uKnit: A Position-Aware Reconfigurable Machine-Knitted Wearable for Gestural Interaction and Passive Sensing using Electrical Impedance Tomography

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Figure 1: uKnit is a scarf-like reconfigurable wearable which can recognize its current body location placement and perform a variety of gesture recognition and sensing tasks.

ABSTRACT

A scarf is inherently reconfigurable: wearers often use it as a neck wrap, a shawl, a headband, a wristband, and more. We developed uKnit, a scarf-like soft sensor with scarf-like reconfigurability, built with machine knitting and electrical impedance tomography sensing. Soft wearable devices are comfortable and thus attractive for many human-computer interaction scenarios. While prior work has demonstrated various soft wearable capabilities, each capability is device- and location-specific, being incapable of meeting users' various needs with a single device. In contrast, uKnit explores the possibility of one-soft-wearable-for-all. We describe the fabrication and sensing principles behind uKnit, demonstrate several example applications, and evaluate it with 10-participant user studies and a washability test. uKnit achieves 88.0%/78.2% accuracy for 5-class worn-location detection and 80.4%/75.4% accuracy for 7-class gesture recognition with a per-user/universal model. Moreover, it identifies respiratory rate with an error rate of 1.25 bpm and detects binary sitting postures with an average accuracy of 86.2%.

CCS CONCEPTS

• **Human-centered computing → Interaction devices**.

KEYWORDS

Reconfigurable Wearable, Smart Textile, Machine Knitting, Electrical Impedance Tomography, Gestural Interaction

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1 INTRODUCTION

Our clothes are soft, comfortable, and familiar to us. Thus, textile-based soft wearables also feel natural, seamless, and are widely popular (*e.g.*, [56]). This familiarity and seamlessness afford continuous, always-on interactions and, over the years, researchers have proposed many different form factors (*e.g.*, [23, 31, 35, 41, 76]). These devices can sense gestures, postures, and health outcomes, while remaining soft and comfortable. One challenge remains that most soft wearables are rigid in their form-factor and utility. A

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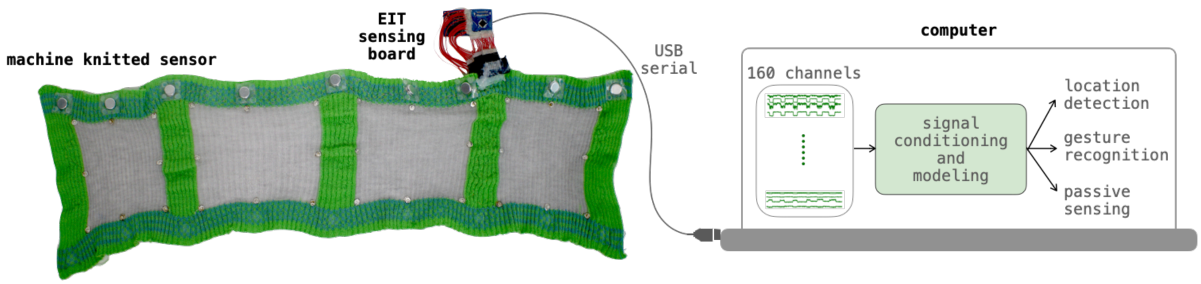

Figure 2: The uKnit includes a machine-knitted sensor using resistive yarn, sensed via electrodes attached to the borders of the resistive patches (gray) using EIT, and signal conditioning and modeling which run on a laptop that interprets the EIT data to detect the sensor location, recognize gestures, and does passive sensing.

glove (*e.g.*, [70]) can only be effectively used when worn on hands. Similarly, a smart sock has limited utility when the user wears shoes. Given the wearables' potential, there is a need for soft wearables that can deform and adapt to the user's context and requirements. A user should be able to customize their wearables and reconfigure them to their exact use case. This idea of customizable wearables is not new. Jarusariboonchai and Häkkilä [21] studied the space of commercial wearables that afford some form of customizability. Similarly, Seyed *et al.* [59] and Khurana *et al.* [30] have explored the reconfigurability of smartwatches. However, a reconfigurable wearable that is soft, comfortable, and conforms to the user's body can be significantly more customizable than a watch, particularly in terms of form factors, worn locations, and interaction modalities. Thus, it can offer a wide range of capabilities.

We draw inspiration from a reconfigurable accessory: gaiter scarves. Gaiter scarves are multi-functional tubular scarves that can be wrapped, folded, and scrunched to put on different places of human bodies. These scarves are popular for outdoor activities where it is inconvenient or infeasible to carry many accessories, such as a wristband, a headband, or a balaclava. Similar scenarios could occur with smart accessories.

We present *uKnit*, a knitted wearable that can morph into different functional forms and afford unique spatial awareness. uKnit is position-aware and adapts its sensing capabilities as users wear it on different parts of the body (Figure 1). It enables sensing active gestures such as touch and deformations, as well as passive respiratory rate and body posture monitoring. The sensor is machine-knitted and thus can be manufactured at scale. Knitted fabric is also lightweight, stretchable, and breathable and thus is comfortable to wear for a long time.

To achieve such a device, we used electrical impedance tomography (EIT) as the sensing approach to capture impedance changes of the knitted fabric to open up the possibilities of a rich set of gestures with a small number of rigid components. To design and build models for diverse sensing tasks, we collected data from 10 participants for each study. Our machine-learning (ML) models achieved 88.0 % and 78.2 % accuracy for 5-class location detection for a per-user and universal model, respectively. For 7-class gesture recognition, our models achieved 80.4 % and 75.4 % accuracy for a per-user and universal model, respectively. Our signal conditioning and modeling algorithms can also identify the user's respiratory rate with an error rate of 1.25 bpm and detect if the wearer is slouched or sitting straight in a chair with an average accuracy of 86.2%. Furthermore, we performed a washability test to study the durability of uKnit: although remained mechanically intact after 12 washes of increasing destructiveness, it lost its electrical functionality after a single mild wash. Lastly, we showed example applications to demonstrate uKnit's potential as a reconfigurable wearable. The main contributions of this paper are:

- a process to prototype a novel *reconfigurable* machine-knitted soft wearable sensor with spatial awareness using off-the-shelf yarns;
- validation of using electrical impedance tomography (EIT) on anisotropic knitted resistive fabric;
- machine-learning (ML) models that show the feasibility of (a) on-body localization, (b) gesture recognition, and (c) passive sensing; and,
- example applications and demonstrations of uKnit's utility in a wearer's daily life.

Though this paper focuses on using uKnit as a wearable device, its strengths stem from a flexible, deformation- and stretch-sensitive fabric. The fabric could be used to make other devices of different sizes and purposes, and the techniques can be generalized to those. For example, a smart swaddle for babies can track the baby's movements and breathing, as well as tell if their hands are out of the swaddle or if the baby has rolled over. Removable accessories for physical objects like smart water bottle sleeves or sofa covers can track daily water consumption or augment furniture. We believe our work paves the way for unlocking a wealth of such everyday applications.

2 USER STORY AND DESIGN REQUIREMENTS

We present an example user story here to convey how a reconfigurable soft wearable can be multi-functional and can augment a day in the user's life. This example also highlights the design and technical requirements for the wearable.

> Kate wakes up on a winter morning with uKnit wrapped around her waist. While she was sleeping, uKnit monitored her sleep quality by tracking her belly movement and respiration rate. She gets out of bed, and uKnit detects her body posture, inferring Kate has started her day. Afterward, she goes for a run while

> wearing uKnit as a headband. While running, she changes songs and volumes on her wireless earphones using presses and directional swipes on uKnit, without taking out her smartphone. Later, as Kate prepares her breakfast, she puts uKnit on her elbow so that when her hands get dirty, she can press her elbow against her torso to scroll the recipe on her smart home hub. Then on her way to work, she wears it as a scarf that keeps her warm and functions as a music player. The input modalities could be switched to a hands-free control or remain the same as touch and swipes recognition. When she gets to work, she puts it on her waist, and uKnit helps her maintain a good sitting posture. After work, she goes to the gym, she puts uKnit on different body parts to log each exercise. Kate can also put uKnit around her waist to monitor the respiratory rate while taking a rest between exercises. At the end of the day, she puts it back on her waist before she goes to bed.

If Kate had one device for each application, she would need to carry several distinct devices throughout the day, even when they are not needed at the moment. In contrast, uKnit allows her to carry only a single wearable that can be used just as an accessory but functions as an alternative input and sensing channel on demand. To enable this vision, uKnit has the following design requirements:

(1) **maximize the resemblance to an ordinary accessory** so that the wearable remains familiar and affords reconfigurability;
(2) **ensure the wearable is optimally-sized**, such that it is large enough to be worn comfortably around the waist, but not become bulky after multiple wraps on smaller body parts, *e.g.*, knee or elbow;
(3) **minimize the number and sizes of hard components** so that the device remains flexible and easily reconfigurable;
(4) **supports a wide range of sensing capabilities** to enable different applications in different configurations.

To satisfy these requirements, we chose machine knitting as the fabrication technique. Knitting is a popular fabrication technique used in accessories, and thus meeting (1). Knitted fabrics are stretchable, and thus satisfying (2). Furthermore, knitted fabrics are breathable, and thus make the device comfortable while performing different activities over a long time. To meet (3) and (4), we chose electrical impedance tomography as the sensing technique to minimize the number of wires and rigid components while enabling a large interaction area with multiple sensing capabilities.

3 BACKGROUND AND RELATED WORK

Metallic threads have been used for decorating garments for centuries. In 1883, an illuminated hair accessory was part of a ballet costume [68]. Researchers started prototyping electronic textiles in the 1990s [17, 55]. Conductive materials and electronic components can be integrated into fabrics during the manufacturing processes [1, 32, 38, 52, 56]. Industrial weaving [56] and knitting machines [14, 38, 46] make E-textiles fabrication scalable. Textile technologies opened up opportunities for soft robotics, autonomous garments, and wearable devices [57]. Thanks to recent research efforts, smart textile can now be augmented with many capabilities, including sensing, displaying [11, 13], mechanically actuating [2], self-cleaning [8], wireless communicating [22], and energy harvesting [26].

We divide relevant prior work into: (1) sensing with smart textiles; (2) reconfigurable interfaces; (3) Electrical Impedance Tomography (EIT), which we used as a sensing principle for uKnit; (4) knitted user interfaces; and (5) on-body localization.

3.1 Sensing with Smart Textiles

Researchers have experimented with various sensing techniques on textiles [23, 66, 76]. Project Tasca combines inductive sensing, capacitive sensing, resistive sensing, and NFC to create a smart pocket that can take user inputs and recognize objects [75]. Capacitive sensing on e-textiles allows for gesture recognition [56, 74], proximity sensing [50], nutrition monitoring [10], contact-based object recognition [77], motion tracking [6], *etc.* ThreadSense employs impedance sensing to localize 1D touch input on a thread [34]. In this work, we use impedance sensing to enable a diverse set of gestural interactions on the knit surface while also making the system automatically adapt to different on-body locations for reconfigurability.

3.2 Reconfigurable Interfaces

Many everyday objects are reconfigurable and inspire reconfigurable user interfaces [31]. Many shape-configurable interfaces are modular and involve disassembling: game controllers [49] , screens [16], haptic devices [69], smartwatches [30], soft wearable prototyping kits [25, 35], *etc.* SensorNets is a soft multimodal electronic skin composed of distributed sensor networks [72]. It can sense a multitude of gestures and can be easily customized to adapt to its curvatures; however, the system requires fabricating sensors for different applications. Another approach to implementing reconfigurable wearables is through miniaturized locomotion robots that can move along users' bodies on demand [12, 58]. Our work achieves shape reconfiguration by deformation, an intrinsic property of textiles. I/O braid is an interactive textile cord that can augment everyday objects, *e.g.*, touch-sensitive headphones and interactive drawstrings in garments [50]. In contrast, uKnit provides larger interaction areas and affords frequent location changes. Somewhat similar to uKnit, the smart handkerchief [61] is a deformable user interface that can recognize its physical form and allow simple gestural interactions. It was designed to lay flat, folded along a certain axis and/or held in hands to sense touch and strain changes. With this regard, uKnit offers a greater degree of freedom in deformation as it can be deformed into any irregular shape, just like an ordinal scarf. This property allows uKnit to be a flexible and pervasive wearable for different tubular body parts.

3.3 Electrical Impedance Tomography

Electrical impedance tomography (EIT), a non-invasive imaging technique to infer internal conductivity characteristics, was first proposed for medical imaging [20] and geophysical imaging [54]. In recent years, EIT gained traction in the human-computer interaction (HCI) community for, *e.g.*, hand gesture recognition [82], paper-based interfaces [83], and touch localization on irregular objects [3, 84]. EIT is now an accessible and versatile sensing method for a conductive surface thanks to open-sourced toolkits [86] and projects [85], but applying EIT onto conductive textile remains underexplored. In soft robotics research, EIT is used to create artificial skin that senses deformation and tactile distributions [29, 47]. MultiSoft uses a multi-layer soft and stretchable sensor with silicon substrate for real-time contact localization and deformation classifications [78]. Though MultiSoft is a customizable soft sensing approach, different sensors still need to be fabricated for different applications. In contrast, uKnit uses a single reconfigurable piece of fabric for all applications. In other words, it is the first to enable reconfigurable touch and deformation sensing on knitted wearables that automatically adapt to different physical placements, thus enabling a plethora of applications with the same physical device.

3.4 Knitted User Interfaces

Knitted fabric is lightweight, breathable, flexible, stretchable, and conforming, making it a great fit for a reconfigurable soft wearable interface. Machine knitting design tools [24, 28, 48, 79] facilitate prototyping knitted interfaces, and we refer readers to McCann *et al.* for a thorough overview of machine knitting [45]. Knitted sensors have a variety of sensing approaches [51]. Earlier works explored the loop structures for strain/stress sensing [81] and enabled respiratory rate monitoring [7, 19]. More recently, Knitted Keyboard combines capacitive and piezoresistive sensing for a multimodal interaction [73]. KnitUI employs resistive sensing to create customizable interfaces [39]. uKnit can duplicate many of the interactions mentioned above with a single reconfigurable knitted sensor. Closer work was proposed by Alirezaei *et al.* who used EIT on knitted fabric that has conductive paint sprayed as a post-proccess [4]. In contrast, we embed conductive yarn using intarsia, a knitting technique used to incorporate areas of colors, thereby making our approach more scalable, and the final wearable more comfortable than using conductive paint.

3.5 On-body Localization

Since we are creating a wearable device that can be put on different body parts, two key factors to consider are placement and form language [15, 80]. Such a reconfigurable wearable device needs to be contextually aware of the physical configuration information [71] and body placement locations [65]. In our case, the placement decides the form because wrapping the same scarf around the waist and the wrist results in a different number of wraps. From the localization perspective, the form can predict the placement. Prior work on on-body localization used IMU sensors [33, 67] or vision sensors [5] to recognize the position passively. Our location detection algorithms use the fact that the wrapped sensor responds to the same gesture differently when it is located on different body parts.

4 FABRICATION

Our reconfigurable sensing wearable prototype (shown in Figure 2) consists of a machine-knitted structure connected to an EIT-based data acquisition circuit. This section provides more detail on the knit

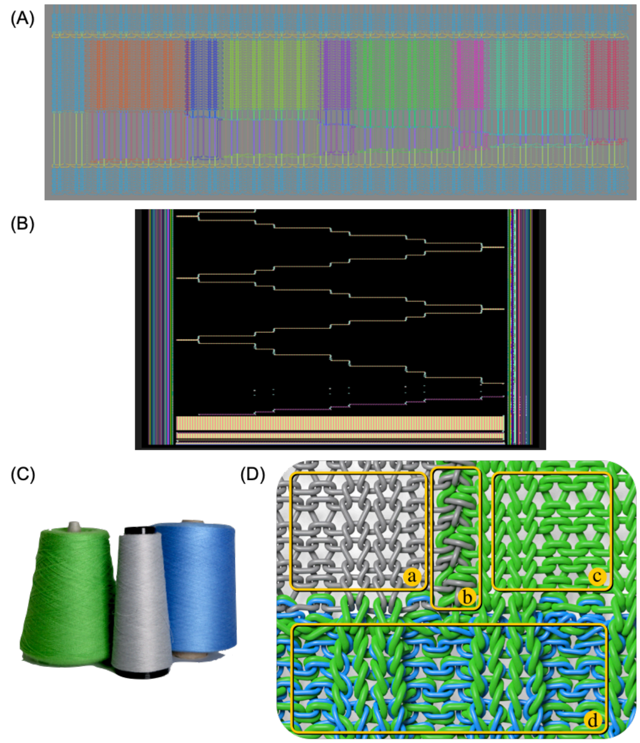

Figure 3: A: a small (0.2x) version of the knitting program for our scarf, visualized with [79]. Each color represents yarn from a single carrier, showing the intarsia technique used to knit the conductive-yarn patches. B: The beginning of the machine knitting program once converted for use in KnitPaint [60]. C: The resistive yarn (grey), non-conductive acrylic yarn (green), and decorative rayon yarn (blue) used in producing the wearable. D: The low-level knit structure of our sensor- conductive yarn patches (a) are connected to non-conductive patches (c) by columns of plated stitches (b); and plating is also used in the border (d) for decorative effects. The entire scarf is a 2x2 rib for stretchiness.

structure, the connection methodology, and the data acquisition circuit.

4.1 Machine-knitted Structure

The structure of our sensing textile was knitted on an industrial v-bed knitting machine (Shima Seiki SWG091N2, 15 gauge). We chose machine knitting because it allowed for the repeatable fabrication of large fabric structures under programmatic control. For an introduction to v-bed knitting machines, we refer the interested reader to [45]. The overall knitting program and the yarns used are shown in Figure 3. We measured 17 cm and 14 cm in the course and wale direction of each patch in an unstretched state. Resistance measurements between opposite electrodes in the course and wale direction of each patch are around 2.3M Ω and 50K Ω respectively.

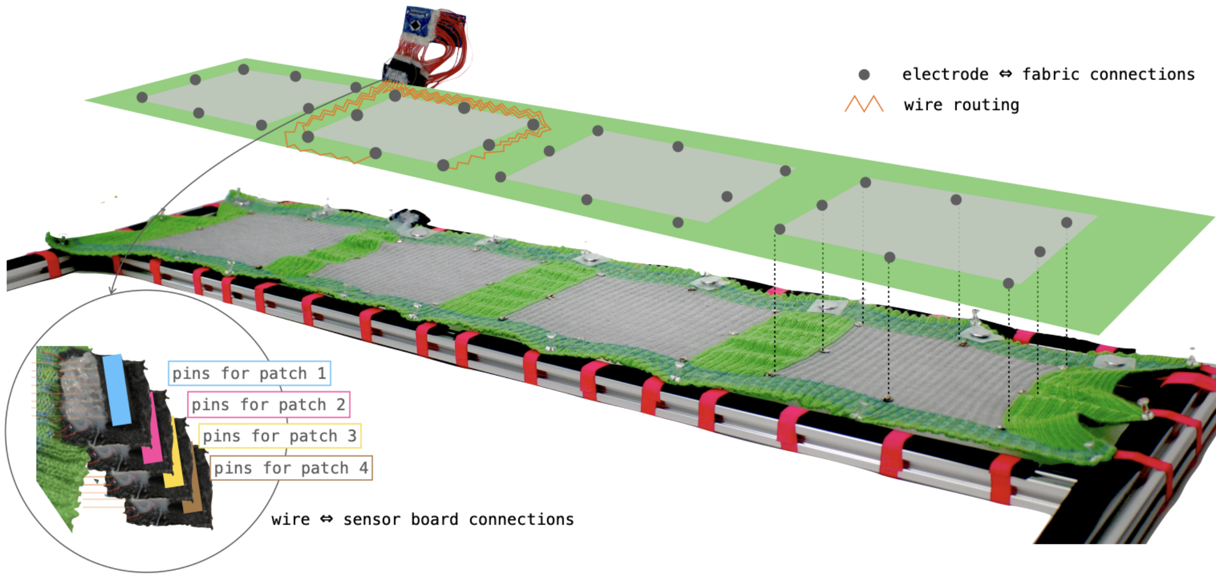

Figure 4: The layout of the connections between the EIT sensing board and the fabric electrode.

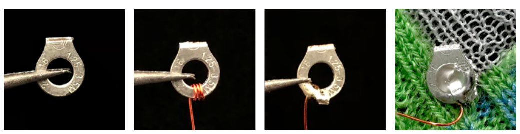

Figure 5: Attaching a wire to our sensor, left-to-right: a washer from a ring terminal, wrapped with enameled wire, soldered, and conductive-epoxied to the fabric.

For our conductive yarn, we used Baekert BK 9036129[1], a Bekinox-polyester blend in 50/2 Nm with a specified resistance of 20 Ω/cm. For non-conductive yarn, we used Tamm Petit 2/30 in Lime (T4285), a basic acrylic yarn. For decoration, we used a thin, blue rayon yarn from Winning.

The scarf was knitted in courses along its long axis, using the intarsia technique – a knitting technique used to incorporate areas of colors by assigning one carrier to each block of same-type yarn, for a total of nine carriers, five threaded with insulating yarn, and four with conductive yarn – to fabricate the electrode patches. Plating (running two yarn carriers over the same stitch) was used for decoration in the border and to connect the conductive and non-conductive patches together at course-wise edges. The overall scarf structure is 2×2 rib – an alternating pattern of two front- and two back-bed knit wales – for stretchability while keeping the loops tight enough to reduce hysteresis in sensing. These structures and techniques are shown in an up-close synthetic rendering in Figure 3(D).

The knitting program uses two different stitch size settings[2] for the majority of the scarf: 35 (with leading 25) for non-conductive knits and 25 (with leading 20) for conductive knits. The stitch settings are different because the yarn diameters are different, leading to different overall loop sizes with the same stitch size setting. The complete pattern is generated in the knitout language [44] by a JavaScript program, which is included in the supplemental material.

[1]Though this is an old catalog number, with BK 9028098 being the substantially similar current replacement.
[2]Numbers in machine-specific units that correspond to loop sizing on the machine, with large numbers resulting in larger loops.

Table 1: Estimated duration of uKnit's fabrication steps.

Fabrication Step	Time (hours)
automatic knitting machine operation	4
electrode ↔ wire connections	0.5
fabric ↔ electrode connections	0.5
fabric ↔ electrode curing	6
wire routing	6
wire ↔ sensing board connections	0.5
wire ↔ sensing board curing	0.5
magnet attachment	0.5
magnet attachment curing	0.5
total	19

4.2 Connectors

One of the challenges in working with any soft electronics project is making hard-soft connections [64]. For our sensor, we settled on the following strategy, as shown in Figure 4:

- ***Electrode* ↔ *Wire** connections*: We first soldered thin enameled wires (Remington PN155 28AWG) to conductive washers harvested from ring terminals (Wirefy Heat Shrink Ring Terminals #6),
- ***Fabric* ↔ *Electrode** connections*: We then glued these electrodes to the edges of the conductive fabric patches with conductive epoxy (MG Chemicals 8331D) for a strong and consistent connection. We placed eight electrodes on each

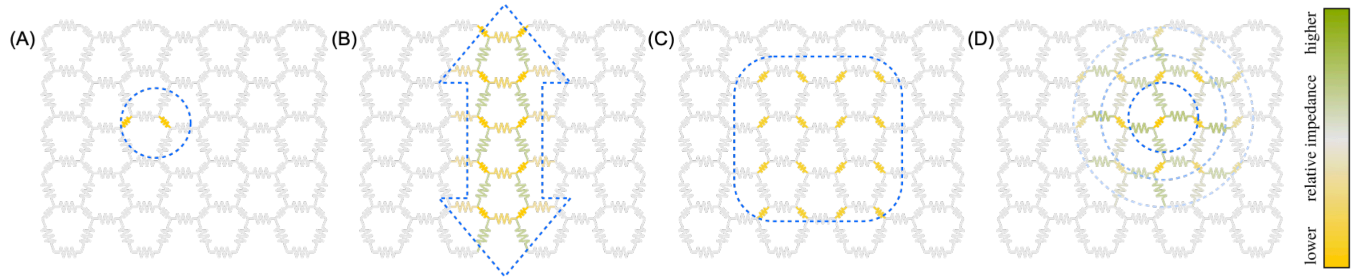

Figure 6: Our conjecture as to why different gestures change the impedance. A: touches compress stitch-stitch contacts, lowering contact impedance for a few stitches. B: in-plane stretching lowers contact impedance and also drags yarn between courses/wales, modifying along-the-yarn impedances. C: grabs apply pressure to many stitch-stitch contacts, lowering contact impedance over many stitches; D:pinch-and-pull stretches yarn along both courses and wales, modifying contact and along-the-yarn impedances over a large area. Note that the relative changes to stitch-stitch contact impedance are much larger than along-the-yarn impedance because contact impedance is initially much higher.

resistive patch, four on the corners and four in the midpoints of the edges.[3]

- ***Wire Routing***: We then routed the thin enameled wires from the electrodes to the EIT sensing board connectors by hand-stitching in serpentine traces.
- ***Wire ↔ Sensing Board** connections*: Finally, to minimize the noise introduced by changes in capacitance in the wires between the EIT sensing board and the scarf, we used short connection wires, held in place with silicone (GE Supreme Silicone) for insulation and strain relief.

In addition, we used silicone to glue sewable hidden magnets onto the prototype to allow the scarf to connect to itself mechanically in various configurations when worn. The entire fabrication of uKnit takes roughly 19 hours, and Table 1 details the estimated time of each fabrication step. We further discuss the limitations in Section 11.

4.3 Data Acquisition

We used an existing EIT sensing board design originally developed by Zhang *et al.* for interactive paper interfaces [84]. This sensing board uses a Voltage Controlled Current Source (VCCS) and Direct Digital Synthesis (DDS) IC which produces 200 kHz sinusoidal waves. These signals are injected into VCCS to produce a constant AC current that can drive up to 6 Vpp while outputting 3.3V AVDD with 1.65V bias between a pair of electrodes selected by two multiplexers. Then it measures the voltage differences between another pair of electrodes selected by another two multiplexers. We set up the sensing board to use a four-pole EIT measurement scheme (Figure 7), injecting current into each pair of neighboring electrodes (8 per patch) and measuring the impedance to all non-adjacent pairs (5 per patch), for a total of 160 measurements (4 patches × 8 sources × 5 measurements) per frame. We configured the device to wait for 80 microseconds for each reading to stabilize and to use 500 samples for its root-mean-square measurements; resulting in a 16 Hz measurement frame rate. The board sends these measurements via serial-over-USB to a host computer for further analysis.

[3]While conventional wisdom for EIT suggests avoiding corners [18], our prototype seems to work well in its current configuration.

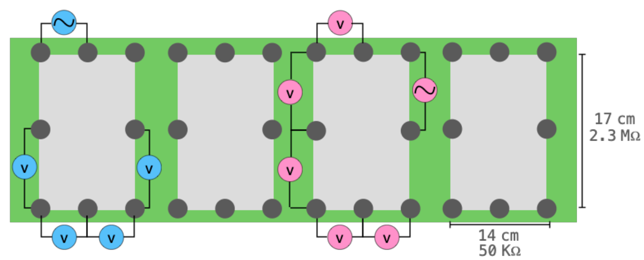

Figure 7: Our sensor uses the four-pole EIT sensing scheme. The EIT sensor board injects alternating current into every adjacent pair of electrodes and measures the voltage differences on the five other pairs of adjacent electrodes in the patch; this results in 160 pair-pair impedance measurements.

5 SENSING

In this section, we explain the uKnit's theory of operation, interaction space, and signal conditioning and modeling.

5.1 Theory of Operation

Though we do not model uKnit's yarn-level circuit, we include an overview of impedance and conjecture why impedance measurement works on uKnit. Impedance, Z, is a complex number that relates the current in a circuit to the applied AC voltage at a given frequency, ω, and phase ϕ:

$$|V|e^{j(\omega t+\phi_V)} = Z|I|e^{j(\omega t+\phi_I)} \tag{1}$$

, where $j = \sqrt{-1}$ denotes the complex unit and V and I are voltage and current phasors, respectively. The impedance of a passive RLC circuit with resistance R, capacitance C, and inductance L is the sum of the resistance, capacitive reactance, and inductive reactance:

$$Z = R + \frac{1}{j\omega C} + j\omega L \tag{2}$$

Our system works by measuring changes in impedance. As shown in Figure 6, we conjecture that these changes are primarily due to changing resistance in yarn-yarn contacts [81], which have lower resistance when force is applied. Preliminary observations with an

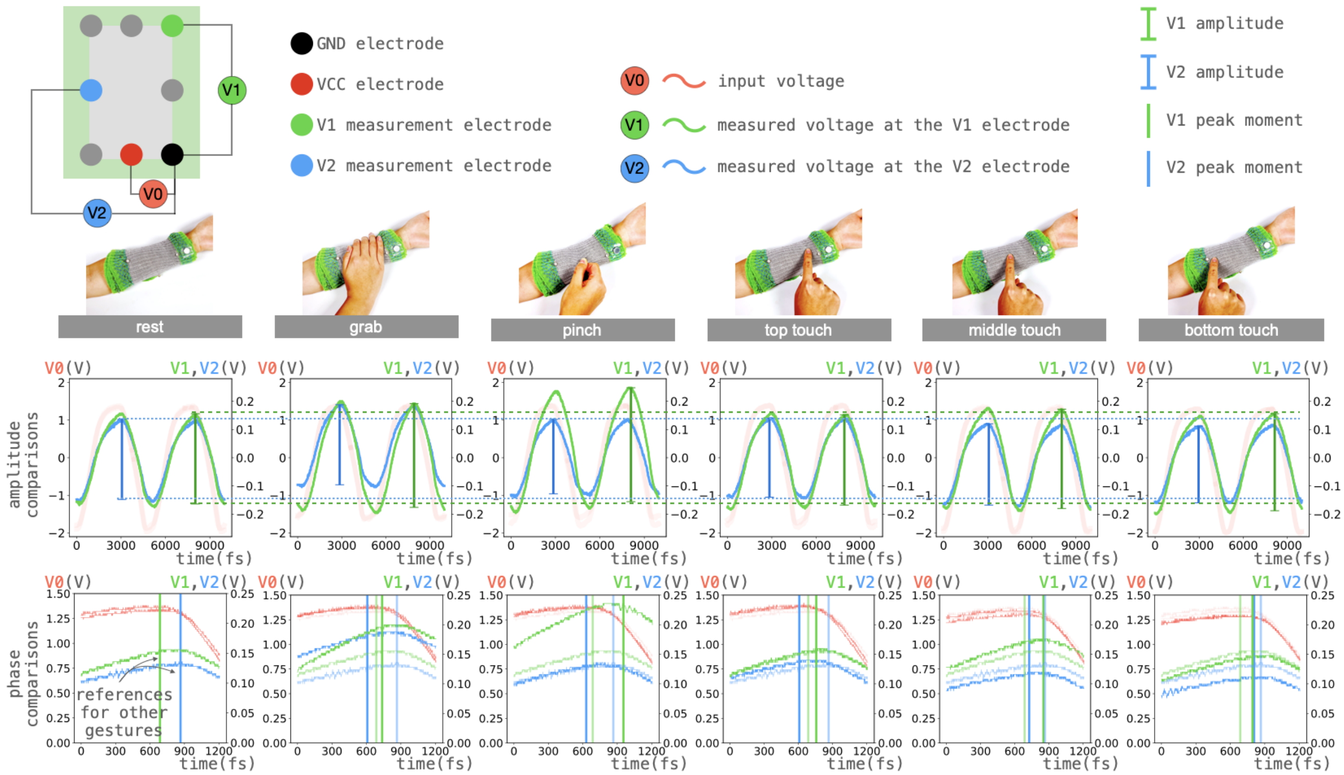

Figure 8: Relative impedance change experiment with an oscilloscope. The top plots show the changes in the amplitude of the AC signal for the "rest" gesture and other example gestures. The bottom plots are zoom-in views that show the phase change comparisons. The peak moments shifts indicate phase shifts. The faded-colored vertical lines are references to the peak moments of the "rest" gesture. Gestures induce significant amplitude changes and small phase changes. Note that the time axis is in femtoseconds (1e-15 seconds).

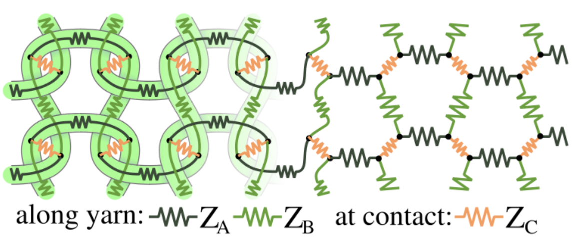

Figure 9: A circuit model of the fabric in our sensor. Impedance along yarns (Z_A, Z_B) is generally much lower than between yarns (Z_C), leading to lower impedance in the course (horizontal) direction than in the wale (vertical) direction. In use, local impedance changes are dominated by contact forces (which lower Z_C), and deformation (which change the length of yarn between contact points, altering Z_A, Z_B).

oscilloscope (SIGLENT SDS 1202X-E) using a single pair of injection electrodes and two measurement electrodes (Figure 8) show visible phase shift and suggest some capacitive[4] effects. However, gestures induce significant amplitude changes and small phase shifts. As explained in Section 4.3, uKnit measures the root-mean-square of 500 samples, so the changing amplitude is the major factor and the biggest contributor to signal change that our algorithms model. The small capacitive changes present in the signals make uKnit more sensitive to light touches, with little deformation, compared with a purely resistive tomography approach.

However, knit fabric is not a simple, uniform, resistive sheet. Rather, it is an anisotropic resistor network (Figure 9), having reasonably conductive paths along yarns in the course direction and much higher resistance paths via yarn-yarn contacts in the wale direction. Furthermore, the hysteresis effect in resistance caused by friction and structural changes in the knitted fabric [62] makes it difficult to study the absolute impedance values. Therefore, instead of using the traditional inverse tomography algorithms that attempt to reconstruct a distribution of impedance values, we use ML algorithms with the measured voltage differences directly.

5.2 Interaction Space

The EIT signals measured by our system depend on where, how much, and for how long the sensor is deformed. Accordingly, we

[4]Both capacitors and inductors cause a phase shift as per (2); but the direction of the shift we observed suggested that capacitance was the dominant effect.

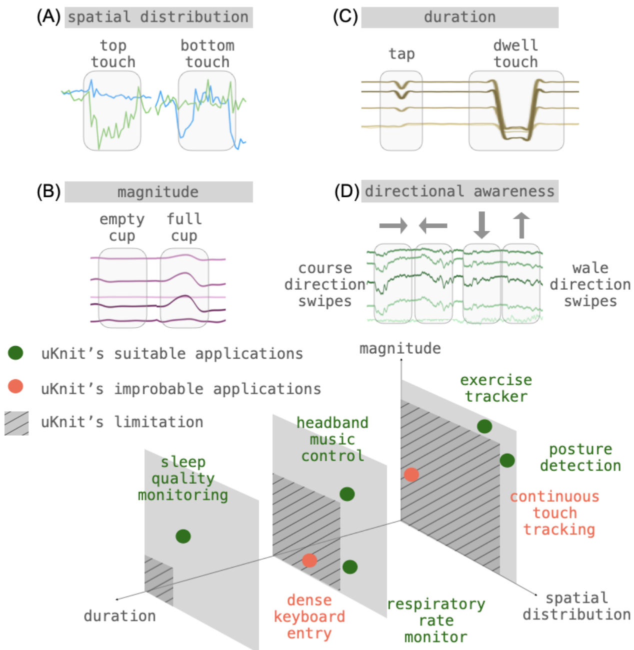

Figure 10: The effects of spatial distribution, magnitude, and duration on EIT signals (only 5 of the 40 signals with the same injecting electrodes from one patch are shown for clarity). (A) Spatial Distribution: events in different area impacts signal differently. (B) Magnitude: larger strain creates larger signals. (C) Duration: longer touches/gestures allow the signals to settle. Combining the identified axis offers more capabilities like directional awareness, shown in (D). uKnit is more sensitive to changes in the wale direction owing to the higher starting resistance. Example applications are mapped to the space spanned by the identified three axes.

look at interaction events from three axes: spatial distribution, magnitude, and duration, which is illustrated in Figure 10.

Definition 5.1. Spatial Distribution. The location and size of the area being impacted by the event. A pin-point press has a small spatial distribution since only a tiny part of the scarf is impacted; respiratory rate monitoring has a large spatial distribution because the entire scarf is stretched. Localizing two pin-point presses far away from each other is easier than localizing two larger presses near each other.

Definition 5.2. Magnitude. How much deformation is induced by the event. A slice of angel food cake resting on the sensor is a low-magnitude event – the cake is airy and doesn't press the sensor very hard; a slab of cheesecake resting on the sensor is a high-magnitude event – it applies a much greater deformation owing to its greater load.

Definition 5.3. Duration. How long the event lasts. A quick tap is a low duration; a dwell touch is a higher duration.

Generally, events that are further along one or more of these axes are easier for uKnit to detect, and vice versa. For example, continuous touch location tracking is unlikely to work accurately as the movement has a short duration, low magnitude, and small spatial extent while requiring high spatial precision. Like this, the introduced three axes provide a good framework for designing interactions with uKnit.

5.3 Signal Conditioning and Modeling

Given that the captured impedance changes depend on the spatial distribution, magnitude, and duration of the sensor deformation, we perform signal conditioning and modeling for recognition and monitoring purposes.

5.3.1 Worn Location and Gesture Recognition. To distinguish different classes of the measured signals (*i.e.*, location and gesture), we trained ML models. The location model and the gesture model have the same architecture (Figure 11). We provide data in 3-second windows of the continuously sampled 160 channels of signals transformed into a matrix of size (the number of channels) × (the number of samples). For each row (*i.e.*, time-series data per channel), we calculate the following nine statistical features: `mean`, `median`, `standard deviation`, `skewness`, `kurtosis`, `max`, `min`, `argmax`, and `argmin`. Then all $160 \times 9 = 1440$ features are aggregated and input into the respective Random Forest Classifier[5] for training/predicting. For real-time predictions to enable the demonstrated applications, we use the latest 3s of data as the input window to the model. We do not perform any post-processing on the output of these window-level results.

5.3.2 Passive Sensing. For sensing the wearer's respiratory rate and body posture, we condition and process the received signals more than for gesture or location recognition (Figure 12). Additional signal conditioning helps us identify useful channels without much training data. For example, respiratory rate sensing involves no ML. We initially filter out the low- and high-frequency components with detrending, demeaning using a Butterworth low-pass filter (cut-off = 0.2 Hz, order = 2) and a median filter of size 11. Given all 160 channels of uKnit would not react uniformly to the expansion and contraction of the wearer's torso, we then identify the most sensitive signals. Here, we only use signals with a lower than the 20th percentile number of zero crossings and higher than the 80th percentile of the overall variance. This approach helps us find signals that are not noisy (noisy signals will have higher zero crossings due to noise and lower amplitude and, thereby, variance). The selected signals are again median filtered (size = 25). We perform this additional and more aggressive filtering after identifying signals of interest because otherwise the zero crossing estimates became inaccurate. The signal conditioning process remains the same for posture detection. The signals in Figure 12 show three examples of original and conditioned signals.

For estimating respiratory rate, we identify peaks in all conditioned and selected signals using SciPy' findpeaks function[6] and calculate the median estimate. For recognizing posture, we calculate five features on a window of size 155 samples (9s of data, 50% overlap): (1) 5th percentile of the window, (2) sign of the mean value, (3) slope, and (4) intercept of a line fitted to the window values, and

[5] Default scikit-learn (v1.1.2) parameters: 1000 trees, 30 max depth
[6] ScipPy.Signal v1.9.1. Default parameters.

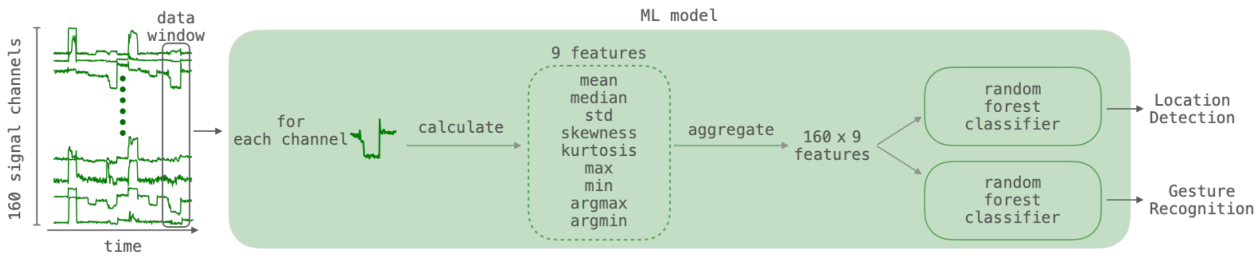

Figure 11: ML models pipeline for worn-location and gesture recognition. The two models share the same architecture.

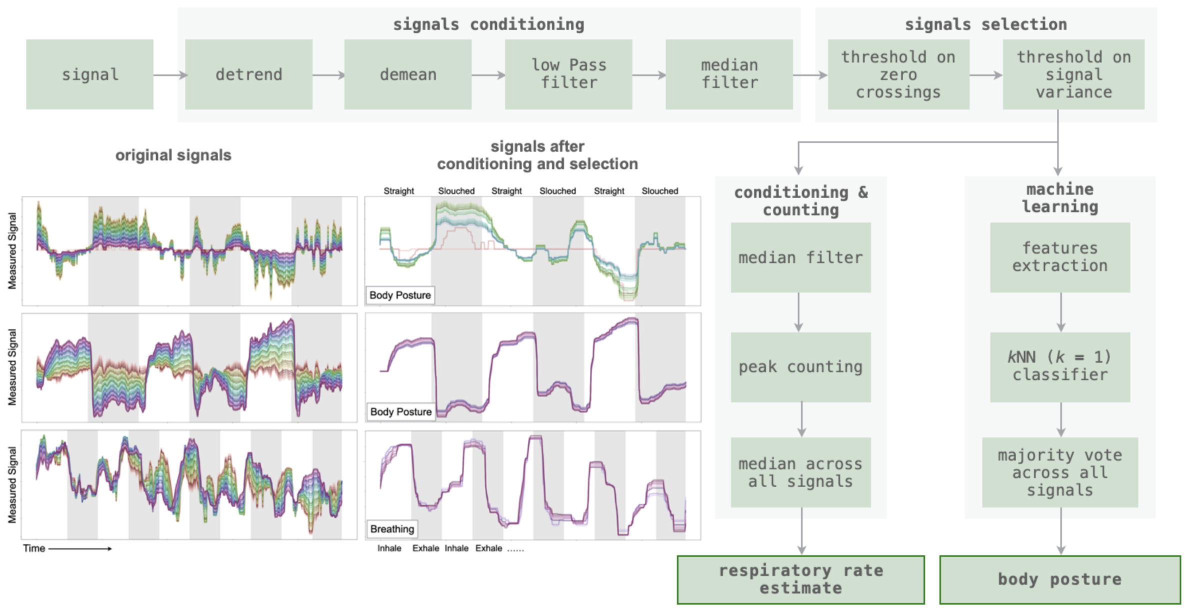

Figure 12: Signal conditioning and modeling pipeline for passive sensing. The signals show examples of original signals and conditioned signals.

(5) median of the values in the middle of the window (sub-window of size 60 samples). These features aim to capture the amplitude, direction of change, and any big signal shifts due to a change in posture. We then use the first straight and slouched posture of each trial as a training gesture for a kNN classifier with $k = 1$. Finally, we do a majority vote on outputs among all selected signals.

6 STUDY 1: LOCATION DETECTION

First, we conducted a study to verify the reconfigurability of our system, that is, whether the system can identify where on the body it is attached. We collected data while the user wore uKnit on different body parts and performed gestures with the device. We plan to use these gestures as a calibration step where users perform a quick action (*e.g.*, a touch) to let the system know the attached location on the body. We evaluated reconfigurability on five different body parts: head, neck, waist, leg, and arm. The arm label is an aggregation of the wrist, elbow, and upper arm. The leg label is an aggregation of the knee and thigh. The set of locations we chose is informed by the form factor of our scarf device as well as prior work about on-body localization [37, 80].

6.1 Procedure

The experiment used an Apple MacBook Pro 15" (2019), and data was transmitted from the sensor board using a USB serial connection. We recruited ten participants (five male and five female) via online communication and word-of-mouth. They were all in their 20's and right-handed. For each of the five body parts, there are three sessions. Before each session, an experimenter helped the participant put uKnit on because wiring makes it slightly unwieldy. Between the sessions, the participant rewore the device to add natural variability. For each session, there are three trials for performing different gestures. We chose a set of four gestures (Figure 13): touch, swipe, grab, and pinch.

For each body part, we first showed a brief demonstration of each gesture to the participants. We then generated a randomized order of the gestures and the participants performed them in order. After we repeated this process three times for one location, we asked

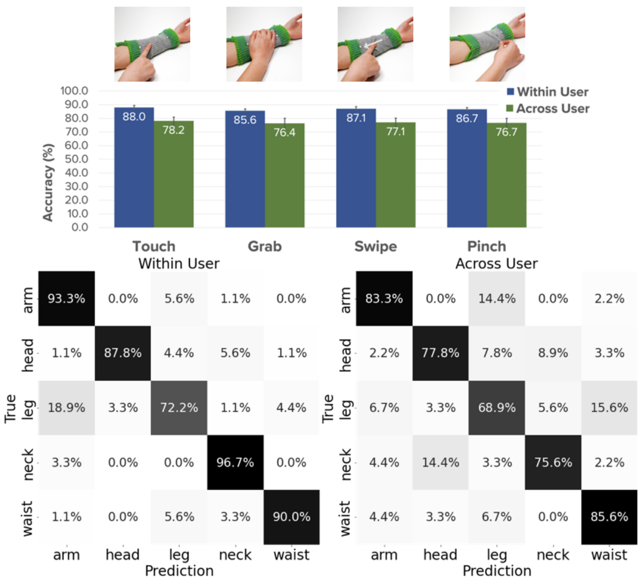

Figure 13: Top: Bar chart shows the accuracy of the within-/across-user models for the location detection by the four different calibration gestures. Error bars indicate standard error. Bottom: Confusion matrices of location detection using "touch" as the calibration gesture. Within-user cross validation (left) achieves 88.0 % and across-user cross validation (right) achieves 78.2 %.

the participants to take off and attach the device to the next body part. While performing gestures, the participants heard instructions from the computer regarding when to start and end the gesture. We recorded 3 seconds for each gesture and the instruction began and ended at the 0.5- and 2.5-seconds points within the range. Most of the data were collected while the participants were seated except for some participants who felt easier to perform the gestures standing when uKnit placed on their waists. All participants were free to move between gesture trials. It took roughly 2 hours to complete the three sessions. The participants were paid $15 for their participation.

6.2 Results

For each calibration gesture, we trained and evaluated two models: within-user model and across-user model. For the within-user model, we used a leave-one-session-out cross validation to simulate a situation where users who have already completed the calibration step put on the device to a body location later. For the across-user model, we used a leave-one-participant-out cross validation to simulate a situation where new users who have not done the calibration put on the device. Figure 13 presents the results. All four gestures had similar performances. Since "touch" is the simplest gesture with the potential to seamlessly integrate into the process of putting on uKnit, we conclude that "touch" is the best calibration gesture. "touch" has location detection accuracy of 88.0 % for the within-user model and 78.2 % for the across-user model. The confusion matrices can also be found in Figure 13.

6.3 Discussion

When generating the across-user model for the location detection, there is a consistent around 10% accuracy decrease. We suspect the major reason is different body sizes. Shown in the confusion matrix in Figure 13: within user, neck is never confused with head, and head is confused 5.6% of the time with neck; but across users, neck is confused with head 14.4% of the time, and head is confused with neck 8.9% of the time. Similar results showed between legs and arms as the body sizes vary across users. Another possible contributing factor is different human body impedance [42], but the high contact impedance makes this unlikely. Participants wore a mix of long and short sleeve tops of different materials. There was one participant who wore shorts, uKnit lying on the skin when placed on the leg, and all others wore trousers. We found there are no significant differences with respect to participants' clothing. Furthermore, given our universal model adapts well across users, we believe the calibration gesture is the dominant factor for signal differences.

7 STUDY 2: GESTURE RECOGNITION

Next, we conducted a study to examine the system's ability to recognize gestures. Here, we attached our device to the participants' wrists and collected data while they performed different gestures. We tested gesture recognition on the wrist because this is a common location for varied on-body interactions. We included six gestures: top touch, middle touch, bottom touch, swipe, pinch, and grab; as well as a no-gesture case, which we call "rest." Top, middle, and bottom touches are along the mid-line of the sensor, with the top closest to the hand and the bottom furthest from the hand; grab and pinch happen at the center of the sensing patch; and swipe runs from the top touch area to the bottom touch area. These gestures are shown in Figure 14.

7.1 Procedure

We recruited ten participants (five male and five female) in the same manner as in Study 1. Two of them had also participated in Study 1. They were all in their 20's and right-handed. There were three sessions in the data collection and each session consisted of ten trials. We showed a brief demonstration of each gesture to the participants before the first session started. Note that there were no explicit visual indications on the device for the gesture locations (*e.g.*, dots) and the participants performed each gesture as they thought matched the given instructions.

We used the same apparatus as we used in Study 1. Before starting each session, the participants attached or re-attached the device to their left wrist. Within a session, they performed randomly-presented gestures in order until we obtained ten trials for each of the seven gestures. In the same manner as Study 1, we recorded 3 seconds for each gesture and the participants were instructed to begin and end a gesture at the 0.5- and 2.5-seconds points within the range. Throughout the data collection, we let the participants rest their left forearm on a flat plane. The study took roughly 30 minutes and the participants were paid $15 for their participation.

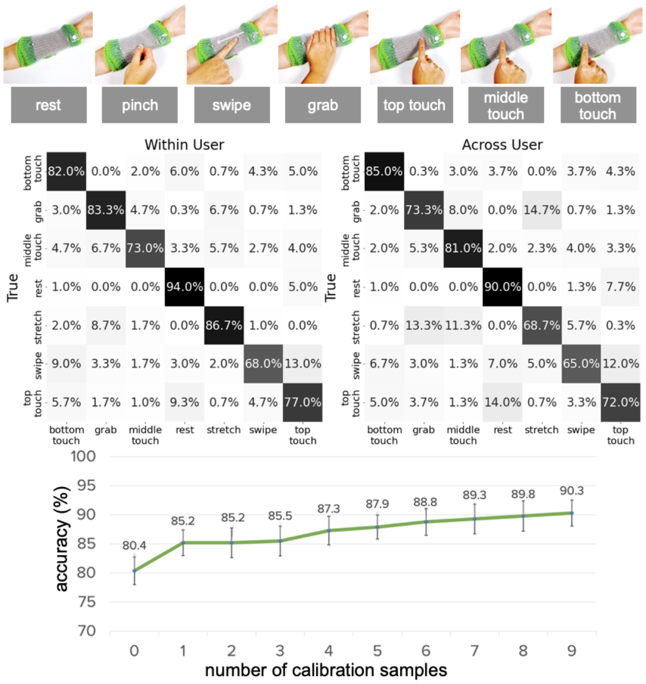

Figure 14: Confusion matrices of 7-gesture recognition. Within-user cross validation (left) achieves 80.4 % and across-user cross validation (right) achieves 75.4 %. Gesture recognition becomes more accurate when calibration gestures are added. For example, adding three calibration gestures results in a 5% accuracy increase. Note that the Y-axis starts from 70%. Error bars indicate standard error.

7.2 Results

Similar to Study 1, we trained a within-user model and an across-user model, and evaluated with leave-one-session-out and leave-one-user-out cross validation, respectively. When training the model, we used 40 channels instead of 160 channels to calculate features. The sensor placement made all 4 patches overlap since one patch is wide enough to wrap our wrists. The used 40 channels correspond to a single patch. The accuracy of the two models was 80.4 % and 75.4 %, respectively. Confusion matrices are shown in Figure 14.

Additionally, the within-user within-session model was introduced to see how much accuracy could be gained in a scenario where a user is willing to provide calibration data after reconfiguring the sensor. We trained this model by using a few samples from one session of the participant and all data outside of that session, including the other participants' data. Figure 14 presents how the accuracy increases as we increase the number of trials for the calibration.

7.3 Discussion

This study demonstrated gesture recognition feasibility at the wrist location. Collecting data at all locations would have made data collection uncomfortably long, so we decided to only test one location. In our pilots, the signal changed predictably for each gesture at each location and there was no reason to believe that the recognition would not work at any of the tested locations. In the confusion matrices (Figure 14), we observe that "top touch" was often confused with "rest", but the symmetric "bottom touch" did not exhibit similar behavior. We conjecture that the fabrication variation and proximity to electrodes could be contributing factors. Figure 14 shows that within-session calibration samples effectively increase the recognition accuracy as the sensor orientation highly affects sensor readings.

8 STUDY 3: PASSIVE MONITORING

We conducted a study to validate the system's capability for passive sensing. While many useful applications could already be built on the gestures from the studies, we also find it useful to think beyond these tested gestures. The two tasks we investigated are respiratory rate monitoring and posture detection. uKnit is placed on the waist for both tasks and the participants are seated. For respiratory rate monitoring, participants performed guided breathing at two different rates: 10 and 15 breaths per minute (bpm), given normal adult resting number of respiration is between 12 and 20 bpm [43]. For posture detection, participants were instructed to sit straight and slouched while using their phones to simulate a real-world scenario.

8.1 Procedure

We recruited ten participants (five male and five female) in the same manner as Study 1 & 2. Two of them had also participated in Study 1, and another participant participated in Study 2. They were all in their 20's. There were three sessions in the data collection, and each session consisted of three trials for each task. Again, before starting each session, the experimenter helped the participants to attach or re-attach the device to their waist.

We used the same apparatus as used in the first two studies. Within a session, the users performed randomly-presented tasks until we obtained three trials each for two respiratory rate tasks (10 bpm and 15 bpm) and the posture task. For respiratory rate tasks, participants were instructed to breathe with their normal patterns but listen to the audio cue for inhale/exhale. For 10 bpm, participants breathed in/out for 3s each and repeated it five times. For 15 bpm, participants breathed in/out for 2s each and repeated it five times. For the sitting posture detection task, we instructed participants to sit straight/slouched for 10s based on audio cues. The study took roughly 30 minutes and the participants were paid $15 for their participation.

8.2 Results

For detecting respiratory rate, uKnit does not use any ML model and directly counts peaks on conditioned signals (Section 5.3.2). uKnit's algorithms recognized respiratory rate with an average error of 1.25 bpm (SD = 0.75). There was no significant difference in performance between the two breathing rates. uKnit detected a user's body posture while sitting (straight *vs.* slouched) with an accuracy of 86.2%. Figure 15 shows the example signal of breathing and changing postures.

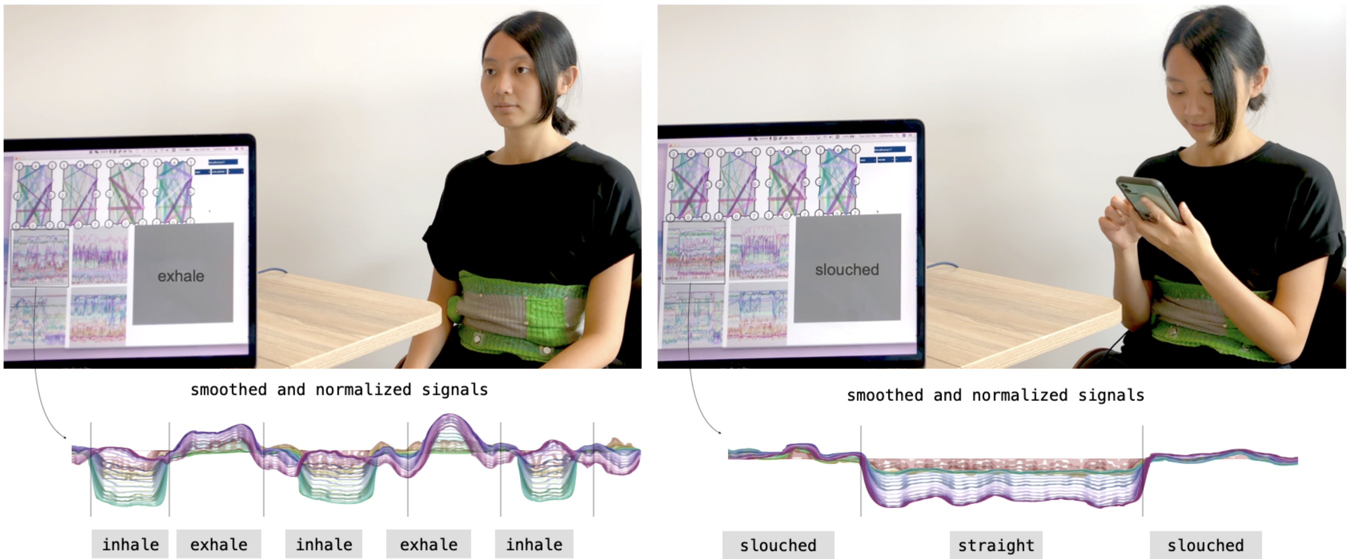

Figure 15: When worn on the waist, uKnit's outputs (zoomed in on 40 channels on one patch) reflect respiration rate (left) and correlates with posture (right).

8.3 Discussion

The study provides a preliminary feasibility of using uKnit for measuring respiratory rate and sitting posture. We believe that the sitting posture detection accuracy could have improved if the data labels were more accurate. During our data collection process, participants were instructed to react to audio cues to change their posture or breathe in or out. The labels are aligned with the start of the cues. We observed that many participants had inconsistent reaction times and thus the data and labels had inconsistent offsets. Though minor, we observed that the errors clustered around the timestamps where the labeled posture changes. For the respiratory rate data collection, we asked the participants to breathe at a fixed rate for a short period of time, but for uKnit to further demonstrate its ability as a passive sensor, we need to deploy it in everyday settings for longer periods. Such studies will allow the evaluation of uKnit against factors critical to practical uses: rain, dust, heat, mud, stain, sweat, *etc.* It will be insightful to see how the signals change when the wearer's breathing is natural/irregular at very different rates (*e.g.*, when the user is on the move or exercising), and how the signals shift over time. This remains an important future work.

9 DURABILITY OF UKNIT

Textile sensors need to be durable if they are to be worn every day. While a complete durability test would require longitudinal deployment, we tested uKnit's washability. Washability is integral for daily uses and prolonged device lifetimes. Although it was not a key design consideration for uKnit, we conducted a washing test to observe the behaviors of the machine-knitted sensing textile and connection mechanisms after washes.

9.1 Procedure

We used a newly fabricated machine-knitted sensing textile and attached 8 connectors to a single patch as described in Section 4. The only component that was left out of the washing test was the detachable sensor board. uKnit was washed 12 times in the order of 3 hand washes in clear water, 3 hand washes in soapy water[7], 3 machine[8] washes (delicate mode, 45 minutes) with clear water, and 3 machine washes with detergent[9]. After each wash, uKnit was first press-dried with paper towels and then left to air-dry. Before and after each wash, we measured (a) the resistance in the course (horizontal) and wale (vertical) directions; and (b) the number of intact connectors. These two measurements evaluated the sensing capability of the textile and the connectors, respectively.

9.2 Results

The resistance measurements are plotted in Figure 16. We observed similar trends between vertical and horizontal measurements. During the initial hand-wash cycles, regardless of whether the soap was used, the resistance was not heavily affected. After machine-washing with clear water, the resistance increased drastically, and it stabilized after one wash. When we added detergent to the machine-washes, the resistance slowly decreased. Note the vertical resistance became so large that it was out of the measurement range for the digital multimeter used after machine-washes with clear water, so we were not able to observe the exact behavior. After two machine-washes with detergent, the resistance decreased enough to be back in the range. We are unsure of the source of this resistance increase-then-decrease behavior; it certainly requires further study if wearable textile sensors are to be widely deployed. Regarding the connectors, they all remained mechanically intact after 12

[7]Nécessaire The Body Bar
[8]a standard home washing machine, Samsung SuperSpeed Stream VRT
[9]Tide Pods

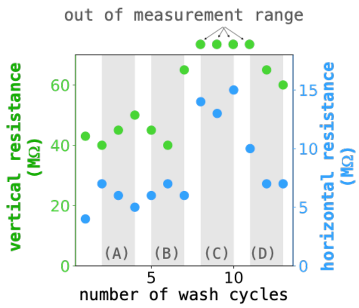

Figure 16: Resistance measurements from the washing test: vertical resistance (green) and horizontal resistance (blue). Washing methods include (A) hand-washes with clear water, (B) hand washes with soapy water, (C) machine-washes with clear water and (D) machine washes with detergent.

washes. However, the conductive epoxy lost its conductivity at the Fabric ↔ Electrode connections. To further evaluate the sensing performance, we applied additional conductive epoxy to reconnect the connectors with the fabric electrically, collected preliminary data for a single user, and trained a within-user gesture recognition model as described in Section 5.3. The leave-one-session-out cross validation was not comparable with the results in the user study.

9.3 Discussion

We selected a set of washing methods and conducted them in the order of increasing destructiveness because knitted goods are typically delicate and have a range of washing limitations for commercial products. However, uKnit lost its functionality after the mildest wash. The obvious shortcoming was the conductive epoxy's loss of conductivity, even though the product we used is supposed to be water-resistant[10]. The other issue lies in the resistance changes in the sensing textile. The brochure[11] of the conductive yarn used in uKnit states that the performance maintains after 200 industrial washes, but because the yarn is originally designed for anti-static textile fabrication, the performance metrics vary. This highlights the need for continuing work on robust materials and connectors for sensing textiles.

10 EXAMPLE APPLICATIONS

We implemented real-time predictors using the ML model discussed in Section 5.3 to demonstrate uKnit's potential as a reconfigurable wearable (Figure 17). The live predictor inputs the latest 3-second of data to the ML model which takes a matrix of size 48 (the number of samples in 3s)× 160 (the number of data channels) and continuously predicts the gesture. Some of the demonstrated gestures (*e.g.*, head-tilt, shoulder shrug) were not evaluated formally in the above studies, which suggests extended use cases of uKnit. Gestures are then mapped for controlling and logging. Since the mappings can be conveniently modified, future work could develop a uKnit platform with user-defined customizable scenarios and functionalities.

Headband Music Player. uKnit can be wrapped around the head as a headband. When running, it can be a music player to control wireless headphones. The gestures we used are: right press → play/pause, right back-to-front swipe → increase volume, right front-to-back swipe → decrease volume, back right press → next song, and back left press → previous song. Including the rest state, the 6-class classifier classifies gestures that control the music player.

Neck-scarf Music Player. On a cold winter morning, uKnit can be worn as a neck-scarf that not only keeps the user warm but also function as a hands-free music player so that the user can keep their hands warm. The gestures we used are: shoulder shrug → play/pause, back head-tilt → increase volume, front head-tilt → decrease volume, left head-tilt → next song, and right head-tilt → previous song. As in the headband music player, the 6-class classifier classifies gestures that control the music player.

Knee-band Squat Counter. When uKnit is placed at joints, it can be used to log exercises. We demonstrate a knee-band squat counter. The two gestures used here are rest and squat. When the user returns to the rest condition after a squat, the logger increments the counter.

Elbow-band Recipe Scroll Controller. uKnit can be placed at different body parts when the hands are unavailable. The user's hands get wet and dirty from cutting vegetables. We demonstrate an elbow-band recipe scroll controller, but modifying the mapping can easily make the same setup and calibration suitable for other applications (*e.g.*, picking up a phone call). The two gestures used here are rest and pressing the elbow against the body. When the user returns to the rest condition after a press, the recipe is scrolled.

11 LIMITATIONS AND FUTURE WORK

The three formal studies and anecdotally-tested example applications highlight the broad sensing potential of uKnit. In the rest of the section, we will discuss the limitations of the current implementation.

Knitted resistive sensor. We noticed that when the knitted fabric is slightly stretched, the signals are the cleanest and most responsive. By design choice, we wanted the fabric to be stretchable so that a single scarf can fit on body parts of different sizes without being too bulky. Shyr *et al.* discovered that a mock rib with less horizontal stretch minimizes hysteresis in knitted sensors [62]. Thus, a systematic evaluation of different types of resistive yarn, knitted patterns, and stitch sizes can potentially improve the system's performance.

Knitted fabric with EIT. Silvera-Tawil *et al.* identified that EIT is not suitable for high temporal frequencies and millimetric spatial resolution, which are limitations for our system as well [63]. However, our system has lower temporal resolution and spatial resolution compared with other EIT-based systems for a few reasons. First, knitted sensors have a hysteresis effect, which could be mitigated with elastic yarns for higher sensitivity [9]. Secondly, knitted fabric is an anisotropic material so equal physical distance does not correlate to equal impedance distribution; and our electrode placement could be redesigned to address this anisotropic structure. Another potential solution is to try anisotropic EIT [36]. We also plan to investigate the possibility of reducing the number

[10]https://www.mgchemicals.com/products/adhesives/electrically-conductive-adhesives/silver-conductive-epoxy
[11]https://www.bekaert.com/-/media/Files/Download-Files/Basic-Materials/Textile/Bekaert-anti-static-textiles-brochure.pdf

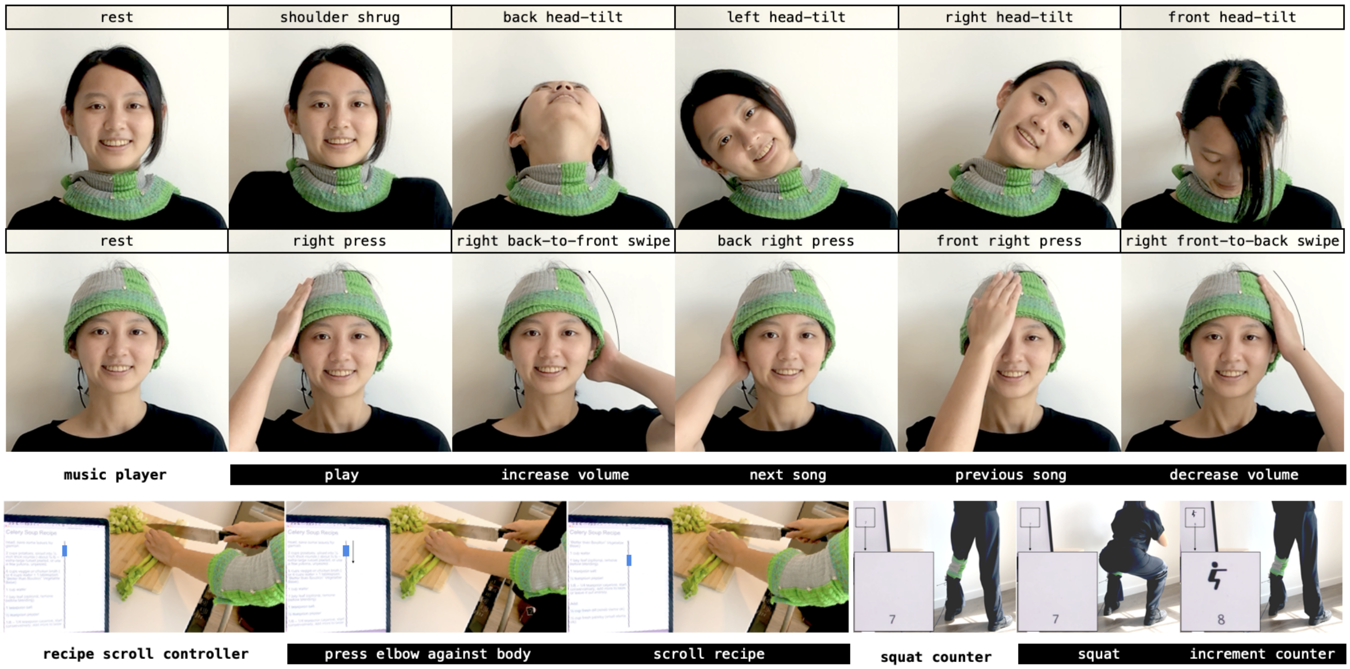

Figure 17: Example applications: neck-scarf and headband music players (the mapping between gestures and the instructions can be conveniently customized), elbow-band hands-free recipe scroll controller, and a knee-band squat counter.

of wires by reducing the number of electrodes while maintaining high accuracy [40].

EIT drive pattern. uKnit's read-back scheme only measures EIT within electrodes on the same patch. However, when the scarf is wrapped or folded over, multiple patches can come into contact (indeed, the resultant decrease in impedance likely enables uKnitto detect sensor location so effectively). It might be interesting, in these scenarios, to switch to a mode that measures between-patch impedances (giving, potentially more useful signals for gesture recognition).

Form factor. We only took advantage of wrapping and folding in our test gestures but it is also natural to scrunch and twist the scarf-like accessory. A study of further affordances might turn up even more interesting use cases. As the shape configurations diversify, a comparison among sensing performances of different shape configurations will further inform future implementation choices.

Beyond a wearable, uKnit can also be a removable accessory for physical objects, like water bottles, table tops, *etc.* Future works can expand uKnit's context-awareness using different object impedance and parasitic capacitance.

Connectors. Connecting soft materials with electronics remains a difficult mechanical problem owing to the required stiffness gradients and the propensity of metals to fatigue. We did encounter wire fatigue and breakage in testing our prototype, especially at the electrode↔wire connections with early prototypes using very fine conductive wires that are compatible with sewing machines. After we changed to thicker durable wires, the prototype fabricated using the method detailed in Section 4 had all 32 connectors intact after around 30 hours of testing, pilot studies, and user studies. Our washing test further demonstrates the mechanical robustness of the current connectors mechanisms. Future revisions will need to seek out more durable and water-resistant connection designs [56, 64].

Sensing patches & electrodes. The number of resistive patches is currently limited by the number of carriers on the knitting machine. Increasing the number of patches can potentially improve uKnit's sensing performance. In this initial prototype, we chose four rectangular patches with eight electrodes each. Using four instead of one rectangular patch provides an initial coarse interaction localization to improve sensing accuracy. Eight is conventionally the smallest number of electrodes used in EIT systems, and smaller than that relies on optimal driving patterns. With thirty-two electrodes, EIT still is the most effective solution to minimize the number of wires. With an effective resistive/capacitive matrix approach that fully covers the interactive wearable, given uKnit's size, ~ 952 cm^2, and the number of electrodes, 32, the finest sensing unit area is $952 \div 16 \div 16 =\sim 4$ cm^2, too large for gestures like pinch and short swipes. For reference, the resistive matrix-based sleeve for gesture recognition by Parzer *et al.* has a sensing unit area of ~ 0.81 cm^2 [53]. The dimension of our prototype was informed by average adult body size measurements and roughly estimated in our design. The evaluated prototype was able to fit all recruited participants. Future works on customizing patch shapes, sizes, and the number of electrodes within a patch need to consider the trade-off between the sensing capability and wearability; an increasing number of electrodes to the optimal electrode-number-to-area ratio could increase accuracy but also increase the number of hard components.

Adding actuators. One could add actuators to uKnit at (1) the surface level: using uKnit as a substrate to attach actuators (*e.g.*, LEDs, vibration motors, and EMS electrodes) similar to the magnets on uKnit; and (2) fiber/yarn level: integrating other functional fiber/yarn into (*e.g.*, optical fibers, shape-changing fibers, and textile EMS electrodes) similar to the conductive yarn in uKnit. Additional sensing components such as temperature sensors and IMUs could be integrated in a similar fashion. This would make uKnit a more full-featured input/output system.

Manufacturability. One benefit of using machine knitting is that it is an established manufacturing technique – so producing the knitted portion of our design could readily be done at scale. However, the connector fabrication remains manual. The overall estimated fabrication time of a uKnit prototype is 19 hours (Table 1): 4 hours of automatic machine knitting, 14 hours of connector fabrication (including 6.5 hours of curing time), and 1 hour of magnets attachment (including 0.5 hours of curing time).

The bottleneck of the fabrication effort is at the wire routing step where we manually hand-sew enameled wires because machine-sewing (*e.g.*, [53]) or machine-embroidery of wires requires a denser fabric to avoid tension problems. Wash-away stabilizer [27] might be one solution to the problem. Furthermore, the couching embroidery technique grants more freedom in routing pattern design and wire choices compared with machine sewing: fastening wires using small stitches of normal embroidery threads instead of directly machine-sewing with conductive yarn allows customizable zigzag patterns and durable thick wire usages.

Aesthetic customizability. On-demand machine knitting enables customizable patterns. We already demonstrated that uKnit's aesthetics can be customized by using extra plating carriers in the non-conductive area, but plating can also be used in the conductive area to visually hide the gray conductive patches. In fact, Bozali *et al.* demonstrated that plating conductive yarn with elastic yarn reduces the hysteresis in knitted sensors [62]. This customization could also be extended to the electrode layout, specializing a given scarf for a given use-case (while still providing a general-purpose sensing device).

Recycling and reuse. One of the exciting features of knitted items is that they can be unraveled and re-knitted into different items – allowing yarn-level reuse. This might allow uKnit to be re-knit as fashion trends or personal preferences shift; though testing is needed to see if the wear this process induces on the yarn would be detrimental to uKnit's sensing performance. At a higher level, the form-factor of uKnit means that it retains utility as a comfy scarf even if its electrical sensing properties are no longer working or necessary.

12 CONCLUSION

We built uKnit, a reconfigurable soft wearable sensor with unique spatial awareness, using a machine-knitted structure and electrical impedance tomography sensing. The scarf-like prototype is a proof of concept for a *universal* soft wearable: one wearable which affords and enables various capabilities. Our series of user studies confirmed uKnit's ability to detect on-body location, recognize gestures, monitor respiratory rates, and detect sitting postures. Our proposed fabrication and sensing techniques will pave the way for smart garments that can be manufactured at scale and accepted for everyday use.

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