Scalable and Deformable Machine-knitted Sensors for Humans and Robots

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Abstract

Textiles are familiar and pervasive materials, making them natural candidates for ubiquitous sensing. Recent research efforts on textile-based sensors span a variety of applications. However, it is challenging to manufacture these deformable and stretchable sensors at scale. On the other hand, industrial textile manufacturing is an established process. Efforts such as Project Jacquard by Google and Levis turned woven fabrics into interactive multi-touch surfaces using standard looms and processes. In contrast to these touch-sensitive fabric *surfaces*, knitted fabrics can be manufactured into complex objects (*e.g.* seam-free sweaters) at scale with minimal post-processing. Moreover, they are more stretchable and breathable than woven fabrics. In this thesis, I convert these knitted fabrics into sensors using an off-the-shelf resistive yarn and industrial knitting machines to fabricate sensing textiles. These sensors are scalable, stretchable, parameterizable, and customizable. They measure electrical properties of the conductive areas to sense contact, pressure, strain, proximity, and even its own orientations. I prototyped a multi-layer matrix-style resistive pressure sensor with robust ON/OFF behaviors and applied them to be robotic skins. Though this sensor could be instrumented on humans as well, humans are in much more diverse contexts doing different activities, so the needs for sensors vary often. Thus for humans, I prototyped a gaiter-scarf inspired multi-purpose reconfigurable accessory using electrical impedance tomography for on-body location detection, gesture recognition, and passive monitoring. Fabrication techniques proposed in this work can be further generalized beyond sensing with functional fibres to augment traditional textiles with new purposes towards a future of pervasive smart textiles.

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1 Introduction

When Mark Weiser envisioned the computer for the 21st Century, he said that "The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it" [Weiser(1999)]. Let's take the word of "fabric" literally. Textiles are pervasive in everyday life, from clothing to object coverings (*e.g.*, sofa covers). Metallic threads have been used for decorating garments for centuries. As early as 1883, an illuminated hair accessory was part of a ballet costume [bal(1842)]. Researchers started prototyping electronic textiles in the 1990s [Post and Orth(1997), Gopalsamy et al.(1999)]. Thanks to recent research efforts, smart textile can now be augmented with many capabilities including sensing, displaying [Devendorf et al.(2016), Cherenack et al.(2010)], mechanically actuating [Albaugh et al.(2021)], self-cleaning [Bell et al.(2021)], wireless communicating [Jiang et al.(2019)], and energy harvesting capabilities [Jost et al.(2014)]. When integrating functional materials, textiles become natural candidates for technologies that "disappear". Early works on E-textiles prototyping methods, such as sewing [Parzer et al.(2018)], embroidery [Aigner et al.(2020)], and ironing [Klamka et al.(2020)], demands a lot of time and efforts. But in the very-well established textile industries, there are scalable manufacture processes. If we could just use the same processes, but make the pervasive textiles "smart" by integrating functional materials and components, that would augment all the existing textiles into smart textiles.

Project Jacquard [Poupyrev et al.(2016)] from Google was one of the first to do so. They invented a solderable yarn that looks, feels, and works the same as normal yarn. Using standard looms and processes, woven fabrics are transformed into interactive multi-touch surfaces. Their Jeans jacket collaboration with Levis showed great promises for seamless integration. In contrast to woven fabrics, constructed with many horizontal and vertical yarn interleaved, knitted fabrics are constructed with continuous yarn forming stacked loops. The differences in structures makes knitted fabric a lot more stretchable and breathable. Furthermore, thanks to recent research efforts [Narayanan et al.(2019)], industrial knitting machines can be used as a 3D printer for soft goods. Then, by integrating functional materials and components, industrial knitting machines can 3D print smart textiles at scale.

In this thesis, I present **scalable and deformable Machine-knitted Sensors**. All textile sensors are manufactured using an industrial knitting machine and off-the-shelf yarns. Using these textiles sensors, I prototyped novel sensing systems for humans (uKnit) and robots (robotSweater). In making these sensing systems, I found similarities and differences between designing textile-based sensors for humans and robots. Along with system limitations, they are useful considerations that pave the way for future smart textiles research.

1.1 Contributions and Organization

The thesis document is organized as follows. I first introduce the related work on sensing with smart textiles and machine knitted sensors in Chapter 2. I then describe the main contributions:

- Three different machine-knitted sensor layouts (Chapter 3)
- Two different connectors for machine-knitted sensors (Chapter 4)
- uKnit : A sensing system prototype for humans (Chapter 5)
- robotSweater: A sensing system prototype for robots (Chapter 6)

Next, I discuss considerations and limitations when designing and fabricating machine-knitted sensing systems, along with future work directions in Chapter 7.

2 Related

In this chapter, we will discuss prior works on machine-knitted sensors, reconfigurable user interface (like uKnit), electrical impedance tomography (sensing technique used in uKnit), and tactile skin (like robotSweater).

2.1 Machine-knitted Sensors

Textile technologies opened up opportunities for wearable devices, soft robotics, and autonomous garments [Sanchez et al.(2021)]. Many sensing techniques can be incorporated into textiles [Wu et al.(2020b), Jin et al.(2018), Sugiura et al.(2012)]. Capacitive sensing on e-textiles allows for gesture recognition[Poupyrev et al.(2016), Wu et al.(2020a)], proximity sensing [Olwal et al.(2018)], nutrition monitoring [Cheng et al.(2013)], contact-based object recognition [Wu et al.(2020c)], motion tracking [Atalay et al.(2017)], etc. Using capacitive sensing and standard weaving looms, Project Jacquard realized inexpensive and scalable interactive multi-touch textile that appear and feel the same as conventional woven cloths [Poupyrev et al.(2016)]. Resistive textile sensors are used to sense deformations [Aigner et al.(2020)]. When combining various sensing techniques, smart textile has more potentials. Project Tasca combines inductive sensing, capacitive sensing, resistive sensing, and NFC to create a smart pocket that can take user inputs and recognize objects[Wu et al.(2021)].

Recent efforts in computational design tools [Jones et al.(2021), Narayanan et al.(2019), Kaspar et al.(2021)] and scheduling algorithms [Narayanan et al.(2018)] allow researchers to easily program industrial knitting machines. Knitted fabric is intrinsically soft, flexible, stretchable, conformal and comfortable. Knitting with functional yarn can augment textiles with sensing [Ou et al.(2019)] and actuating [Kilic Afsar et al.(2021)] capabilities while preserving the above qualities. Conductive yarn and the loop structures of knitted fabric enable strain [Atalay et al.(2014)], pressure [Zlokapa et al.(2022)], proximity [Wijesiriwardana et al.(2005)] sensing supported by resistive [Luo et al.(2021b)], capacitive [Ou et al.(2019)], inductive [Kiener et al.(2022 and impedance [Alirezaei et al.(2009)] sensing. Applications span health monitoring [Fan et al.(2020)], user interfaces [Luo et al.(2021b)], tactile sensing [Yoshikai et al.(2009), Luo et al.(2021a)], choreomusical carpet [Wicaksono et al.(2022)], etc.

Two common approaches for machine-knitted user interfaces are resistive and capacitive sensing. KnitUI [Luo et al.(2021b)] is a portable and customizable user inferface using resistive pressure-sensitive sensing units. Short-rows, a knitting technique used to induce curvatures, is used to increase the sensitivity. Read-outs are directly knitted to minimize post processing. Vallett et al. [Vallett et al.(2020)] use Bode analysis to measure changes in signals caused by capacitive touches to improve touch location representation on knitted interface. The two sensing approaches can be combined for multimodal interaction like the knitted music keyboard [Wicaksono and Paradiso(2020)].

Matrix style textile-based tactile sensors commonly have a three-layer structure: a piezoresistive layer sandwiched between two layer with orthogonal conductive traces for readouts. Luo et. al [Luo et al.(2021a)] proposed a novel coaxial piezoresistive fibre to achieve a two-layer design. Use the inlay knitting technique, functional fibre is integrated into garments to collect spatially dense tactile learning information with AI-based workflow. Electrical impedance tomography (EIT) can further reduce the number of wires and layers by placing electrodes on the borders of sensing area [Park et al.(2021)], but increasing resolution spatial and temporal resolution remains an opened research problem. Alirezaei et al. used EIT on knitted fabric that has conductive paint sprayed as a post process [Alirezaei et al.(2009)].

2.2 Reconfigurable Interfaces

Many everyday objects are reconfigurable and inspire reconfigurable user interfaces [Kim et al.(2018)]. Many shape-configurable interfaces are modular and involves disassembling: game controllers [Nintendo(2021)], screens [Goguey et al.(2019)], haptic devices [Whitmire et al.(2018)], smartwatches [Khurana et al.(2019)], soft wearable prototyping kits [Jones(2019), Lambrichts et al.(2020)], etc. Researchers developed techniques to make on-body electronic fabrication for customizable and stretchable wearable interactive interfaces[Markvicka et al.(2019)]. SensorNets is a soft multimodal electronic skin composed of distributed sensor networks [Wicaksono et al.(2020)]. It can sense the environments in ways our sensor cannot and it can be easily customized to adapt to curvatures, but it requires fabricating sensors for different applications. Our work achieves shape reconfigurations by deformation, an intrinsic property of textiles. Somewhat similar to uKnit, the smart handkerchief [han(2021)] is a deformable user interface (DUI) that can recognize its physical form and allow simple gestural interactions. It is designed to lay flat, folded along a certain axis and/or held in hands to sense touch and strain changes.

Reconfigurable wearable device should be contextually aware of the physical configuration information [Wicaksono et al.(2021)], and body placement locations [Strachan et al.(2007)]. Prior work on on-body localization used IMU sensors to recognize the position without a known priori[Kostikis et al.(2020), Sztyler and Stuckenschmidt(2016)]. For a reconfigurable wearable, the placement decides the form. From the localization perspective, the form can predict the placement.

2.3 Electrical Impedance Tomography

Electrical impedance tomography (EIT), a non-invasive imaging technique to infer internal conductivity characteristics, was first proposed for medical imaging [Henderson and Webster(1978)] and geophysical imaging [Pelton et al.(1978)]. In recent years, EIT gained traction in the human-computer interaction(HCI) community and becoming more accessible [Zhu et al.(2021)] for hand gesture recognition [Zhang and Harrison(2015), Zhang et al.(2016)], paper-based interfaces [Zhang and Harrison(2018)], touch localization on irregular objects [Zhang et al.(2017), Alirezaei et al.(2007)] etc. In soft robotics research, EIT is used to create artificial skin that senses deformation and tactile distributions [Kato et al.(2007), Nagakubo et al.(2007)]. MultiSoft uses a multi-layer soft and stretchable sensor with silicon substrate for real-time contact localization and deformation classifications [Yoon et al.(2018)]. MultiSoft is a customizable soft sensing approach, but different sensors still need to be fabricated for different applications.

2.4 Tactile Skin

Among many functions of robot skin [Shah et al.(2019), Heng et al.(2021), Kawai et al.(2022)] such as shape changing, self-healing, enabling locomotion, tunable stiffness, etc., tactile sensing allows robots to learn and react to the physical environment. More specifically, pressure sensing methods include using functional (piezoresistive, piezocapacitive, triboelectric, iontronic, magnetic, biomimetic, or fiber optic) material based and vision based approaches [Pang et al.(2021)]. One challenge in adopting these innovative technologies is the lack of scalable manufacturing methods that generalizes to different robot shapes [Wang et al.(2018)]. Rigid tactile sensors can cover large areas using modular approaches [Cheng et al.(2019)]. Flexible tactile sensors can be bent to fit cylindrical surfaces [Liu et al.(2020)], but for more complex and uneven shapes, stretchable tactile skin is needed [Alirezaei et al.(2009), Luo et al.(2021a)]. Prior work on large-area flexible e-skin commonly use printing technique[Senthil Kumar with flexible printed circuit and nanomaterial synthesis [Dahiya et al.(2019)]. Manufacturing techniques from the textiles industry can be used to make stretchable tactile skin at scale. Alirezaei et al. used highly conductive knitted fabric to make a strain-sensitive stretch-insensitive tactile sensor by measuring the contact impedance between the knitted fabric and another layer of highly resistive yarn traces [Alirezaei et al.(2009)]. Day et. al [Day et al.(2018)] proposed a scalable fabric tactile resistive array with a 3-layer design of sandwiching resistive fabric between non-conductive fabrics with ironed-on conductive readouts.

3 Knitted Patterns

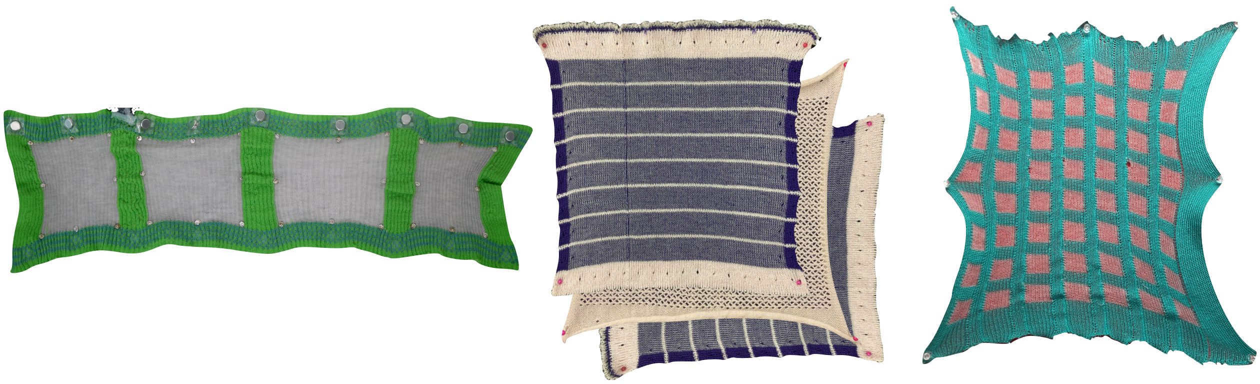

Figure 1: Knitted artifacts using the three different layout designs. Left-to-right: a patch layout sensor, a multi-layer matrix layout sensor, and a grid layout sensor.

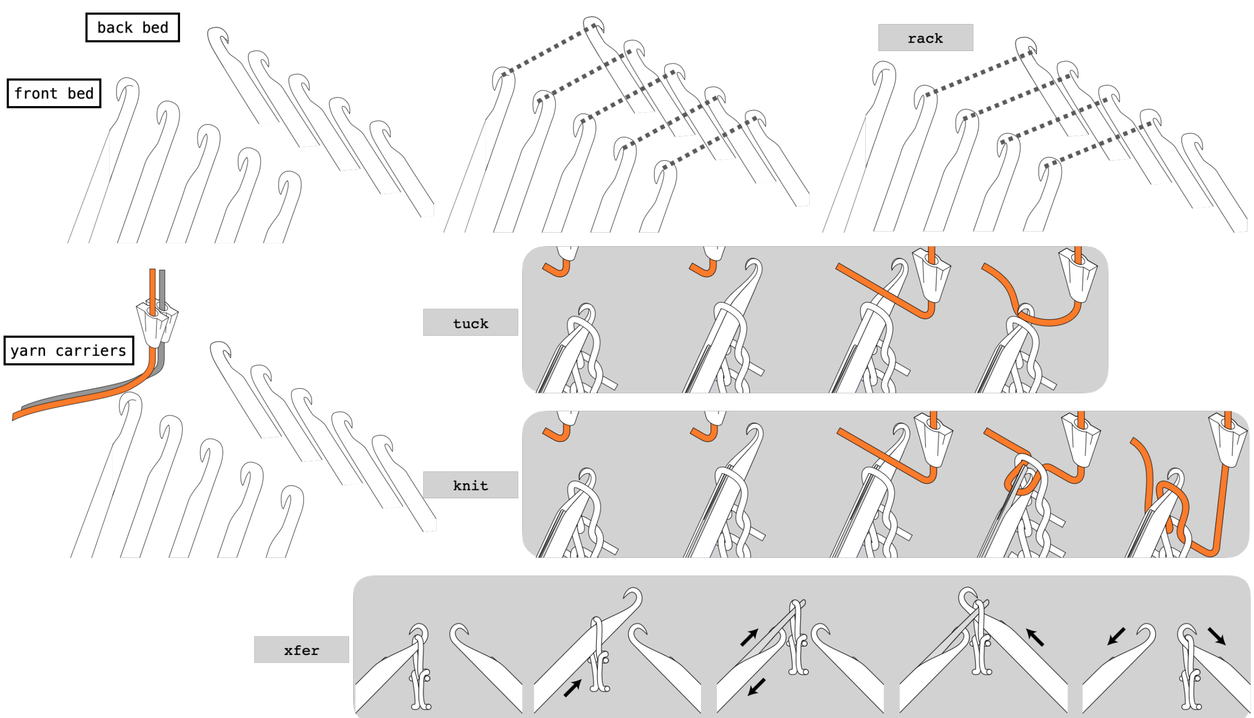

Figure 2: A brief introduction on machine knitting. llustrations taken and modified with permission from Albaugh et al [Albaugh et al.(2019)]. The front and the back beds of the machine are aligned to each other. `rack` can be used to offset the alignment. Yarn is brought to needles by yarn carriers between the two beds to needles. Needles can manipulate and form loops using operations like `tuck`, `knit`, and `xfer`.

This chapter explains the fabrication method of three different knitting structures. Readers interested in sensing principals, evaluations and applications can skip to Chapter 5.

We include a brief introduction on machine knitting using `knitout` [McCann(2017)] here in Figure 2, and readers can refer to [McCann et al.(2016)] for more details. On a v-bed knitting machine, there are two *beds*: front and back beds. The alignment between the two beds can be offset using the `rack` operation. Yarn is brought to needles by *yarn carriers* between the two beds. Each bed consists a row of hook-shaped *needles*. Each needle can form and manipulate yarn loops, using `knit` and `tuck` operations. Each needle can also pass loops from one bed to another, using `xfer` and `split` operations. Using this small set of primitive operations, one can program the knitting machine to knit complex and interesting patterns and shapes. We do not do 3D shaping in this work, and instead, we focus on different ways to program 2D fabric: sensor sheets. Note that because knitted fabric is flexible and stretchable, 2D fabric can be stretched and wrapped to fit 3D shapes like tubes, shapes found in humans and robots body parts.

Definition 1. Plating. A knitting technique used to run two yarn carriers over the same stitch.

Definition 2. Intarsia. A knitting technique used to incorporate areas of color.

Definition 3. Entrelac. A knitting technique used to create diagonal basketweave pattern.

The machine knitted sensor designs are largely motivated by applications and sensing principles (Chapter 5, 6). In this work, we present three different layout designs (Figure 1): a patch layout, a multi-layer matrix layout, and a grid layout. All three designs have an overall rib structure for good stretchability. All the parameterizable patterns are generated in the knitout language [McCann(2017)] by JavaScript programs and can be visualized using a web-based tool[1] [?]. Then the knitout instructions are translated to machine-specific instructions

[1]https://textiles-lab.github.io/knitout-live-visualizer/

	patch layout	matrix layout	grid layout
spatial accuracy	low	high	high
reading accuracy	low	medium	high
minimal wire connections	high	medium $2N$ wires for N^2 units	low N wires for N units
knitting techniques	plating, intarsia	plating	plating, entrelac

Figure 3: Overview of the three knitted patterns.

and executed on an industrial v-bed knitting machine (Shima Seiki SWG091N2, 15 gauge) with conductive yarn, Baekert BK 9036129[2], a Bekinox-polyester blend in 50/2Nm with a specified resistance of 20 Ω/cm..

Overview 3 for the sections in this chapter:

- Patch (Section 3.1) layout for a large sensing area where spatial accuracy is not crucial and minimal wire connections
- Multi-layer matrix layout (Section 3.2): for sensing areas where spatial accuracy is crucial and minimal wire connections
- Grid Layout (Section 3.3): or sensing areas where spatial & reading accuracies are crucial

3.1 Patch Layout

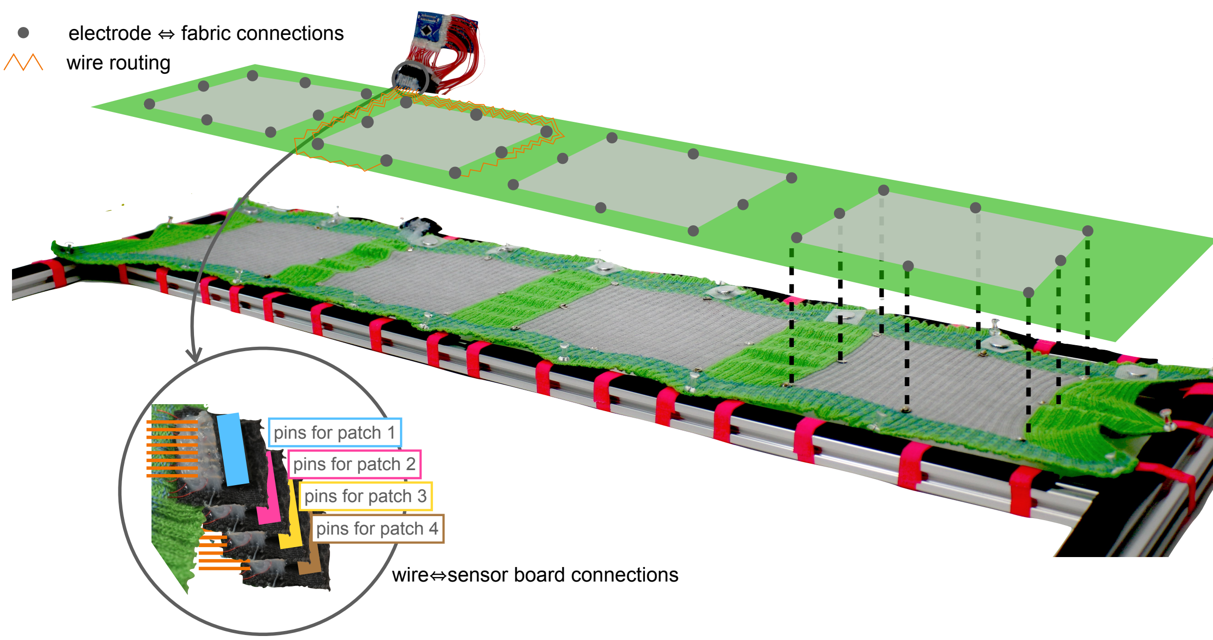

Figure 4: Layout of the connections between the a sensing board and the fabric electrodes.

For some applications and sensing principles, a small number of sensing units are needed. This layout is also useful for prototyping to experiment with different stitch types and settings. In a high level, this layout simply places disjoint sensing patches in a row along with non-conductive margins.

[2]Though this is an old catalog number, with BK 9028098 being the substantially similar current replacement.

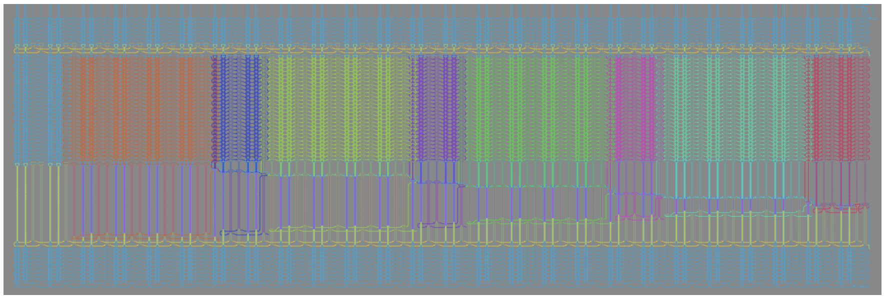

Figure 5: A small (0.2x) version of the knitting program for the 4-patch design, visualized with [Yu and McCann(2020)]. Each color represents yarn from a single carrier, showing the intarsia technique used to knit the conductive-yarn patches.

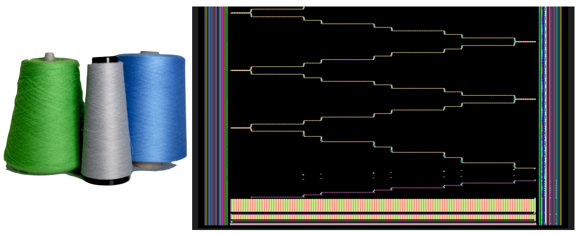

Figure 6: Left: The resistive yarn (grey), non-conductive acrylic yarn (green), and decorative rayon yarn (blue) used in producing the scarf. Right: The beginning of the machine knitting program once converted for use in KnitPaint [Shima Seiki(2011)].

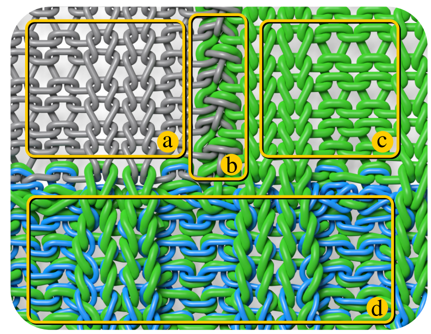

Figure 7: The low-level knit structure of the patch pattern. Conductive yarn patches (a) are connected to non-conductive patches (c) by columns of plated stitches (b). Plating is also used in the border (d) for decorative effects. The entire scarf is 2x2 rib for stretchiness.

The overall knitting program and the yarns used are shown in Figure 6. For non-conductive yarn we use Tamm Petit 2/30 in Lime (T4285), a basic acrylic yarn. For decoration, we use a thin, blue rayon yarn from Winning.

The scarf is knit in courses along its long axis, using the intarsia technique – assigning one carrier to each block of same-type yarn, for a total of nine carriers, five threaded with insulating yarn, four with conductive – to fabricate the electrode patches. Plating is 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 up-close in Figure 7.

The knitting program uses two different stitch size settings[3] for the majority of the pattern: 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.

3.2 Multi-layer Matrix Layout

Multi-layer matrix style read-outs on a piezoresistive sheet is a popular approach [Liu et al.(2020), Wicaksono et al.(2022)]. We take a similar multi-layer matrix style layout, but instead of sandwiching a piezoresistive sheet in between two orthogonal layers of conductive stripes, we sandwich a insulating sheet in between two orthogonal layers of piezoresistive stripes. Such design ensures a robust ON/OFF behavior.

There are three machine-knitted layers in our sensor design (Figure 8). The top and the bottom *resistive stripes layers* have the same knitting structures, and a middle layer of *insulating mesh* is sandwiched in between. *Eyelets* are placed along the borders of each layer for alignment and read-out purposes.

[3]Numbers in machine-specific units that correspond to loop sizing on the machine, with large numbers resulting in larger loops.

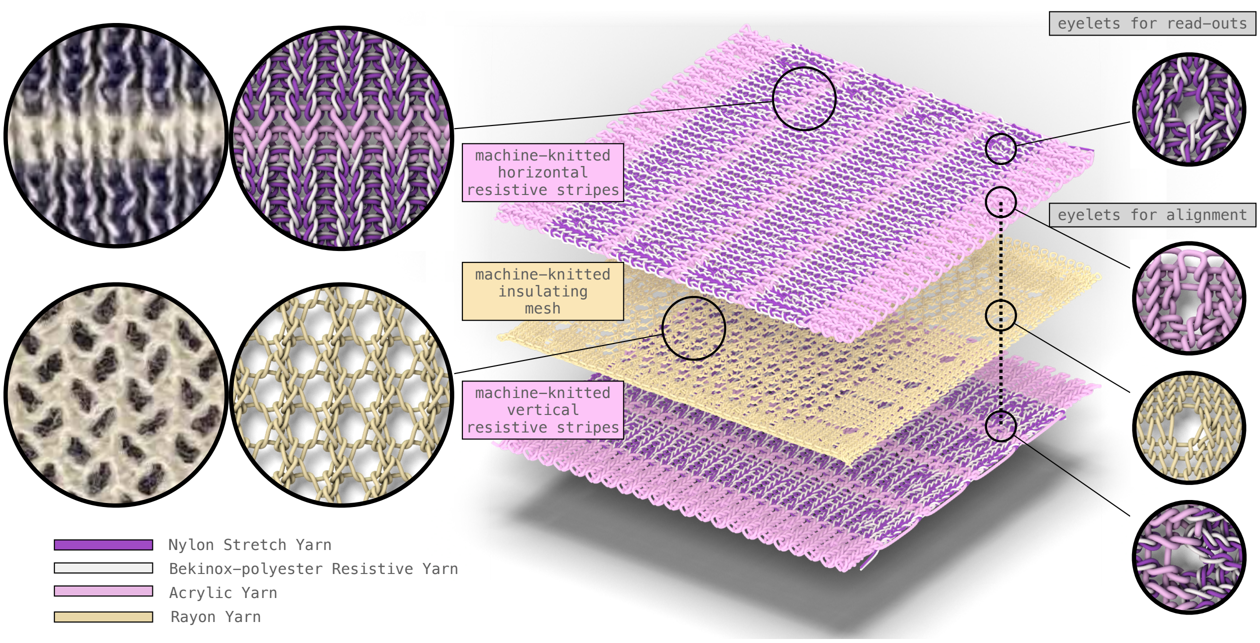

Figure 8: An exploded view of the three-layer design: a porous insulating mesh layer is sandwiched between two orthogonal layers of resistive stripes. Eyelets are placed along the borders for alignment and read-outs purposes.

Resistive Stripes Layers. We chose a 1x1 rib structure for high extension potential, good elastic recovery, and minimal strain-induced hysteresis [**?**]. The insulating stripes separate neighboring rows/columns of resistive stripes. Insulating stripes are knitted with acrylic yarn (Tamm Petit 2/30). Resistive stripes are co-knitted with nylon stretch yarn (Maxi Lock Stretch Textured Nylon) and the conductive yarn. The high-elastic nylon stretch yarn lowers the hysteresis effect [Bozali et al.(2021)]. The resistive yarn is plated outside of the nylon yarn (top left in Figure 8) to maximize conductive contacts when pressure applied and sensitivity ranges. The resistive stripes have a smaller stitch setting than the insulating stripes do due to the different yarn diameters.

Insulating Mesh Layer. We used a lace structure(bottom left in Figure 8) to create the insulating mesh, and a stockinette stitch (denser than the lace) for borders so that the eyelets are surrounded by dense stitches to avoid ambiguities. A rayon yarn (Winning) is used to knit the middle layer. The diameter of the yarn and the size of the mesh holes affect the sensing performance. From our early experiments, sensors with thinner yarn and smaller holes perform better on flat surfaces, and sensors with thicker yarn and bigger holds perform better on curved curved surfaces.

Eyelets. Eyelets (right in Figure 8), small holes in fabrics, are machine knitted by transferring loops from one needle to the neighboring one. Aligning eyelets on different fabric layers helps with consistent layer alignment. Eyelets on conductive stripes allow repeatable connection points for read-outs.

3.3 Grid Layout

Many disjoint sensing units on a single layer of fabric can be useful in designing machine knitted sensors. Drawbacks of using the resistive matrix are the ghosting and cross-talking effects [Shu et al.(2014)]. To knit a grid using the conventional intarsia technique (used in 3.1) requires one carrier per disjoint area. With a 10-carrier machine, one can knit at max 4 grids per row like shown in Figure 6: 4 carriers threaded with conductive yarn and 5 carriers thread with insulating yarn. This limitation further constraints the use of other techniques like plating as it requires additional carriers. Learning from entrelac this algorithm allows making $M \times N$ disjoint grids on a V-bed knitting machine using only 2 carriers. It can be further generalized to make non-uniform disjoint shapes.

In Figure 9, we illustrate a small example of a 3×2 grid. On the top left, it is the knitted artifact using the algorithm: teal areas are the non-conductive margins, and grey areas are the conductive grids. The ribbed stretchable direction is along the horizontal axis. The algorithm splits the design into five vertical chunks (bottom left), and the order of operations start form left to right. For a $M \times N$ grid, there are be $2M + 1$ chunks. As indicated by the dotted order of operations line, Within the chunk, the other of operations are scheduled vertically; among the chunks, the other of operations alternate between top-to-bottom and bottom-to-top. In the middle, it is a screenshot of the knitting program visualized using the web-based knitout

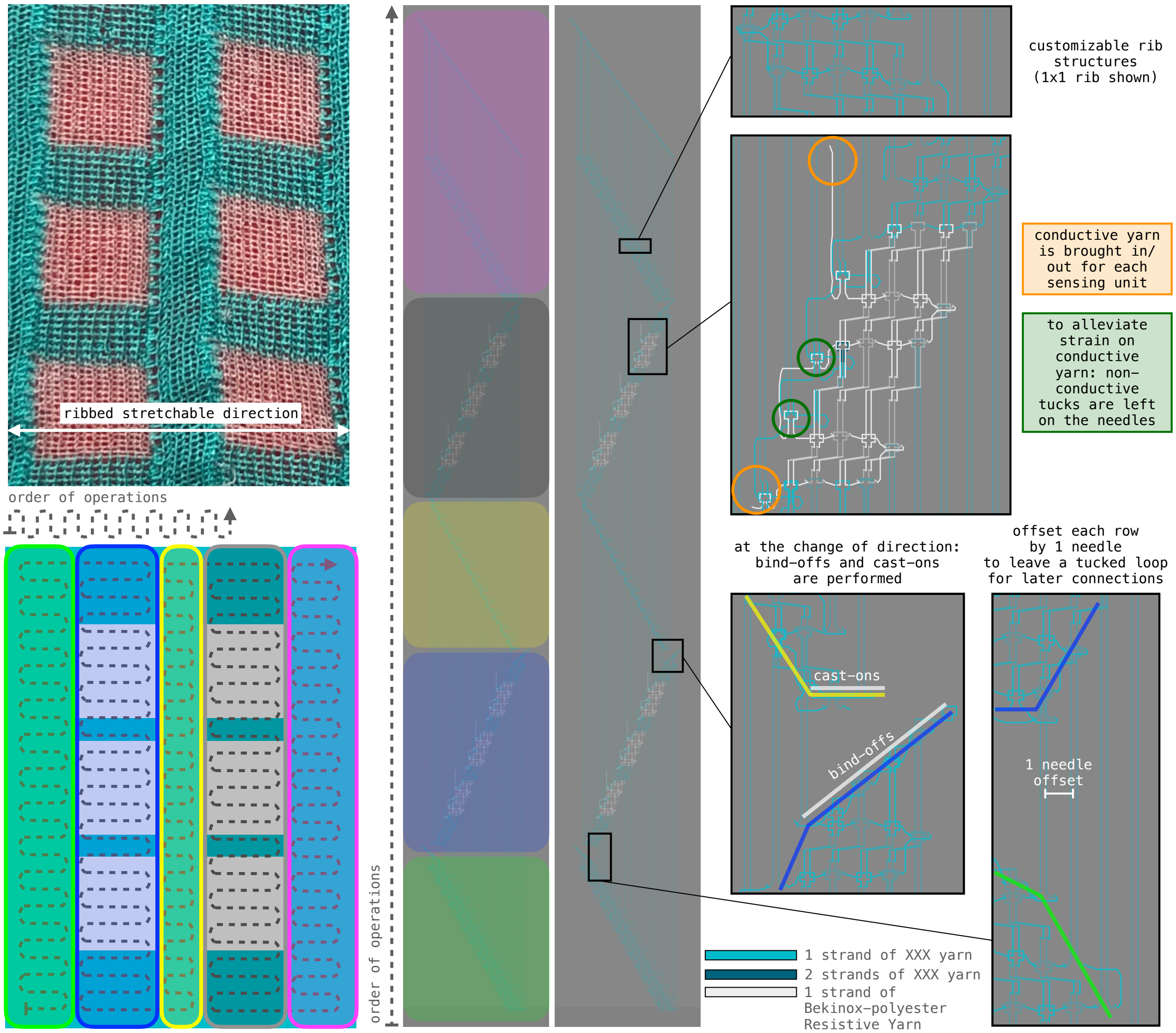

Figure 9: Top Left: a 3×2 conductive grid knitted using the algorithm; Bottom Left: order of operations w.r.t. the knitted output; Middle: screenshots from the knitout visualizer [Yu and McCann(2020)]; Right: close-up views of the visualization explaining the algorithm. The green, blue, yellow, grey and pink shaded areas in the bottom left and middle figures are final patterns corresponding to the instructions. The green, blue, yellow, grey, and pink solid lines in the bottom left and right figures are borders in final patterns corresponding to the instructions.

visualizer[4] [Yu and McCann(2020)]. Going from bottom to top in the close-up views of the visualization:

- **align knit stitches; keep tuck stitches for connections**: After each row of stitches,

[4]https://textiles-lab.github.io/knitout-live-visualizer/

the entire row of the knit stitches is shifted (first transfer to the other bed and then transfer back) by 1 needle. The direction of the offset depends on the current chunk; The tuck stitch at the end, is kept in place and remain on the needle for later connections. In this area, the tucks along the green line are later connected to the knits along the blue line.

- **border bind-offs and cast-ons**: At the beginning of each chunk, cast-ons are used to start. The number of stitches to cast on is the width of the chunk. Bind-offs are used to end the chunk;
- **conductive area**: The conductive yarn is brought in/out at the start/end of each conductive area so that the conductive areas are disjoint without any post processing. Because the conductive yarn is weak, additional non-conductive tucks are used to alleviate the strain on conductive yarn; and
- **customizable rib structure**: the customizable rib structure is preserved throughout the process.

4 Connectors

One of the challenges in working with any soft electronics project is making hard-soft connections [Stanley et al.(2021)]. In this work, we present conductive-glued connectors and buttoned connectors. In this chapter, we will first describe the two different connectors and then compare the then.

4.1 Conductive-glued Connectors

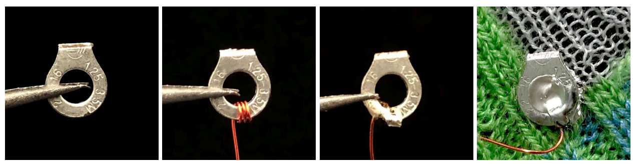

Figure 10: Attaching a wire to our sensor. Left-to-right: a washer from a ring terminal, wrapped with enameled wire, soldered, and conductive-epoxied to the fabric.

For the conductive-glued connectors , we settled on the following strategy, Figure 10:

- ***Electrode*** ↔ ***Wire*** *connections*: We first solder a thin enameled wires (Remington PN155 28AWG) to conductive washers harvested from ring terminals (Wirefy Heat Shrink Ring Terminals #6), Figure 10.
- ***Fabric*** ↔ ***Electrode*** *connections*: We then glue 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 resistive patch, four on the corners and four in the midpoints of the edges.[5]
- ***Wire Routing***: We then route 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 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.

4.2 Buttoned Connectors

Snap fasteners, commonly used to fasten cloths, are good candidates for e-textile connectors [wir(2011)]. We stick the snap fastener cap through the read-out hole and the ring

[5]Note that conventional wisdom for EIT suggests avoiding corners [Gray and Lutz(1990)], still our prototype seems to work well in its current configuration regardless.

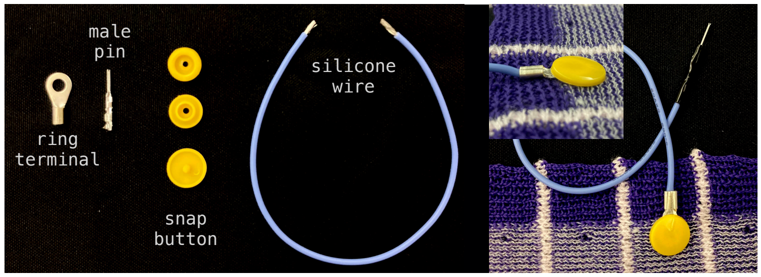

Figure 11: Left: ring terminal, male pin, snap buttons, and silicone wires are used to connect the fabric to the sensing board; Right: an assembled connection.

terminal, and then connect to the socket/stud. This way, robust and stable contacts between the conductive fabric and ring terminals are established.

4.3 Comparisons

The two designs have their own characteristics. The glued connectors use small rigid components. The solid core enameled wire has minimal AC noise as it remains mostly stationary. And the soldered and glued connections allow consistent contact impedance even when the sensor is moved a lot. The buttoned connectors, on the other hand has strong wire connections. Stranded silicone wire are flexible. And the buttons allow easy assembly. The contact impedance is consistent when there is little movements.

Their differences make them suitable for different applications. The glued connector should be used when textile shape changes frequently and is good for working with AC signals. The buttoned connector should be used when textile shape changes infrequently and is good for working with DC signals for purely resistive sensing.

5 Machine Knitted Sensors for Humans: uKnit

Our clothes are soft, comfortable, and familiar to us. Thus, textile-based soft wearables also feel natural, seamless, and are widely popular (*e.g.*, [Poupyrev et al.(2016)]). Textile-based wearable devices can sense gestures, postures, and health outcomes, while remaining soft and comfortable. Their familiarity and seamlessness affords continuous, always-on interactions and, over the years, researchers have proposed many different form factors (*e.g.*, [Markvicka et al.(2019), Wu et al.(2020b), Jin et al.(2018), Kim et al.(2018), Lambrichts et al.(2020)]). One challenge that still remains is that most soft wearables are rigid in their form-factor and utility. A glove (*e.g.*, [Whitmire et al.(2017)]) 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. The idea of customizable wearables is not new. Jarusariboonchai and Häkkilä [Jarusriboonchai and Häkkilä(2019)] studied the space of commercial wearables that afford some form of customizability. Similarly, Seyed *et al.* [Seyed et al.(2016)] and Khurana *et el.* [Khurana et al.(2019)] 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 and can offer a wide range of capabilities.

Figure 12: 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.

We draw inspiration from reconfigurable accessories – gaiter scarves. Gaiter scarves are multi-functional tubular scarves that can be wrapped, folded, and scrunched to put on different places of human bodies. We present *uKnit*, a knitted scarf that is a universal and reconfigurable soft sensor/input device. uKnit is able to duplicate many of the interactions enabled by textile interfaces with a single reconfigurable knitted sensor that is location-aware and adapts to the configurations (Figure 12). It recognizes several touch and deformation gestures, body postures, and physiological signals such as breathing patterns. The sensor is machine knitted, and thus can be manufactured at scale. This knitted fabric is also lightweight, stretchable, and breathable and thus is comfortable to wear for a long time.

While prior work has demonstrated a rich set of soft wearable capabilities, each capability is specific to a device designed to be worn at a single location, so a user who needs a variety of capabilities throughout the day will need to carry many devices. In contrast, we explore the possibility of one-soft-wearable-for-all with machine knitting and electrical impedance tomography. Our user study with 10 participants showed promise, detecting its location (among 5 locations) with 88.0% and 78.2% accuracy for a per-user model and universal model respectively, and identifying gestures (among 7 gestures) with 80.4% and 75.4% accuracy for a per-user model and universal model, respectively. The main contribution of this work are:

- prototyping the first *reconfigurable* soft wearable sensor;
- describing how to fabricate this reconfigurable sensor from off-the-shelf yarn using machine knitting;
- demonstrating that electrical impedance tomography works with anisotropic knitted resistive fabric; and,
- machine learning models that show the feasibility and accuracy of (a) identifying different body placements, (b) gesture classification, (c) and passive monitoring with uKnit.

5.1 User Story and Design Requirements

We present an example user story here to convey how a reconfigurable soft wearable can be multi-functional throughout a day. This example also highlights the design and technical requirements for the wearable. Kate wakes up on a winter morning with the uKnit wrapped around her waist, while she was sleeping, uKnit monitored her sleep quality by tracking her movement and respiration rate. She gets out of the bed and stretches the wearable out to start her coffee machine remotely. She relies on a deformation gesture here because simpler touch gestures will be harder to discern as she wears uKnit to bed at night. Afterward, she goes for a run and wears uKnit as a headband. While running, she changes songs on her wireless earphones using directional swipes. 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 or head to scroll the recipe on her smart home hub. Then on her way to work, she wears it as a scarf that not only keeps her warm but also functions as a hands-free music player by tilting her head. After she gets to work, she puts it on her back like a shawl for posture detection. After work, she goes to the gym, she puts uKnit on target body parts to track muscle activation, and logs her exercise. Kate can also put uKnit around her waist to monitor the respiratory rate while exercising. At the end of the day, she puts it back on her waist before she goes to bed. If Kate has one device for each application, she would need several distinct devices, but instead, she can have one device for all the applications.

To enable this vision, uKnit has following design requirements:

1. **maximize the resemblance to an ordinary scarf** 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.*, wrist;

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. Many scarves are knitted, and thus meeting (1). Knitted fabrics are stretchable, and thus meeting (2). Furthermore, knitted fabrics are breathable, and thus makes 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 while enabling a large interaction area with several sensing capabilities.

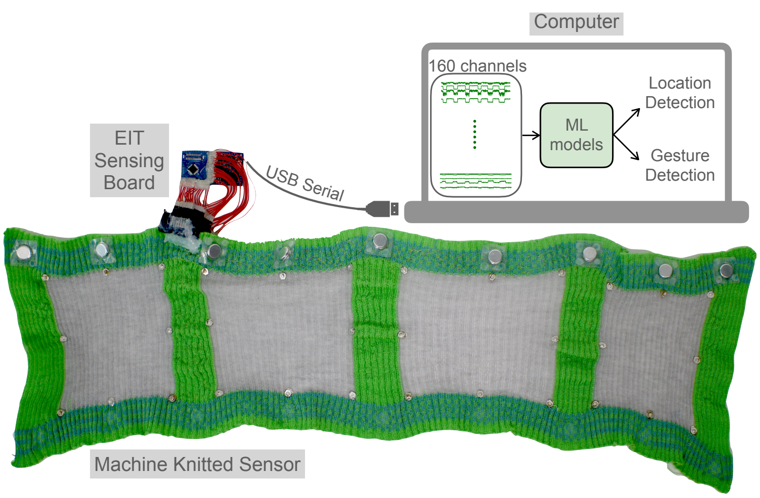

Figure 13: The uKnit implementation includes a machine knitted sensor using resistive yarn, sensed via electrodes attached to the borders of the resistive patches using EIT, and machine learning models running on a laptop which interpret the EIT data to detect the sensor location and recognize gestures.

5.2 Data Acquisition

Our prototype reconfigurable sensing scarf, Figure 13, consists of a machine-knitted structure(Section 3.1) connected to a EIT-based data acquisition circuit. In this section we provide more detail on the knit structure, the connection methodology, and the data acquisition circuit.

We use an existing EIT sensing board design originally developed by Zhang et al. for interactive paper interfaces [Zhang et al.(2017)]. 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 to 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 14), 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 80 microseconds for each reading to stabilize and to use 500 samples for its root-mean-square measurements; resulting in a 16Hz measurement frame rate. The board sends these measurements via serial-over-USB to a host computer for further analysis.

5.3 Sensing

Impedance, Z, is a complex number which 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 inductance of a passive circuit with resistance R, capacitance C, and inductance L is the sum of the resistance, capacitive reactance, and inductive reactance:

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

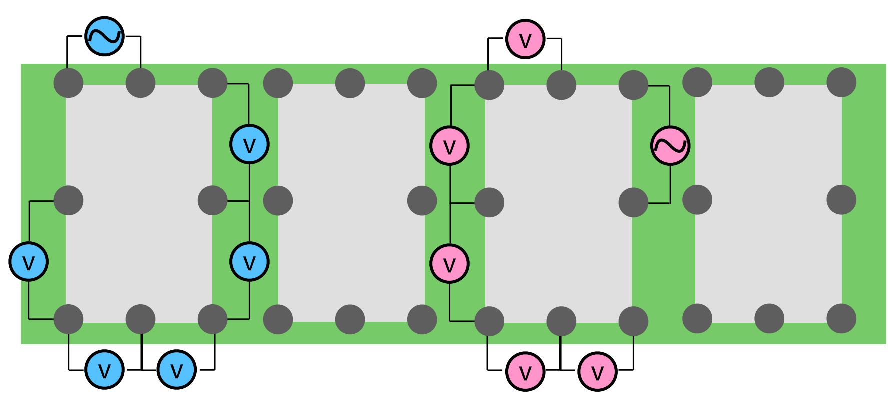

Figure 14: Our sensor uses the four-pole EIT sensing scheme. The EIT sensor board injects alternating current into every adjacent pair of electrodes and measures the voltage differences on the five other pairs of adjacent electrodes in the patch; this results in 160 pair-pair impedance measurements.

Our system works by measuring changes in impedance; we conjecture, Figure 15, that these changes are primarily due to changing resistance in yarn-yarn contacts [Zhang and Tao(2012)], which have lower resistance when force is applied.

However, knit fabric is not a simple, uniform, resistive sheet. Rather, it is an anisotropic resistor network, Figure 16, 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 [Shyr et al.(2011)] makes it difficult to study the absolute impedance values. And, finally, preliminary observations with an oscilloscope and signal generator do

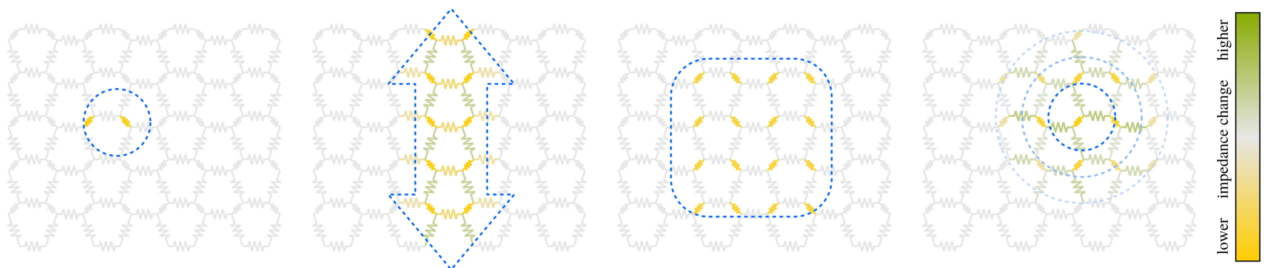

Figure 15: Our conjecture as to why different gestures change impedance. From left-to-right: touches compress stitch-stitch contacts, lowering contact impedance for a few stitches; in-plane stretching lowers contact impedance and also drags yarn between courses/wales, modifying along-the-yarn impedances; grabs apply pressure to many stitch-stitch contacts, lowering contact impedance over many stitches; and 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.

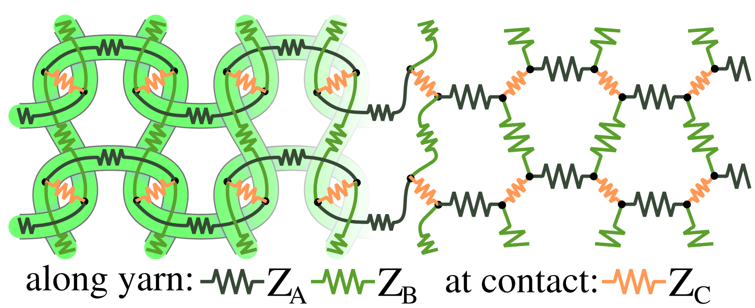

Figure 16: A circuit model of the fabric in our sensor. Impedance along yarns (Z_A, Z_B) is generally much lower than between yarns (Z_C), leading to lower impedance in the course (horizontal) direction than the wale (vertical) direction. In use, local impedances depend on contact forces (which lower Z_C), and deformation (which change the length of yarn between contact points, altering Z_A, Z_B).

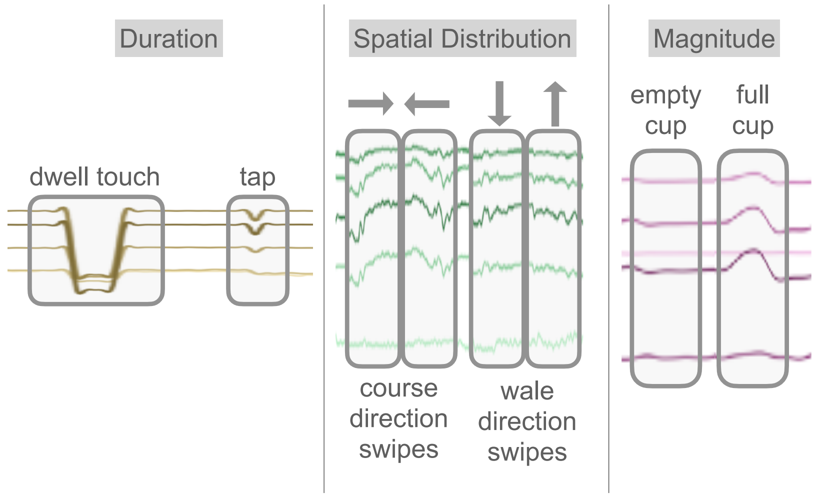

Figure 17: The effects of duration, spatial distribution, and magnitude on EIT signals (only five of the 40 signals from one patch are shown for clarity). (a) Duration: longer touches/gestures allow the signals to settle. (b) Spatial Distribution: our system is more sensitive to changes in the wale direction owing to the higher starting resistance. (c) Magnitude: larger strain creates larger signals; e.g., an empty paper cup produces a more minor response than a full one.

show a phase shift, suggesting that some capacitive[6] effects may also be in play.

Therefore, instead of using the traditional inverse tomography algorithms, which attempt to reconstruct a distribution of resistance values, we use machine learning algorithms with the measured voltages differences directly, and more specifically, we focus on the changes in the measurements.

5.3.1 Events

The EIT signals measured by our system depend on where, how much, and for how long the sensor is deformed. We, therefore, find it useful to think about interaction events in terms of three axis: spatial distribution, magnitude, and duration; Figure 17.

Definition 4. 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.

Definition 5. 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 weight.

[6]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.

Definition 6. Duration. How long the event lasts. A quick tap is low duration, a long press is higher duration.

Generally, events that are further along one or more of these axes are easier for our system to detect; making them useful when thinking about potential applications.

5.3.2 Machine Learning

To distinguish different classes of the measured signals (i.e., location and gesture), we trained a machine learning model. We use Scikitlearn's Random Forest Classifier (default parameters, 1000 trees, 30 max depth). The measured data is a matrix of (the number of channels) $\times$ (the number of samples). For each row (i.e., time-series data per channel), we calculated the following statistical nine features: mean, median, standard deviation, skewness, kurtosis, max, min, argmax, and argmix.

5.4 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 swipe) 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 set of locations we chose are informed by the form factor of our scarf device as well as prior works on-body localization [Zeagler(2017), Lee et al.(2021)].

5.4.1 Procedure

The experiment used an Apple MacBook Pro 15", 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. For each session, there are three trials for performing different gestures. We chose a set of four gestures (Figure 18): touch, swipe, grab, and pinch. We first showed a brief demonstration of each gesture to the participants.

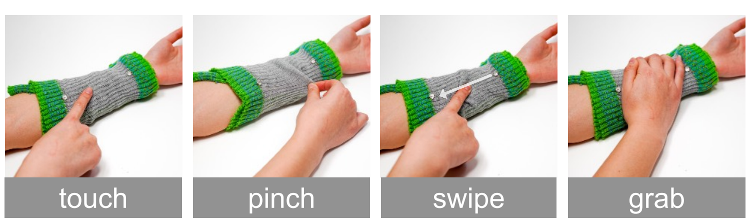

Figure 18: The four calibration gestures used for Study 1.

For each session, we generated a randomized order of the *body parts*. By following the order, participants put the device to the corresponding location. 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 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. All data were collected while the participants were seated and they 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.

5.4.2 Results

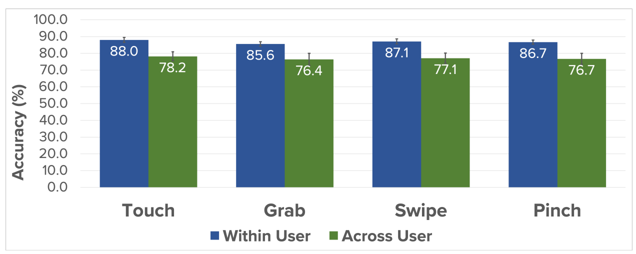

Figure 19: Accuracy of the within-/across-user models for the location detection by different calibration gestures. Error bars indicate standard error.

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 a 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 19 presents the result. From this figure, we concluded that "touch" is the best calibration gesture for the location detection (88.0 % for the within-user model and 78.2 % for the across-user model). The confusion matrices can be found in Figure 20.

5.5 Study 2: Gesture Recognition

Next, we conducted a study to examine the system's ability to recognize gestures. Here, we attached our device to 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. Here, 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 top closest to the hand and bottom furthest from the hand; grab and pinch happen at the center of the sensing patch;

Figure 20: 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 %.

and swipe runs from the bottom touch area to the top touch area. These gestures are shown in Figure 21.

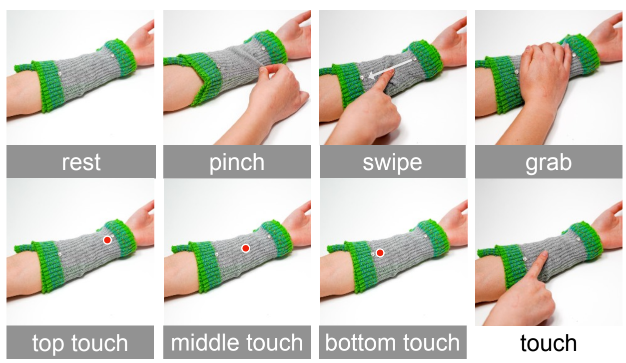

Figure 21: The seven gestures used for Study 2. Touch was performed at three different points(indicated by the dots), shown in the bottom row.

5.5.1 Procedure

We recruited ten participants (five male and five female) in the same manner as 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 with 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.

5.5.2 Results

In a manner similar to Study 1, we trained a within-user model and an across-user model, both of which were evaluated using across session cross validation. When training the model, we used the first 40 channels instead of the 160 channels to calculate features. The used 40 channels correspond to a single patch on which all gestures occurred during the study since one patch is wide enough to wrap our wrist. The accuracy of the two models were 80.4 % and 75.4 %, respectively. The confusion matrices can be found in Figure 22. Additionally, the

Figure 22: Confusion matrices of gesture recognition. Within-user cross validation (left) achieves 80.4 % and across-user cross validation (right) achieves 75.4 %.

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 23 presents how the accuracy increases as we increase the number of trials for the calibration.

5.6 Other Capabilities

We think that a reconfigurable wearable like uKnit holds promise for a range of applications. While many useful applications could already be built on the gestures from the studies (e.g., a music playback control headband which supports left and right taps to change tracks); we also find it useful to think beyond these tested gestures.

The duration, spatial distribution, and magnitude axes that we discussed earlier provide a good framework for understanding the feasibility of potential applications. For example, a keyboard for text entry seems unlikely to work well (key presses have a short duration, small spatial extent and require high spatial precision, and low magnitude); but a breath monitor (long duration, wide spatial distribution, medium-low magnitude) would seem to be feasible,

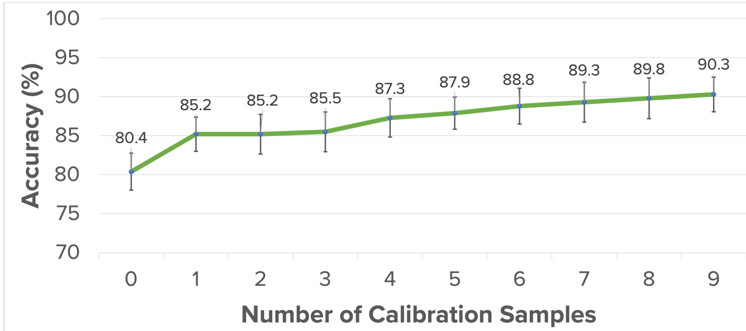

Figure 23: Gesture recognition becomes more accurate when calibration gestures are added. For example, adding three calibration gestures results in a 5% accuracy increase. Note that the Y-axis starts from 70%. Error bars indicate standard error.

and initial data collection supports this (Figure 24 top). Moreover, posture recognition could be enabled. For example, when a person wears the scarf on their shoulder, uKnit knows whether the person is sitting straight or slouched (Figure 24 bottom). Other applications that

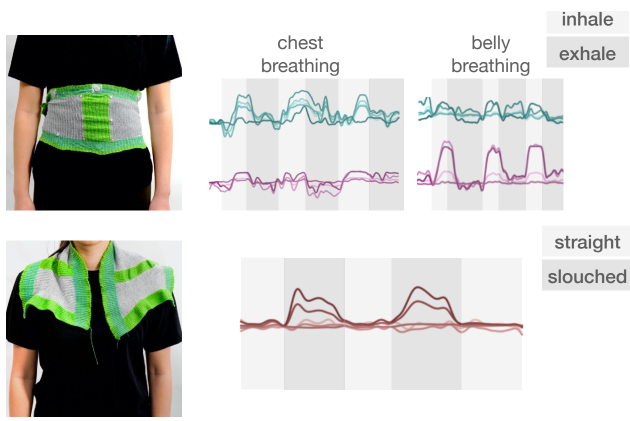

Figure 24: Top: When worn on the waist, uKnit's outputs reflect respiration rate and breathing style; Bottom: When worn as a shawl, uKnit's outputs correlate with posture.

seem practical given the axes along which the sensor excels are exercise tracking (medium-high magnitude), posture detection (wide spatial extent), and sleep quality monitoring (long duration). Given uKnit's form, it can be a smart swaddle for babies. It can track the baby's movements, breathing, tell if their hands are out of the swaddle, and if the baby has rolled over.

6 Machine Knitted Sensors for Robots

Researchers have studied robot skins that can sense pressure, strain, shear force, temperature, proximity, textures, humidity, etc. However, it remains a challenge to properly cover robots of different and complex shapes using functional skin at scale and low costs. Rigid sensors can partially cover a large area using a modular approach to form a skin network [Cheng et al.(2019)], but fabrication and instrumentation at-scale is difficult. Flexible robot skin can be arbitrarily shaped to cover robot arms [Liu et al.(2020)], but it is still less comfortable compared with soft and stretchable human skin. Flexible, stretchable and deformable robot skin [Wang et al.(2018)] is ideal for applications like safe interactions if they can be be reliable, scalable and generalizable.

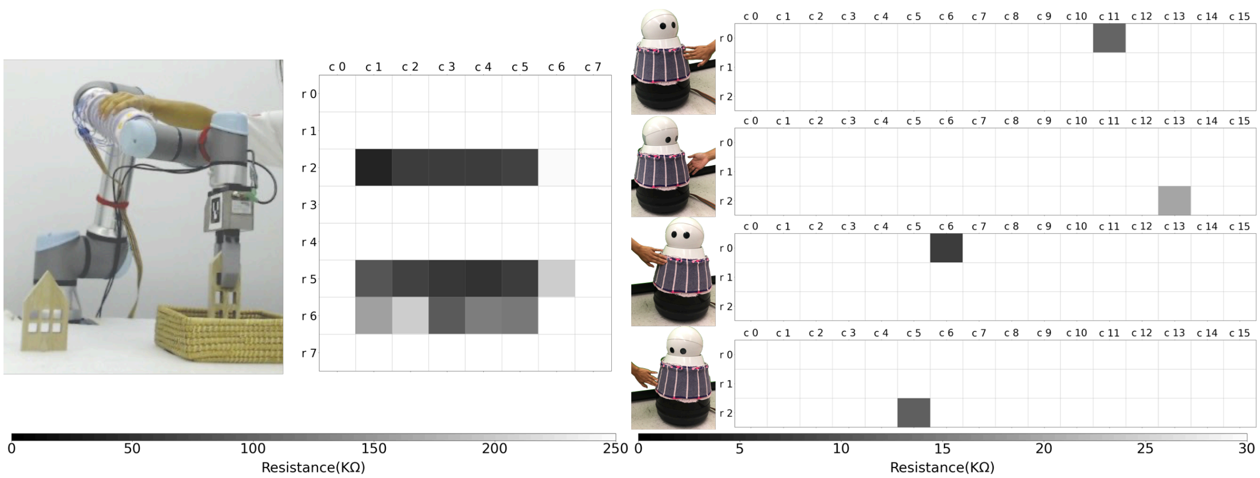

Figure 25: robotSweater in use on a robot arm (left) and a mobile companion robot (right) along with the tactile sensor readings visualized.

6.1 robotSweater

In this work, we propose a low-cost machine-knitted tactile sensor with pressure sensitivity, robust ON/OFF switches, manufacturing scalability, and generality. Among other textile fabrication techniques, knitting produces intrinsically stretchable fabric. Industrial knitting machines can make large knitted skin that conform to complex 3D shapes with minimal post-processing,[Narayanan et al.(2018), Jones et al.(2021)]. We machine knitted a multi-layer parameterizable design using off-the-shelf conductive and non-conductive yarn. Unlike prior matrix pattern resistive tactile sensors[Wicaksono et al.(2022), Day et al.(2018)] sandwiching a piezoresistive layer between two layers of orthogonal highly conductive traces, our sensor design is sandwiching a porous insulating layer between two layers of orthogonal piezoresistive traces. This design enables an open circuit at the taxel unit without pressure, and a piezoresistor at the taxel unit when pressure applied. This robust ON/OFF switches ensures accurate contact localization.

The main contributions of this paper are:

- prototyping a parameterized machine-knitted resistive-matrix-style tactile sensor and associated read-out circuitry;
- characterizing the sensor properties and and comparing with our simulation model on both flat and curved surfaces; and,
- demonstrating the application on a robot arm with lead-through teaching, and a mobile robot with motion guidance.

6.2 Sensing

Our sensor design includes: machine-knitted multi-layer sensing textiles (Figure 8), connectors between the textile sensor to a sensing board (Figure 11), and a read-out circuit (Figure 26).

To sense pressure, resistances at the intersections between the top and bottom layers are measured (left in Figure 26). Without pressure, the top and bottom layers are separated by the insulating layer so the circuit is open with infinite resistance values, When pressure is applied, these resistance values change due to the changes in contact resistances between the top and bottom resistive layers and the resistance changes caused by deformations in resistive areas. When pressure increases: (a) the contact area between the two resistive layers in crease, and thus the resistance decreases; and (b) strain and deformation on each resistive layer increases, making tighter contacts between loops, and thus the resistance decreases.

6.3 Data Acquisition

To read these resistance values, we use a circuit (left in Figure 26) that read resistive sensing matrices. The rows are equivalent to horizontal stripes, and the columns are equivalent to the vertical stripes. Controlled by the row multiplexer, Vcc (5V) is switched to connect to different rows. Controlled by the column multiplexer, GND is switched to connect to different rows. Between the sensor and the ground, there is a reference resistor used as a voltage divider. Finally, we use an Arduino internal ADC to read the voltage difference across the reference resistor.

The power consumption for the systems were measured by measuring the system currents and then multiply with the voltages. The systems were powered by 9V batteries. When using an Arduino Uno with a 4x4 sensor grid, the power consumed is 0.39W. When using an Arduino Nano with a 16x3 and 8x8 sensor grids, the power consumed are both 0.18W. These measurements are very close to the ones measured when the micro-controllers are in idle states.

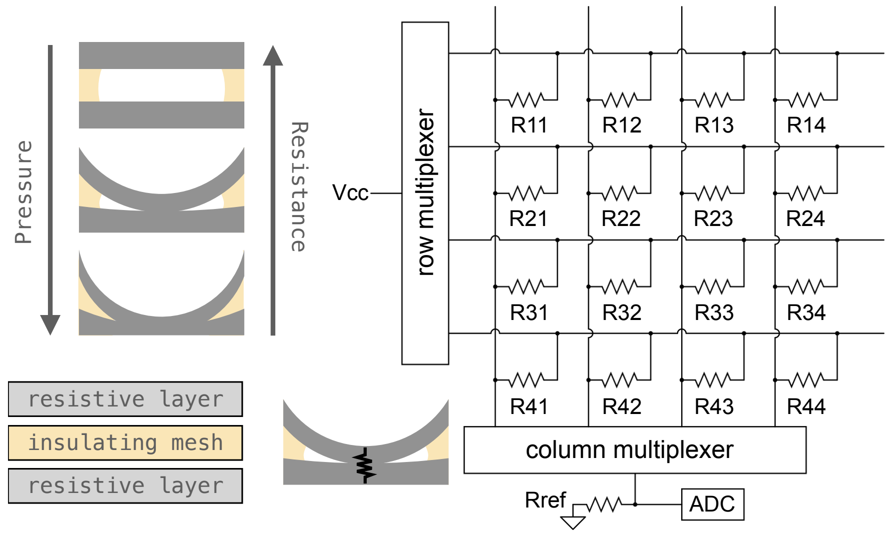

Figure 26: Top left: resistance decreases as pressure increases; Bottom left: at each column-row intersection, resistance value depends on: contact resistance and resistance change caused by deformation; Right: schematic of the read-out circuit.

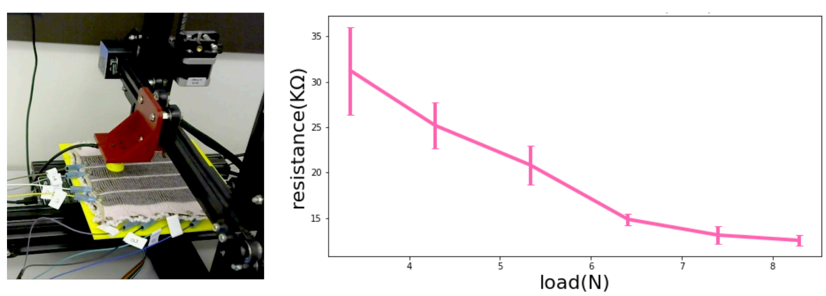

Figure 27: Left: Testing setup using a 3D printer rig to apply loads to the fabric sensor. Right: The relationship between loads and resistance of the sensing unit. As load increases, the mean and standard deviation of the resistances decrease.

6.4 Characterization

To characterize the sensor, we fabricated a 4x4 gird. As shown in figure [?], we repurposed a 3D printer as a rig to apply load to the fabric sensor. An ATI Nano 17 Force Torque sensor is used to measure the load applied using the 3D-printed indenter. The relationship between the sensor resistance and the load applied is plotted on the right in figure [?]. As the load increases, the mean and standard deviation of the resistance measured decreases because the conductive layers are compressed and better connected.

6.5 Applications

We fabricated a cylinder-shaped tactile sensor for the forearm link of Ur5E robot. The sensor has an 8 by 8 matrix-like sensing grid fitting the robot arm link size as shown on the left in Fig 25. Humans can interact with the tactile sensing area on the robot link and teach lead the robot by controlling the 3 DoF translational movement of the end-effector (EE) of the robot arm based on tactile feedback. We directly control the velocity of EE given the contact locations and forces. We define the moving direction as the direction from the contact point with maximum forced applied to the center of the cylinder. Then the magnitude of the velocity is linearly correlated to the forced applied. We also implement the gripper control based on gesture recognition from tactile reading. If the contact is pin-point contact, the robot is guided by the velocity control of EE. If the contact is a large-area pressing, the gripper is controlled to close or open for grasping based on the current gripper's state. We demonstrate the sensor usage on a robot arm by guiding the robot to grasp an object and drop in a target location as shown in Fig 25.

We also fabricated a cone-shaped tactile sensor for the Kuri robot. The sensor has an 16 by 3 matrix-like sensing grid fitting the body Kuri as shown on the right in Fig 25. Humans can interact with the tactile sensing area on Kuri's body and Kuri will look at different directions based on areas of contacts.

7 Discussion

While designing, evaluating, and applying the knitted sensors, we summarized the following knitted sensor design considerations (Section 7.1), limitations (Section 7.2), and scalability challenges (Section 7.3). We hope the following discussion contributes to a future where everyone will have a smart wardrobe, find smart textiles everywhere we go, and more of the robots will have their customized smart sweaters.

7.1 Considerations in Machine-knitted Sensors Design

Due to the intrinsic structures of knitted sensors and the unique properties of knitted fabrics, we discuss important design considerations below.

Form Factor uKnit is a scarf-like prototype for humans. It only takes advantage of wrapping and folding in our test gestures; however it is also natural to scrunch and twist a scarf. A study of further affordances might turn up even more interesting use cases. uKnit's current implementation only measures EIT within electrodes on the same patch. 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).

robotSweater is a skin-like prototype for robots. Even though it can be stretched and wrapped around shapes that are more complex than a uniform cylinder, future works can investigate sensing skin for complicated 3D shapes using design systems like [Narayanan et al.(2019)] and [Zlokapa et al.(2022)].

Historically, textiles are means of expressions for identities and cultures. As a wearable, textile-based sensors should blend in with conventional clothing and accessories. As robot skins, textile-based sensors can affect human-robot perception. On-demand machine knitting enables customizable patterns. We already demonstrated that uKnit's aesthetics can be customized by using extra plating carriers; but perhaps this customization could also be extended to the sensing capabilities, specializing a given application for a given use-case (while still providing a general-purpose sensing device).

Applications & Sensing Principles Machine-knitted sensor designs are driven by applications and sensing principles. Resistive sensing can be used to sense deformations, and capacitive sensing can be used to sense touch and proximity. Impedance sensing can capture both the resistive and capacitive effects. Project Tasca [Wu et al.(2021)] demonstrated promising applications combining various sensing principles, and it would be exciting to see how the unique properties of knitted fabrics could contribute.

One big difference between designing sensors for humans and for robots are behaviors predictability. For example, humans change clothing and accessories routinely, but once robot skins are instrumented, frequent removals are not expected. Human activity recognition research predicts what humans are doing to provide contexts that can improve sensing accuracy, but many robots perform repeated tasks in controlled environments. And even when the robots have more “freedom”, the actuation mechanisms are still programmed and thus known to the system, which gives more accurate contexts. Although designing machine knitted sensors for humans and robots share many similarities, it is helpful to consider the distinctions when transferring sensor designs among applications.

Once the application and sensing principles are finalized, the exact knitting structures are to be considered. Discussed in Section 5.3.1, three axis can be used to think about interaction events: (1) spatial distribution, (2) magnitude, and (3) duration. These axis are useful for choosing sensing principles for different textile sensors applications. For example, When spatial accuracy is critical, sensing approaches that directly infer locations, like the matrix-layout and the grid-layout, are preferred over indirect ones like using the patch-layout with EIT. In addition to sensing performances, how soft the sensor remains after adding the rigid electronic components is a important factor. Sensing with tomography, like uKnit, reduces the number of wires needed and the number of wires can be further reduced while maintaining high accuracy [Ma et al.(2020)].

Materials In both uKnit and robotSweater, we use the same resistive yarn, a stainless steel Bekinox-polyester blend by Baekert. It knits well on the knitting machine and showed promising performances and results for both resistance and impedance sensing. Luo et al. developed novel piezoresistive yarn [Luo et al.(2021a)] that effectively turned 3-layer sensing structures into 2-layer sensing structures. The requirements (e.g. strengths, thickness, stiffness) for inlayed yarn are much lower than for the yarns directly used to form loops. The novel conductive yarn used in Project Jacquard [Poupyrev et al.(2016)] has great sensing performance and is compatible with standard looms Future works could look into novel fibre/yarn that are functional and compatible with knitting machine operations.

Stitch Patterns Different stitch settings and patterns yield different sensing performances. We observed that when the knitted fabric is more stretched, the cleaner and more responsive the signals are. Tomoaki et al. found that voltage-load performance for pressure sensing decreases when the stitch density is too low. All of the sensor designs in this work use ribs, 1x1 when high stretchability is not required, and 2x2 when it is. Shyr et al. discovered that a mock rib with less horizontal stretch minimizes hysteresis in knitted sensors [Shyr et al.(2011)]. A systematic evaluation on different stitch patterns and stitch density will be valuable for knitted sensor design.

7.2 Limitations for Machine-knitted Sensors

The easy scalability of machine-knitted sensors pave ways for wide adoptions of textile sensors, but some limitations remain in sensing with machine-knitted sensors.

Anisotropy Knitted fabric is an anisotropic material, different from most soft sensors. The yarn paths of the knitted fabric makes the course and wale directions have different mechanical and electrical performances. When designing matrix style readouts, knitted sensors employ multi-layer designs. When stacking layers together, the sensor becomes thicker and inconsistent alignment could occur over time. It would be interesting to see whether are knit patterns that can do matrix style readouts on a single layer.

On knitted fabric, equal physical distance does not correlate to equalr esistance/impedance distribution, which makes the signals unsuitable for popular reconstruction algorithms. For EIT, one potential solution was to try anisotropic EIT [Lee et al.(2017)]. For matrix-style layout, two layers are placed orthogonally to form the matrix. Though the anisotropic property appears to be a drawback, there could be applications and take advantage of it.

Hysteresis Like most textile sensors, knitted sensors also have hysteresis effect. But because knitted sensors are more stretchable, offering more freedom, there are more factors that could contribute to the hysteresis. In robotSweater, we used a stretchable yarn to co-knit with the conductive yarn for better restoration. Elastic yarns, harder to knit on the machine for tensioning difficulties, help with further reducing hysteresis. Note that when co-kniting non-conductive and conductive yarns, which yarn placed on the outside affects the electrical performance[Bozali et al.(2021)]. Again, systematic evaluations on stitch patterns and settings would be useful when designing knitted sensors.

Damage Textiles wear off, can get stained, and need to be washed. These expectations apply for machine-knitted sensors as well. Some knitted sensor designs cover the functional areas with conventional knitted fabrics to protect the sensing regions [Wicaksono et al.(2022)]. For robotSweater, additional top and bottom layers can be used for protections and to eliminate parasitic effects. Though we did not perform waterproof tests on our prototypes, the conductive yarn we used can stand numerous washing cycles.

Connections 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 uKnit; and future revisions will need to seek out more durable connection designs [Poupyrev et al.(2016), Stanley et al.(2021)].

7.3 Scalability for Textile-based Devices

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, wire routings are done manually by hand sewing for uKnit and attaching buttons for robotSweater. Machine-sewing(e.g., [Parzer et al.(2017)]) could automate hand-sewing, but our early explorations revealed that a denser fabric is needed to avoid tension problems. Wash-away stabilizer [Kao et al.(2018)] might be one solution to the problem. Future works could also look into flexible and stretchable PCB technologies. Furthermore, E-textiles research will benefit from comprehensive studies on soft-hard connectors for both prototyping and mass manufacturing.

References

[bal(1842)] 1842. *The Illustrated London News*. William Little.

[wir(2011)] 2011. HARD/SOFT CONNECTIONS. https://www.kobakant.at/DIY/?p=1272

[han(2021)] 2021. https://iis-lab.org/research/handkerchief/

[Aigner et al.(2020)] Roland Aigner, Andreas Pointner, Thomas Preindl, Patrick Parzer, and Michael Haller. 2020. *Embroidered Resistive Pressure Sensors: A Novel Approach for Textile Interfaces*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376305

[Albaugh et al.(2019)] Lea Albaugh, Scott Hudson, and Lining Yao. 2019. Digital fabrication of soft actuated objects by machine knitting. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–13.

[Albaugh et al.(2021)] Lea Albaugh, James McCann, Scott E. Hudson, and Lining Yao. 2021. *Engineering Multifunctional Spacer Fabrics Through Machine Knitting*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411764.3445564

[Alirezaei et al.(2007)] Hassan Alirezaei, Akihiko Nagakubo, and Yasuo Kuniyoshi. 2007. A highly stretchable tactile distribution sensor for smooth surfaced humanoids. In *2007 7th IEEE-RAS International Conference on Humanoid Robots*. IEEE, 167–173.

[Alirezaei et al.(2009)] Hassan Alirezaei, Akihiko Nagakubo, and Yasuo Kuniyoshi. 2009. A tactile distribution sensor which enables stable measurement under high and dynamic stretch. In *2009 IEEE Symposium on 3D User Interfaces*. IEEE, 87–93.

[Atalay et al.(2017)] Asli Atalay, Vanessa Sanchez, Ozgur Atalay, Daniel M. Vogt, Florian Haufe, Robert J. Wood, and Conor J. Walsh. 2017. Batch Fabrication of Customizable Silicone-Textile Composite Capacitive Strain Sensors for Human Motion Tracking. *Advanced Materials Technologies* 2, 9 (2017), 1700136. https://doi.org/10.1002/admt.201700136

[Atalay et al.(2014)] Ozgur Atalay, William Richard Kennon, and Erhan Demirok. 2014. Weft-knitted strain sensor for monitoring respiratory rate and its electro-mechanical modeling. *IEEE Sensors Journal* 15, 1 (2014), 110–122.

[Bell et al.(2021)] Fiona Bell, Alice Hong, Andreea Danielescu, Aditi Maheshwari, Ben Greenspan, Hiroshi Ishii, Laura Devendorf, and Mirela Alistar. 2021. Self-DeStaining Textiles: Designing Interactive Systems with Fabric, Stains and Light. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 631, 12 pages. https://doi.org/10.1145/3411764.3445155

[Bozali et al.(2021)] B. Bozali, J. J. F. van Dam, L. Plaude, and K. M. B. Jansen. 2021. Development of hysteresis-free and linear knitted strain sensors for smart textile applications. In *2021 IEEE Sensors*. 1–4. https://doi.org/10.1109/SENSORS47087.2021.9639613

[Cheng et al.(2019)] Gordon Cheng, Emmanuel Dean-Leon, Florian Bergner, Julio Rogelio Guadarrama Olvera, Quentin Leboutet, and Philipp Mittendorfer. 2019. A comprehensive realization of robot skin: Sensors, sensing, control, and applications. *Proc. IEEE* 107, 10 (2019), 2034–2051.

[Cheng et al.(2013)] Jingyuan Cheng, Bo Zhou, Kai Kunze, Carl Christian Rheinländer, Sebastian Wille, Norbert Wehn, Jens Weppner, and Paul Lukowicz. 2013. Activity Recognition and Nutrition Monitoring in Every Day Situations with a Textile Capacitive Neckband. In *Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication* (Zurich, Switzerland) *(UbiComp '13 Adjunct)*. Association for Computing Machinery, New York, NY, USA, 155–158. https://doi.org/10.1145/2494091.2494143

[Cherenack et al.(2010)] Kunigunde Cherenack, Christoph Zysset, Thomas Kinkeldei, Niko Münzenrieder, and Gerhard Tröster. 2010. Wearable Electronics: Woven Electronic Fibers with Sensing and Display Functions for Smart Textiles (Adv. Mater. 45/2010). *Advanced Materials* 22, 45 (2010), 5071–5071. https://doi.org/10.1002/adma.201090145

[Dahiya et al.(2019)] Ravinder Dahiya, Nivasan Yogeswaran, Fengyuan Liu, Libu Manjakkal, Etienne Burdet, Vincent Hayward, and Henrik Jörntell. 2019. Large-area soft e-skin: The challenges beyond sensor designs. *Proc. IEEE* 107, 10 (2019), 2016–2033.

[Day et al.(2018)] Nathan Day, Jimmy Penaloza, Veronica J Santos, and Marc D Killpack. 2018. Scalable fabric tactile sensor arrays for soft bodies. *Journal of Micromechanics and Microengineering* 28, 6 (2018), 064004.

[Devendorf et al.(2016)] Laura Devendorf, Joanne Lo, Noura Howell, Jung Lin Lee, Nan-Wei Gong, M. Emre Karagozler, Shiho Fukuhara, Ivan Poupyrev, Eric Paulos, and Kimiko Ryokai. 2016. "I Don't Want to Wear a Screen": Probing Perceptions of and Possibilities for Dynamic Displays on Clothing. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 6028–6039. https://doi.org/10.1145/2858036.2858192

[Fan et al.(2020)] Wenjing Fan, Qiang He, Keyu Meng, Xulong Tan, Zhihao Zhou, Gaoqiang Zhang, Jin Yang, and Zhong Lin Wang. 2020. Machine-knitted washable sensor array textile for precise epidermal physiological signal monitoring. *Science advances* 6, 11 (2020), eaay2840.

[Goguey et al.(2019)] Alix Goguey, Cameron Steer, Andrés Lucero, Laurence Nigay, Deepak Ranjan Sahoo, Céline Coutrix, Anne Roudaut, Sriram Subramanian, Yutaka Tokuda, Timothy Neate, Jennifer Pearson, Simon Robinson, and Matt Jones. 2019. *PickCells: A Physically Reconfigurable Cell-composed Touchscreen.* Association for Computing Machinery, 1–14. `https://doi.org/10.1145/3290605.3300503`

[Gopalsamy et al.(1999)] Chandramohan Gopalsamy, Sungmee Park, Rangaswamy Rajamanickam, and Sundaresan Jayaraman. 1999. The Wearable Motherboard™: The first generation of adaptive and responsive textile structures (ARTS) for medical applications. *Virtual Reality* 4, 3 (1999), 152–168.

[Gray and Lutz(1990)] LJ Gray and E Lutz. 1990. On the treatment of corners in the boundary element method. *J. Comput. Appl. Math.* 32, 3 (1990), 369–386.

[Henderson and Webster(1978)] Ross P Henderson and John G Webster. 1978. An impedance camera for spatially specific measurements of the thorax. *IEEE Transactions on Biomedical Engineering* 3 (1978), 250–254.

[Heng et al.(2021)] Wenzheng Heng, Geng Yang, Gaoyang Pang, Zhiqiu Ye, Honghao Lv, Juan Du, Guodong Zhao, and Zhibo Pang. 2021. Fluid-Driven Soft CoboSkin for Safer Human–Robot Collaboration: Fabrication and Adaptation. *Advanced Intelligent Systems* 3, 3 (2021), 2000038.

[Jarusriboonchai and Häkkilä(2019)] Pradthana Jarusriboonchai and Jonna Häkkilä. 2019. Customisable wearables: exploring the design space of wearable technology. In *Proceedings of the 18th International Conference on Mobile and Ubiquitous Multimedia*. 1–9.

[Jiang et al.(2019)] Yutong Jiang, Lulu Xu, Kewen Pan, Ting Leng, Yi Li, Laith Danoon, and Zhirun Hu. 2019. e-Textile embroidered wearable near-field communication RFID antennas. *IET Microwaves, Antennas & Propagation* 13, 1 (2019), 99–104.

[Jin et al.(2018)] Haojian Jin, Zhijian Yang, Swarun Kumar, and Jason I. Hong. 2018. Towards Wearable Everyday Body-Frame Tracking using Passive RFIDs. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 4 (Jan 2018), 145:1–145:23. `https://doi.org/10.1145/3161199`

[Jones et al.(2021)] Benjamin Jones, Yuxuan Mei, Haisen Zhao, Taylor Gotfrid, Jennifer Mankoff, and Adriana Schulz. 2021. Computational Design of Knit Templates. *ACM Transactions on Graphics (TOG)* 41, 2 (2021), 1–16.

[Jones(2019)] Lee Jones. 2019. A Co-Design Toolkit for Wearable e-Textiles. In *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous*

Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers (London, United Kingdom) *(UbiComp/ISWC '19 Adjunct)*. Association for Computing Machinery, New York, NY, USA, 363–366. https://doi.org/10.1145/3341162.3349303

[Jost et al.(2014)] Kristy Jost, Genevieve Dion, and Yury Gogotsi. 2014. Textile energy storage in perspective. *Journal of Materials Chemistry A* 2, 28 (2014), 10776–10787.

[Kao et al.(2018)] Hsin-Liu Cindy Kao, Abdelkareem Bedri, and Kent Lyons. 2018. SkinWire: Fabricating a self-contained on-skin PCB for the hand. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 3 (2018), 1–23.

[Kaspar et al.(2021)] Alexandre Kaspar, Kui Wu, Yiyue Luo, Liane Makatura, and Wojciech Matusik. 2021. Knit sketching: from cut & sew patterns to machine-knit garments. *ACM Transactions on Graphics (TOG)* 40, 4 (2021), 1–15.

[Kato et al.(2007)] Yo Kato, Toshiharu Mukai, Tomonori Hayakawa, and Tetsuyoshi Shibata. 2007. Tactile Sensor without Wire and Sensing Element in the Tactile Region Based on EIT Method. In *2007 IEEE SENSORS*. 792–795. https://doi.org/10.1109/ICSENS.2007.4388519

[Kawai et al.(2022)] Michio Kawai, Minghao Nie, Haruka Oda, Yuya Morimoto, and Shoji Takeuchi. 2022. Living skin on a robot. *Matter* (2022).

[Khurana et al.(2019)] Rushil Khurana, Mayank Goel, and Kent Lyons. 2019. Detachable smartwatch: more than a wearable. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 2 (2019), 1–14.

[Kiener et al.(2022)] Kevin Kiener, Aishwarya Anand, William Fobelets, and Kristel Fobelets. 2022. Respiratory Inductive Plethysmography System for Knitted Helical Coils. *Engineering Proceedings* 15, 1 (2022), 7.

[Kilic Afsar et al.(2021)] Ozgun Kilic Afsar, Ali Shtarbanov, Hila Mor, Ken Nakagaki, Jack Forman, Karen Modrei, Seung Hee Jeong, Klas Hjort, Kristina Höök, and Hiroshi Ishii. 2021. OmniFiber: Integrated Fluidic Fiber Actuators for Weaving Movement Based Interactions into the 'Fabric of Everyday Life'. In *The 34th Annual ACM Symposium on User Interface Software and Technology*. 1010–1026.

[Kim et al.(2018)] Hyunyoung Kim, Celine Coutrix, and Anne Roudaut. 2018. *Morphees+: Studying Everyday Reconfigurable Objects for the Design and Taxonomy of Reconfigurable UIs*. Association for Computing Machinery, 1–14. https://doi.org/10.1145/3173574.3174193

[Klamka et al.(2020)] Konstantin Klamka, Raimund Dachselt, and Jürgen Steimle. 2020. *Rapid Iron-On User Interfaces: Hands-on Fabrication of Interactive Textile Prototypes.*

Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376220

[Kostikis et al.(2020)] N. Kostikis, G. Rigas, N. Tachos, S. Konitsiotis, and D. I. Fotiadis. 2020. On-Body Sensor Position Identification with a Simple, Robust and Accurate Method, Validated in Patients with Parkinson's Disease. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC)*. 4156–4159. https://doi.org/10.1109/EMBC44109.2020.9175913

[Lambrichts et al.(2020)] Mannu Lambrichts, Jose Maria Tijerina, and Raf Ramakers. 2020. SoftMod: A Soft Modular Plug-and-Play Kit for Prototyping Electronic Systems. In *Proceedings of the Fourteenth International Conference on Tangible, Embedded, and Embodied Interaction (TEI '20)*. Association for Computing Machinery, 287–298. https://doi.org/10.1145/3374920.3374950

[Lee et al.(2017)] Hyosang Lee, Donguk Kwon, Haedo Cho, Inkyu Park, and Jung Kim. 2017. Soft Nanocomposite Based Multi-point, Multi-directional Strain Mapping Sensor Using Anisotropic Electrical Impedance Tomography. *Scientific reports* 7, 1 (2017), 1–10.

[Lee et al.(2021)] Seol-Yee Lee, Md. Tahmidul Islam Molla, and Cindy Hsin-Liu Kao. 2021. *A 10-Year Review of the Methods and Purposes of On-Skin Interface Research in ACM SIGCHI*. Association for Computing Machinery, New York, NY, USA, 84–90. https://doi.org/10.1145/3460421.3480424

[Liu et al.(2020)] Jixiao Liu, Manfei Wang, Peng Wang, Funing Hou, Chuizhou Meng, Kazunobu Hashimoto, and Shijie Guo. 2020. Cost-Efficient Flexible Supercapacitive Tactile Sensor With Superior Sensitivity and High Spatial Resolution for Human-Robot Interaction. *IEEE Access* 8 (2020), 64836–64845.

[Luo et al.(2021a)] Yiyue Luo, Yunzhu Li, Pratyusha Sharma, Wan Shou, Kui Wu, Michael Foshey, Beichen Li, Tomás Palacios, Antonio Torralba, and Wojciech Matusik. 2021a. Learning human–environment interactions using conformal tactile textiles. *Nature Electronics* 4, 3 (2021), 193–201.

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

[Ma et al.(2020)] Gang Ma, Zhiliang Hao, Xuan Wu, and Xiaojie Wang. 2020. An optimal electrical impedance tomography drive pattern for human-computer interaction applications. *IEEE transactions on biomedical circuits and systems* 14, 3 (2020), 402–411.

[Markvicka et al.(2019)] Eric Markvicka, Guanyun Wang, Yi-Chin Lee, Gierad Laput, Carmel Majidi, and Lining Yao. 2019. ElectroDermis: Fully Untethered, Stretchable, and Highly-Customizable Electronic Bandages. In *Proceedings of the 2019 CHI*

Conference on Human Factors in Computing Systems (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/3290605.3300862

[McCann(2017)] James McCann. 2017. The "Knitout" (.k) File Format. [Online]. Available from: https://textiles-lab.github.io/knitout/knitout.html.

[McCann et al.(2016)] James McCann, Lea Albaugh, Vidya Narayanan, April Grow, Wojciech Matusik, Jennifer Mankoff, and Jessica Hodgins. 2016. A compiler for 3D machine knitting. *ACM Transactions on Graphics (TOG)* 35, 4 (2016), 1–11.

[Nagakubo et al.(2007)] Akihiko Nagakubo, Hassan Alirezaei, and Yasuo Kuniyoshi. 2007. A deformable and deformation sensitive tactile distribution sensor. In *2007 IEEE International Conference on Robotics and Biomimetics (ROBIO)*. 1301–1308. https://doi.org/10.1109/ROBIO.2007.4522352

[Narayanan et al.(2018)] Vidya Narayanan, Lea Albaugh, Jessica Hodgins, Stelian Coros, and James Mccann. 2018. Automatic machine knitting of 3D meshes. *ACM Transactions on Graphics (TOG)* 37, 3 (2018), 1–15.

[Narayanan et al.(2019)] Vidya Narayanan, Kui Wu, Cem Yuksel, and James McCann. 2019. Visual knitting machine programming. *ACM Transactions on Graphics (TOG)* 38, 4 (2019), 1–13.

[Nintendo(2021)] Nintendo. 2021. Nintendo Labo Toy-Con 04 VR Kit — Nintendo Switch — Nintendo. [Online]. Available from: https://www.nintendo.com/my/switch/adfx/index.html.

[Olwal et al.(2018)] Alex Olwal, Jon Moeller, Greg Priest-Dorman, Thad Starner, and Ben Carroll. 2018. I/O Braid: Scalable touch-sensitive lighted cords using spiraling, repeating sensing textiles and fiber optics. In *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology*. 485–497.

[Ou et al.(2019)] Jifei Ou, Daniel Oran, Don Derek Haddad, Joseph Paradiso, and Hiroshi Ishii. 2019. SensorKnit: architecting textile sensors with machine knitting. *3D Printing and Additive Manufacturing* 6, 1 (2019), 1–11.

[Pang et al.(2021)] Gaoyang Pang, Geng Yang, and Zhibo Pang. 2021. Review of robot skin: A potential enabler for safe collaboration, immersive teleoperation, and affective interaction of future collaborative robots. *IEEE Transactions on Medical Robotics and Bionics* (2021).

[Park et al.(2021)] Hyunkyu Park, Kyungseo Park, Sangwoo Mo, and Jung Kim. 2021. Deep neural network based electrical impedance tomographic sensing methodology for large-area robotic tactile sensing. *IEEE Transactions on Robotics* 37, 5 (2021), 1570–1583.

[Parzer et al.(2018)] Patrick Parzer, Florian Perteneder, Kathrin Probst, Christian Rendl, Joanne Leong, Sarah Schuetz, Anita Vogl, Reinhard Schwoediauer, Martin Kaltenbrunner, Siegfried Bauer, and Michael Haller. 2018. RESi: A Highly Flexible, Pressure-Sensitive, Imperceptible Textile Interface Based on Resistive Yarns. In *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology (UIST '18)*. Association for Computing Machinery, 745–756. https://doi.org/10.1145/3242587.3242664

[Parzer et al.(2017)] Patrick Parzer, Adwait Sharma, Anita Vogl, Jürgen Steimle, Alex Olwal, and Michael Haller. 2017. SmartSleeve: Real-time Sensing of Surface and Deformation Gestures on Flexible, Interactive Textiles, using a Hybrid Gesture Detection Pipeline. In *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology (UIST '17)*. Association for Computing Machinery, 565–577. https://doi.org/10.1145/3126594.3126652

[Pelton et al.(1978)] W Hallof Pelton, SH Ward, PG Hallof, WR Sill, and P Hi Nelson. 1978. Mineral discrimination and removal of inductive coupling with multifrequency IP. *Geophysics* 43, 3 (1978), 588–609.

[Post and Orth(1997)] E.R. Post and M. Orth. 1997. Smart fabric, or "wearable clothing". In *Digest of Papers. First International Symposium on Wearable Computers*. 167–168. https://doi.org/10.1109/ISWC.1997.629937

[Poupyrev et al.(2016)] Ivan Poupyrev, Nan-Wei Gong, Shiho Fukuhara, Mustafa Emre Karagozler, Carsten Schwesig, and Karen E. Robinson. 2016. Project Jacquard: Interactive Digital Textiles at Scale *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 4216–4227. https://doi.org/10.1145/2858036.2858176

[Sanchez et al.(2021)] Vanessa Sanchez, Conor J. Walsh, and Robert J. Wood. 2021. Textile Technology for Soft Robotic and Autonomous Garments. *Advanced Functional Materials* 31, 6 (2021), 2008278. https://doi.org/10.1002/adfm.202008278

[Senthil Kumar et al.(2019)] Kirthika Senthil Kumar, Po-Yen Chen, and Hongliang Ren. 2019. A review of printable flexible and stretchable tactile sensors. *Research* 2019 (2019).

[Seyed et al.(2016)] Teddy Seyed, Xing-Dong Yang, and Daniel Vogel. 2016. Doppio: A Reconfigurable Dual-Face Smartwatch for Tangible Interaction. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. 4675–4686.

[Shah et al.(2019)] Dylan S Shah, Michelle C Yuen, Liana G Tilton, Ellen J Yang, and Rebecca Kramer-Bottiglio. 2019. Morphing robots using robotic skins that sculpt clay. *IEEE Robotics and Automation Letters* 4, 2 (2019), 2204–2211.

[Shima Seiki(2011)] Shima Seiki. 2011. SDS-ONE Apex3 Design System. [Online]. Available from: http://www.shimaseiki.com/product/design/sdsone_apex/flat/.

[Shu et al.(2014)] Lin Shu, Xiaoming Tao, and David Dagan Feng. 2014. A new approach for readout of resistive sensor arrays for wearable electronic applications. *IEEE Sensors Journal* 15, 1 (2014), 442–452.

[Shyr et al.(2011)] Tien-Wei Shyr, Jing-Wen Shie, and Yan-Er Jhuang. 2011. The effect of tensile hysteresis and contact resistance on the performance of strain-resistant elastic-conductive webbing. *Sensors* 11, 2 (2011), 1693–1705.

[Stanley et al.(2021)] Jessica Stanley, John A Hunt, Phil Kunovski, and Yang Wei. 2021. A review of connectors and joining technologies for electronic textiles. *Engineering Reports* (2021), e12491.

[Strachan et al.(2007)] Steven Strachan, Roderick Murray-Smith, and Sile O'Modhrain. 2007. BodySpace: inferring body pose for natural control of a music player. In *CHI '07 Extended Abstracts on Human Factors in Computing Systems (CHI EA '07)*. Association for Computing Machinery, 2001–2006. https://doi.org/10.1145/1240866.1240939

[Sugiura et al.(2012)] Yuta Sugiura, Masahiko Inami, and Takeo Igarashi. 2012. *A thin stretchable interface for tangential force measurement*. Association for Computing Machinery, 529–536. https://doi.org/10.1145/2380116.2380182

[Sztyler and Stuckenschmidt(2016)] Timo Sztyler and Heiner Stuckenschmidt. 2016. On-body localization of wearable devices: An investigation of position-aware activity recognition. In *2016 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. 1–9. https://doi.org/10.1109/PERCOM.2016.7456521

[Vallett et al.(2020)] Richard Vallett, Denisa Qori McDonald, Genevieve Dion, Youngmoo Kim, and Ali Shokoufandeh. 2020. Toward Accurate Sensing with Knitted Fabric: Applications and Technical Considerations. *Proceedings of the ACM on Human-Computer Interaction* 4, EICS (2020), 1–26.

[Wang et al.(2018)] Sihong Wang, Jie Xu, Weichen Wang, Ging-Ji Nathan Wang, Reza Rastak, Francisco Molina-Lopez, Jong Won Chung, Simiao Niu, Vivian R Feig, Jeffery Lopez, et al. 2018. Skin electronics from scalable fabrication of an intrinsically stretchable transistor array. *Nature* 555, 7694 (2018), 83–88.

[Weiser(1999)] Mark Weiser. 1999. The computer for the 21st century. *ACM SIGMOBILE mobile computing and communications review* 3, 3 (1999), 3–11.

[Whitmire et al.(2018)] Eric Whitmire, Hrvoje Benko, Christian Holz, Eyal Ofek, and Mike Sinclair. 2018. *Haptic Revolver: Touch, Shear, Texture, and Shape Rendering on a Reconfigurable Virtual Reality Controller*. Association for Computing Machinery, 1–12. https://doi.org/10.1145/3173574.3173660

[Whitmire et al.(2017)] Eric Whitmire, Mohit Jain, Divye Jain, Greg Nelson, Ravi Karkar, Shwetak Patel, and Mayank Goel. 2017. Digitouch: Reconfigurable thumb-to-finger input and text entry on head-mounted displays. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 1–21.

[Wicaksono et al.(2021)] Irmandy Wicaksono, Juliana Cherston, and Joseph A. Paradiso. 2021. Electronic Textile Gaia: Ubiquitous Computational Substrates Across Geometric Scales. *IEEE Pervasive Computing* 20, 3 (Jul 2021), 18–29. https://doi.org/10.1109/MPRV.2021.3078107

[Wicaksono et al.(2022)] Irmandy Wicaksono, Don Derek Haddad, and Joseph Paradiso. 2022. Tapis Magique: Machine-knitted Electronic Textile Carpet for Interactive Choreomusical Performance and Immersive Environments. In *Creativity and Cognition*. 262–274.

[Wicaksono et al.(2020)] Irmandy Wicaksono, Elena Kodama, Artem Dementyev, and Joseph A. Paradiso. 2020. SensorNets: Towards Reconfigurable Multifunctional Fine-grained Soft and Stretchable Electronic Skins. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems (CHI EA '20)*. Association for Computing Machinery, 1–8. https://doi.org/10.1145/3334480.3382866

[Wicaksono and Paradiso(2020)] Irmandy Wicaksono and Joseph Paradiso. 2020. Knittedkeyboard: Digital knitting of electronic textile musical controllers. In *Proceedings of the International Conference on New Interfaces for Musical Expression*.

[Wijesiriwardana et al.(2005)] R Wijesiriwardana, K Mitcham, W Hurley, and T Dias. 2005. Capacitive fiber-meshed transducers for touch and proximity-sensing applications. *IEEE Sensors Journal* 5, 5 (2005), 989–994.

[Wu et al.(2020a)] Tony Wu, Shiho Fukuhara, Nicholas Gillian, Kishore Sundara-Rajan, and Ivan Poupyrev. 2020a. ZebraSense: A double-sided textile touch sensor for smart clothing. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology*. 662–674.

[Wu et al.(2020b)] Te-Yen Wu, Shutong Qi, Junchi Chen, MuJie Shang, Jun Gong, Teddy Seyed, and Xing-Dong Yang. 2020b. *Fabriccio: Touchless Gestural Input on Interactive Fabrics*. Association for Computing Machinery, 1–14. https://doi.org/10.1145/3313831.3376681

[Wu et al.(2020c)] Te-Yen Wu, Lu Tan, Yuji Zhang, Teddy Seyed, and Xing-Dong Yang. 2020c. *Capacitivo: Contact-Based Object Recognition on Interactive Fabrics Using Capacitive Sensing*. Association for Computing Machinery, New York, NY, USA, 649–661. https://doi.org/10.1145/3379337.3415829

[Wu et al.(2021)] Te-Yen Wu, Zheer Xu, Xing-Dong Yang, Steve Hodges, and Teddy Seyed. 2021. *Project Tasca: Enabling Touch and Contextual Interactions with a Pocket-Based Textile Sensor*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3411764.3445712

[Yoon et al.(2018)] Sang Ho Yoon, Luis Paredes, Ke Huo, and Karthik Ramani. 2018. MultiSoft: Soft Sensor Enabling Real-Time Multimodal Sensing with Contact Localization and Deformation Classification. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 3 (Sep 2018), 145:1–145:21. https://doi.org/10.1145/3264955

[Yoshikai et al.(2009)] Tomoaki Yoshikai, Hiroko Fukushima, Marika Hayashi, and Masayuki Inaba. 2009. Development of soft stretchable knit sensor for humanoids' whole-body tactile sensibility. In *2009 9th IEEE-RAS International Conference on Humanoid Robots*. IEEE, 624–631.

[Yu and McCann(2020)] Tianhong Catherine Yu and James McCann. 2020. Coupling Programs and Visualization for Machine Knitting. In *Symposium on Computational Fabrication*. 1–10.

[Zeagler(2017)] Clint Zeagler. 2017. Where to Wear It: Functional, Technical, and Social Considerations in on-Body Location for Wearable Technology 20 Years of Designing for Wearability. In *Proceedings of the 2017 ACM International Symposium on Wearable Computers* (Maui, Hawaii) *(ISWC '17)*. Association for Computing Machinery, New York, NY, USA, 150–157. https://doi.org/10.1145/3123021.3123042

[Zhang and Tao(2012)] Hui Zhang and Xiaoming Tao. 2012. From wearable to aware: Intrinsically conductive electrotextiles for human strain/stress sensing. In *Proceedings of 2012 IEEE-EMBS International Conference on Biomedical and Health Informatics*. 468–471. https://doi.org/10.1109/BHI.2012.6211618

[Zhang and Harrison(2015)] Yang Zhang and Chris Harrison. 2015. Tomo: Wearable, Low-Cost Electrical Impedance Tomography for Hand Gesture Recognition. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology (UIST '15)*. Association for Computing Machinery, 167–173. https://doi.org/10.1145/2807442.2807480

[Zhang and Harrison(2018)] Yang Zhang and Chris Harrison. 2018. *Pulp Nonfiction: Low-Cost Touch Tracking for Paper*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3173574.3173691

[Zhang et al.(2017)] Yang Zhang, Gierad Laput, and Chris Harrison. 2017. *Electrick: Low-Cost Touch Sensing Using Electric Field Tomography*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3025453.3025842

[Zhang et al.(2016)] Yang Zhang, Robert Xiao, and Chris Harrison. 2016. Advancing Hand Gesture Recognition with High Resolution Electrical Impedance Tomography. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology (UIST '16)*. Association for Computing Machinery, 843–850. https://doi.org/10.1145/2984511.2984574

[Zhu et al.(2021)] Junyi Zhu, Jackson C Snowden, Joshua Verdejo, Emily Chen, Paul Zhang, Hamid Ghaednia, Joseph H Schwab, and Stefanie Mueller. 2021. EIT-kit: An Electrical Impedance Tomography Toolkit for Health and Motion Sensing. In *The 34th Annual ACM Symposium on User Interface Software and Technology (UIST '21)*. Association for Computing Machinery, 400–413. https://doi.org/10.1145/3472749.3474758

[Zlokapa et al.(2022)] Lara Zlokapa, Yiyue Luo, Jie Xu, Michael Foshey, Kui Wu, Pulkit Agrawal, and Wojciech Matusik. 2022. An Integrated Design Pipeline for Tactile Sensing Robotic Manipulators. *arXiv preprint arXiv:2204.07149* (2022).