia Huang, and Valentin Radu. 2020. Mm-fit: Multimodal deep learning for automatic exercise logging across sensing devices. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 4, 4 (2020), 1–22.

[38] Ryo Takahashi, Wakako Yukita, Tomoyuki Yokota, Takao Someya, and Yoshihiro Kawahara. 2022. Meander Coil++: A body-scale wireless power transmission using safe-to-body and energy-efficient transmitter coil. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–12.

[39] Irmandy Wicaksono, Carson I Tucker, Tao Sun, Cesar A Guerrero, Clare Liu, Wesley M Woo, Eric J Pence, and Canan Dagdeviren. 2020. A tailored, electronic textile conformable suit for large-scale spatiotemporal physiological sensing in vivo. *npj Flexible Electronics* 4, 1 (2020), 1–13.

[40] Tianhong Catherine Yu, Riku Arakawa, James McCann, and Mayank Goel. 2023. uKnit: A Position-Aware Reconfigurable Machine-Knitted Wearable for Gestural Interaction and Passive Sensing using Electrical Impedance Tomography. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–17.

[41] Tianhong Catherine Yu, Manru Mary Zhang, Peter He, Chi-Jung Lee, Cassidy Cheesman, Saif Mahmud, Ruidong Zhang, Francois Guimbretiere, and Cheng Zhang. 2024. SeamPose: Repurposing Seams as Capacitive Sensors in a Shirt for Upper-Body Pose Tracking. In *Proceedings of the 37th Annual ACM Symposium on User Interface Software and Technology*. 1–13.

[42] Michelle Yuen, Arun Cherian, Jennifer C Case, Justin Seipel, and Rebecca K Kramer. 2014. Conformable actuation and sensing with robotic fabric. In *2014 IEEE/RSJ international conference on intelligent robots and systems*. IEEE, 580–586.

[43] Jiahao Zhang, Stephen Gould, and Itzik Ben-Shabat. 2020. Vidat—ANU CVML Video Annotation Tool. https://github.com/anucvml/vidat.

[44] Bo Zhou, Daniel Geissler, Marc Faulhaber, Clara Elisabeth Gleiss, Esther Friederike Zahn, Lala Shakti Swarup Ray, David Gamarra, Vitor Fortes Rey, Sungho Suh, Sizhen Bian, et al. 2023. Mocapose: Motion capturing with textile-integrated capacitive sensors in loose-fitting smart garments. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 7, 1 (2023), 1–40.

[45] Jingwen Zhu and Hsin-Liu Kao. 2022. Scaling E-Textile Production: Understanding the Challenges of Soft Wearable Production for Individual Creators. In *Proceedings of the 2022 ACM International Symposium on Wearable Computers*. 94–99.

[46] Chengxu Zuo, Yiming Wang, Lishuang Zhan, Shihui Guo, Xinyu Yi, Feng Xu, and Yipeng Qin. 2024. Loose inertial poser: Motion capture with IMU-attached loose-wear jacket. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*.