Serpentine: A Reversibly Deformable Cord Sensor for Human Input

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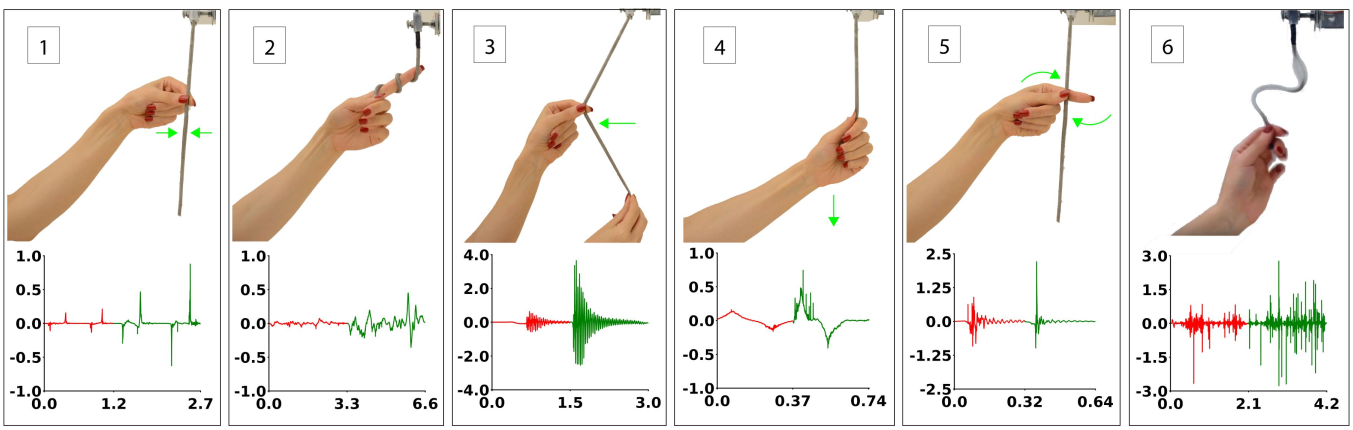

Figure 1: The Serpentine cord prototype demonstrating six user interactions - Wave-forms of 2 levels (first red, then green) of intensity for each interaction: 1) Double Pinch, 2) Twirl, 3) Pluck, 4) Stretch, 5) Twist and 6) Wiggle. The y-axis represents open circuit voltage in volts and the x-axis is time in seconds.

ABSTRACT

We introduce Serpentine, a self-powered sensor that is a reversibly deformable cord capable of sensing a variety of human input. The material properties and structural design of Serpentine allow it to be flexible, twistable, stretchable and squeezable, enabling a broad variety of expressive input modalities. The sensor operates using the principle of Triboelectric Nanogenerators (TENG), which allows it to sense mechanical deformation without an external power source. The affordances of the cord include six interactions—Pluck, Twirl, Stretch, Pinch, Wiggle and Twist. Serpentine demonstrates the ability to simultaneously recognize these inputs through a single physical interface. A 12-participant

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user study illustrates 95.7% accuracy for a user-dependent recognition model using a realtime system and 92.17% for user-independent offline detection. We conclude by demonstrating how Serpentine can be employed in everyday ubiquitous computing applications.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; **Ubiquitous and mobile computing**;

KEYWORDS

tangible interfaces, triboelectric nanogenerator, self-powered sensor, input devices, soft electronics, ubiquitous computing

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1 INTRODUCTION

We propose Serpentine, a highly stretchable self-powered sensing material that can recognize human input based on deformations of its shape. It is fabricated with multiple coaxial layers of silicone, coiled copper and conductive nylon thread. Due to its structural design and specific choice of materials, mechanical deformations create time-varying charge distributions between the conductive nylon and copper thread that generate electric signals. Such signal generation happens based on the well-known triboelectric nanogenerator (TENG) phenomenon that works based on a combination of triboelectrification and electrostatic induction [47].

This paper presents the design parameters that govern the performance of the multi-material Serpentine prototype. The cylindrical, cord-shaped and highly stretchable form factor converts a variety of human interactions, such as a pinch, a stretch, and a twirl (see Figure 1), into a distinct energy signal that can be detected and used as input.

Serpentine is manufactured from readily available materials and does not need any external power source to create a signal that reflects how it is being manipulated. These manipulations are easy to perform, and as we will demonstrate, can be recognized using signal processing and machine learning classification. Because of its simplicity to manufacture and its intuitive interactions, there are a wide array of potential uses for Serpentine, and its derivatives, in everyday situations.

2 CONTRIBUTIONS

Our contributions include:

- A description of how to manufacture the Serpentine sensor inexpensively
- A discussion of the physical operating principles of the system and parameters that can be used to tune performance
- A recognizer that can distinguish six different interactions with Serpentine
- A 12 participant quantitative and qualitative user study on interacting with Serpentine

3 RELATED WORK

Over the last few decades, there have been numerous efforts to develop novel tangible interfaces, with a variety of form factors and sensing modalities. The form factors include interactive textiles [15, 20, 21, 30, 35, 40] as well as deformable and stretchable reactive objects [1, 6, 11, 14, 25, 28, 34, 37, 38, 49]. Some of the stretchable objects are intended, like our Serpentine prototype, to come in direct contact with human skin [1, 4, 7, 17, 18, 25, 27, 29, 34, 37]. These sensing modalities include optical [43], resistive [28, 29, 38, 40], capacitive [20, 21, 38, 40], piezoresistive [1, 37, 38], and piezoelectric [38] sensing.

Our Serpentine prototype is a deformable cord, similar in spirit to other cord-shaped [5, 24, 31, 32, 38, 39, 43], tangible, and stretchable [23, 43, 45] sensing interfaces. Several works [5, 24, 31, 38] affixed external sensors—bend sensors, piezoelectric cables, pressure sensors, and piezoresistive sensors—to existing cords.Some sensing interfaces use fiber optic cords which require instrumentation for transmitting and receiving light [6, 14, 26, 43]. A cord-shaped inductive sensor [51] would be unreliable for gestures involving simultaneous stretching and bending. Wang et al.[45] presented deformable and flexible conductive materials with sensing capabilities that could be shaped into cord. Our work is more like this latter approach, as the sensing capabilities is built into the materials that make up the cord itself.

While most of the prior work required an external power source for operation, the Schoessler et. al. work was self-powered, based on piezoelectricty [38]. Serpentine is a self-powered solution based on the principles of the triboelectric nanogenerator (TENG), which is a combination of the universal triboelectric effect between two materials and electrostatic induction [47]. Previous attempts to use TENG for sensing interfaces have exploited vibrational deformations [3, 12, 42, 47, 52]. Our work is closest to that of Dong et. al. as it entails a coaxial structure of the TENG device and a helical winding structure of electrodes [12]. Serpentine has the higher affordance for stiffness customizability and higher resistance to environmental conditions like humidity and temperature due to its specific sensor design.

Previous work has demonstrated interactive materials that are some combination of reversibly deformable, self-powered,

Figure 2: The Serpentine sensor prototype

or capable of sensing a range of expressive interactions. Serpentine addresses all three characteristics simultaneously.

4 DESIGNING THE SERPENTINE PROTOTYPE

Triboelectric Nanogenerators

Serpentine is a self-powered sensor; it harvests energy to perform its sensing operation from the phenomenon that it is sensing. In this case the power comes directly from the deformation of the sensor by a human finger. This approach is possible because the layers of materials used to create the Serpentine cord form what is called a *triboelectric nanogenerator*, or TENG [47]. Triboelectrification occurs as a result of charge transfer between two materials of different electronegativity. When these two materials come in contact with each other, or slide across each other, the triboelectrification creates a build up of charges between the layers, resulting in electrostatic induction, or a charge flow that redistributes charges. This redistribution is observed as a current. Thus, relative movement of charged dielectric layers and the subsequent charge redistribution generates electrical power. We show that this harvested electrical signal is indicative of the way the Serpentine cord has been manipulated (e.g., stretched, pinched, etc).

5 SENSOR STRUCTURE AND FABRICATION

Any two materials exhibit the triboelectric effect when they come in contact or slide across each other. Serpentine is built using materials that are readily available and exhibit particularly strong triboelectric charge redistribution properties—silicone rubber, copper wire and conductive nylon thread. We designed Serpentine for two different and strong triboelectric effects, one with the human finger and one within the cord itself. This approach required five separate layers of materials.

Figure 3 provides a pictorial representation of the 5-layer fabrication process, resulting in the Serpentine sensor prototype shown in Figure 2.

Preparation of dielectric material: Silicone rubber is used as a dielectric layer and for supporting and encapsulating the conductive layers. For the proper stiffness, silicone rubber (Ecoflex 00-50 Platinum Cure Silicone Rubber - Smooth-on.com) and Polydimethylsiloxane (PDMS) (Sylgard 184 Silicone Elastomer - Dow Corning) were mixed. Commercial silicone rubber and PDMS have two parts, a base (B) and a curing (C) agent. For the silicone rubber, these two parts are mixed in 1:1 weight ratio and stirred for 3 minutes. For PDMS, the two parts are mixed in 10:1 weight ratio (B:C) and stirred for 5 minutes. Then, both solutions are mixed in a 4:1 weight ratio (silicone:PDMS) and stirred for 3 minutes.

Layer 1: Form the inner core tube - To fabricate the core structure, the prepared silicone solution is poured into a 2.5 mm inside diameter circular plastic tube. It is solidified in an oven at 60°C for 5 minutes. The solution can also cure at room temperature in 4 hours. The plastic tube is removed, resulting in a solid silicone rubber tube-shape of about 2.5 mm in diameter.

Layer 2: Wind inner electrode around core - A commercial Poly Vinyl Acetal (PVA) enamelled copper wire (0.17mm diameter) was chosen as the inner electrode. It is wound in a tight spiral around the silcone rubber core and density of winding is about 50 turns per centimeter.

Layer 3: Encapsulate with silicone rubber - The entire assembly is coated with more of the silicone rubber solution. We laid the assembly on a flat surface and used a syringe to apply the silicone solution over the entire surface. This structure was then hung vertically for five minutes and then cured for five minutes in an oven at 60°C.

Layer 4: Wind outer electrode around assembly - Commercial silver-plated nylon thread (0.18mm diameter, resistance <100 Ohm per meter, inntex.com) was chosen as the outer electrode. It was also tightly wound around the whole assembly with the same winding density as layer 2.

Layer 5: Encapsulate with silicone rubber solution As was done for Layer 3, we again coated the entire assembly with more of the silicone rubber solution. The final thickness of sensor is about 4.5mm in diameter.

Described fabrication process, although manual, causes modest variability in prototype. All prototypes in our experiments worked with the same set of system parameters and performed consistently.

Sensor Operation

Any interaction with the cord can be separated into two parts: contact from human skin (e.g., a finger) and elongation/contraction along the cylindrical axis of the cord. These basic interactions result in different ways energy is harvested to create a signal.

Contact–separation TENG. As a finger approaches the cord surface, the human skin acts as a dielectric, which is initially neutral. When it first comes into contact with the outer silicone of the cord, electrons are transferred from the skin to

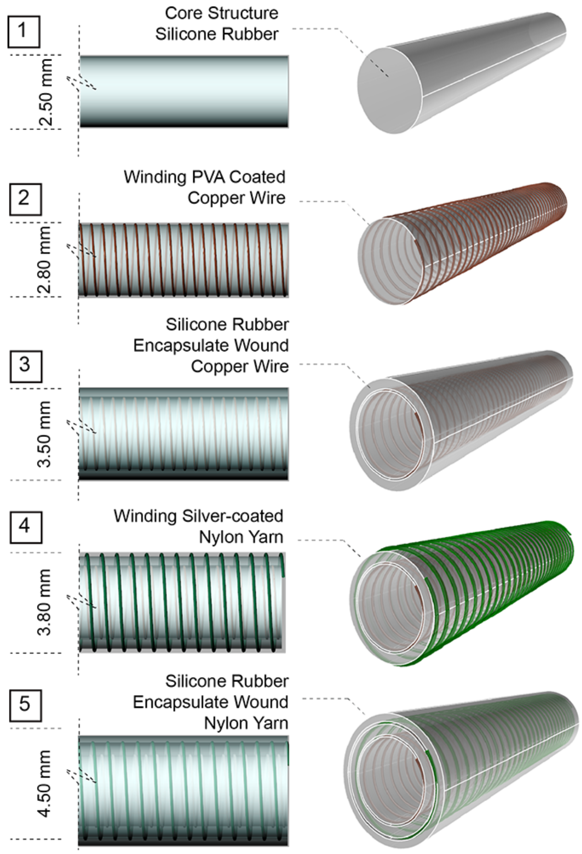

Figure 3: Sensor Fabrication with approximate dimensions

the outer layer of the silicone, making the silicon negatively charged. This triboelectric effect occurs between skin and silicone, where silicone exhibits the property of accepting charge. As the skin moves away from the cord, an electric field, we will call it the outer field, is induced between the finger and the cord, and that field extends throughout the cord. By connecting the two electrodes (the silver-coated nylon thread and the PVA coated copper wire), electrostatic induction occurs as electrons flow from the nylon electrode

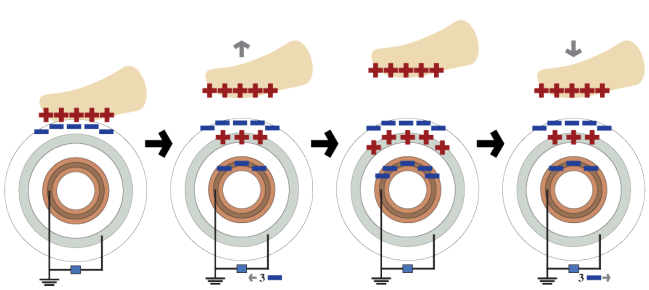

Figure 4: Human touch employs the contact-separation mode of TENG between the skin and the outer silicone layer

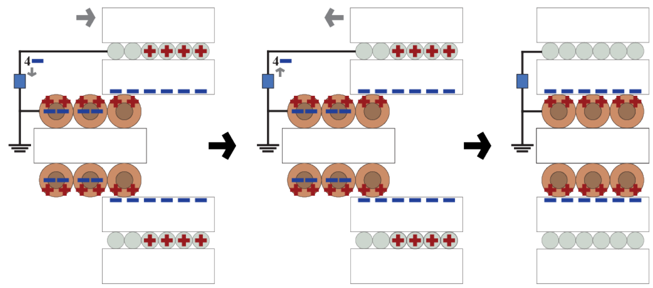

Figure 5: Force along the axis (e.g., stretching) of the cord induces a lateral sliding mode TENG.

to the copper electrode, resulting in an inner electric field to counterbalance the initial outer electric field. When the finger returns to the cord surface, the outer electric field is reduced, so charge flows in the opposite direction between the electrodes. Because it is the contact and separation movement that causes the flow of charge between the electrodes, this mode of TENG is called contact–separation mode.

Lateral sliding mode TENG. A longitudinal force along the cylindrical axis, such as what happens when the cord is stretched, results in a lateral sliding mode of operation for TENG (see Figure 5). Upon stretching, friction between the dielectric silicone in Layer 3 and the PVA insulation around the copper wire makes the former negatively charged and the latter positively charged. In this case the triboelectric effect is between the silicone and the PVA coating. Again, to balance the induced electric field from the triboelectric effect, current flows from the nylon electrode to the copper electrode. As the cord is relaxed, the effect is reversed, and current flows the other way, from copper electrode to nylon electrode.

Sensor Design Parameters

We created an initial prototype of Serpentine for experimental validation. This prototype allows us to understand quantitatively how well the Serpentine concept works for recognizing gestures and what qualitative reactions people have to the concept as a means of accepting human input. There are a number of design parameters in the construction of Serpentine, and each of those parameters impacts the performance and feel of the sensor. We describe major design parameters next, and how they impact features of the sensor. Future applications of Serpentine can choose different values for these parameters to best match the usage scenario.

Silicone rubber substrate. The main substrate for Serpentine is the silicone rubber solution, which constitutes three layers of the sensor. The silicone rubber has two important properties:

- First, it acts as a dielectric with a highly negative triboelectric polarity, meaning it helps to increase the magnitude of the self-powered current resulting from mechanical deformation.
- Second, its elastic properties support the kinds of human interactions we want, because it can be repeatedly squished and stretched and return to an original shape. It is also a familiar material to people, and should be intuitive to manipulate.

The actual silicone rubber we used was a solution of a silicone elastomer and PDMS. Changing the proportions of these two components affects the elasticity of the material. Moreover, the stiffness of the silicone rubber substrate also impacts the signal amplitude due to increased strength of the triboelectric-electrostatic charge.

Electrode coils. Two conductive threads (copper and silver-coated nylon) coiled around the sensor provide both mechanical strength as well as being electrodes to support charge flow. While the silicone rubber can be stretched and pinched, it is prone to tears, punctures, and tensile failures when strained [8, 33, 46, 50].

The inner electrode copper wire has high conductivity and very low resistivity, about 170 $ohm \times m^{-1}$. The outer electrode silver-coated nylon was chosen not only because of its conductivity (< 100 $ohm \times m^{-1}$) but also because of its specific physical properties. It has high tensile strength, high elongation tolerance, high tear strength, and high puncture resistance. Such mechanical properties support the mostly silicone rubber cord under applied loads. In addition, the helical coil provides additional structural support for this kind of flexible electronics [53]. The electrodes are also fairly thin, which helps to keep the overall sensor fairly thin. At rest, no gap exists between successive coils of either electrode. In addition to providing maximum structural reinforcement, this tight coiling maximizes the surface area contact between dielectric layers of silicone rubber and the PVA insulator layer of the copper electrode, improving the triboelectric charging mechanism and overall energy generation.

6 RECOGNIZING HUMAN INTERACTION

Designing the Interactions

As described above, both touch and longitudinal forces produce an electric signal which can be detected. This ability allows for multiple expressive one-handed and two-handed interactions. We evaluated Serpentine for six specific interactions, which have been inspired by affordances of a flexible cord in everyday situations. These are defined below (see Figure 1). These are not the only kinds of interactions that are possible with our prototype, but are a good representative sample.

- *Double Pinch* - pinch as in pinching a piece of clay
- *Twirl* - like the twirling of hair
- *Pluck* - like plucking a harp string or bow
- *Stretch* - like stretching an elastic band
- *Twist* - like rolling a cord between thumb and finger
- *Wiggle* - like ringing a bell using a rope tied to it

Data Processing Pipeline

Our data processing pipeline supports real-time data acquisition and classification, or labeling, of the six basic interactions. We connected our sensor to one of the channel inputs of a Digilent Analog Discovery 2 oscilloscope for data acquisition. That data is sent as a continuous signal via USB to a Macbook Pro laptop for processing and classification using a Python program. This program collects and stores the data stream in a background thread. Another thread continuously analyzes this data, searching for a possible gesture signal. This thread uses energy-based segmentation to filter out part of the input data stream which may contain a possible signal. The segmented data is then passed through a Random Forest classifier to determine which interaction has occurred (Figure 6).

Segmentation. We use two different algorithms for segmenting the signal of interest in the sensor data stream. Both algorithms are based on energy. The first one works on a continuous stream of data to obtain a segment of interest while the second works on this segment of data for finer segmentation.

The first algorithm uses an energy-based sliding window approach to detect the start and end of a gesture. Each sliding window is 1 second long (400 samples) and slides with a 50% overlap. The energy of the window is calculated by summing up the absolute value of all FFT bins. The power threshold is determined empirically during a pilot study and is kept constant across all users afterwards. If the calculated energy is greater than such , we consider this window to contain the beginning of an interaction; otherwise, it is discarded. We then slide the window forward in time to find a window where the energy drops below the threshold to fix it as the end of the signal. We further check the length of this segment to verify that it is more than half a second and less than five seconds, which is the typical duration of our gestures as inferred from our pilot user studies. The threshold and length constraints help to avoid false triggers. This interaction segment is then passed through a second stage to further refine the beginning and ending points of the interaction. We first square the data points to get the magnitude of the signal and take a moving average with window size of 100 points. The averaging helps to fill the parts of the signal where there is an intermediate dip in energy but the signal continues to grow after it. Based on our analysis during the system development, we found that points greater than 60th percentile best represented the signal. So we retain the data points which are greater than the 60th percentile of segmented data and ignore the rest as non-signal component.

Classification. We use a Random Forest machine learning classifier to recognize the interaction. First, we use 40 sample sized window on the segmented signal to calculate features. Amplitude patterns and time duration of interactions (Figure 1) provide an intuition for these features. For instance, in a short term interaction like Pluck, the signal spikes initially and tapers gradually as the sensor ceases to move. In Wiggle, the signal is of a longer time duration and maintains a consistently random pattern throughout.

Features on sample are zero crossing rate, short-term energy, short-term entropy of energy, spectral centroid and spread, spectral entropy, spectral flux, spectral rolloff, Hilbert wavelet transform, root mean square energy, spectral bandwidth, spectral flatness and Haar wavelet.

The length of the segmented data varies with each interaction type and user, we further calculate statistical features(mean, standard deviation, minimum, maximum, median, sum, percentile(10,25,75,90), skew, kurtosis) on the previously calculated feature vector to get a new feature vector of fixed length. We then train a Random Forest based classifier using these features.

In our evaluation study, we demonstrate that the segmentation and classification can happen in realtime. Software determines the latency of the system, which was about 2.5 seconds to sense and recognize a gesture for our system. We also explore the classification performance difference between user-dependent models and user-independent models.

7 APPLICATIONS

We considered three different application scenarios for Serpentine (see Figure 7).

Hoodie string controller. Serpentine is waterproof and fully-functional for interactions underwater. It can be a wearable interface in the form of hoodie strings which is used to manage music control, phone calls, or text messages with discreet micro-interactions. We implemented a music control application on Macbook where the user can turn up or down the volume by Twisting on the left or right string, switch songs by Stretching on the left or right string, or start/pause the music player by Double Pinching on either of the strings.

Expressive switch. The low cost and flexible form factor of Serpentine allows it to be deployed anywhere as a simple device controller, including office, school, home, museum, etc. We conceptually showed Serpentine as an expressive lamp switch. The user can Stretch the cord to turn on/off the lamp just like using an old-fashioned pull switch, Wiggle to switch the color of the light, or Twirl to adjust the brightness.

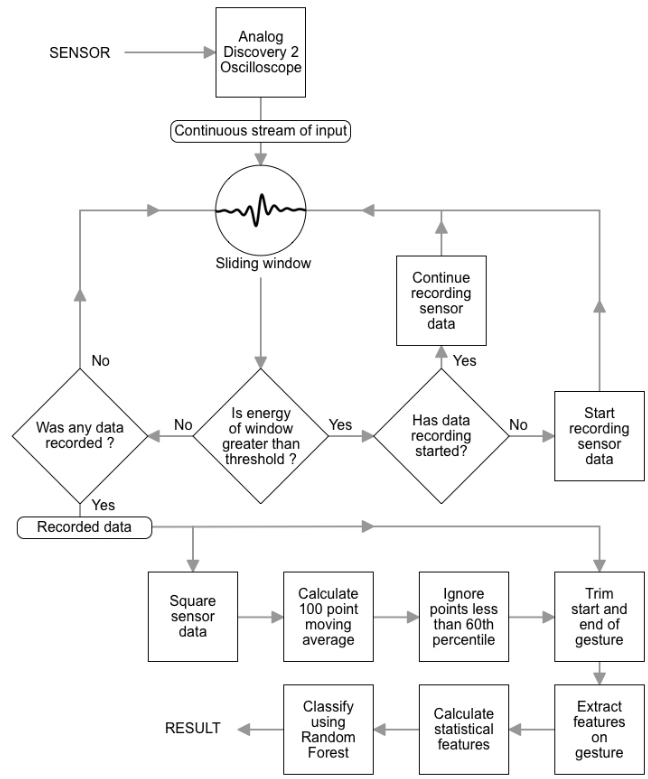

Figure 6: Data processing pipeline

Slingshot game controller. In this scenario, we explored the use of Serpentine as a tangible game controller. Many video games simulate scenarios of bow or sling shooting. With Serpentine clamped at both ends, we implemented a game controller for a simple Unity Slingshot game we developed. The user can "Pluck" the sling with adequate forces as shown in the game, and release to shoot the ball to hit falling targets.

8 EVALUATION

The purpose of our evaluation is to answer the following questions:

- Does the Serpentine prototype successfully detect the 6 basic interactions across a set of users?
- Do users find the interactions intuitive and simple to execute on demand?
- How do users react to potential application scenarios, and can they imagine other usage scenarios?

Participants and Setup

We conducted a user study with 12 participants who were all students or researchers. Each study lasted for about 40–60 minutes per participant. The user study was carried out in

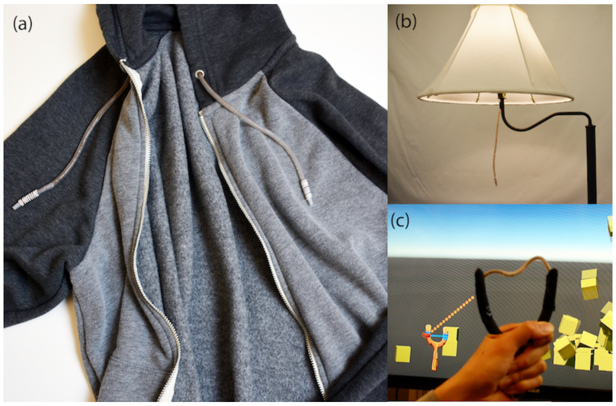

Figure 7: Applications of Serpentine: (a) Wearable hoodie strings (b) Expressive switch (c) Slingshot

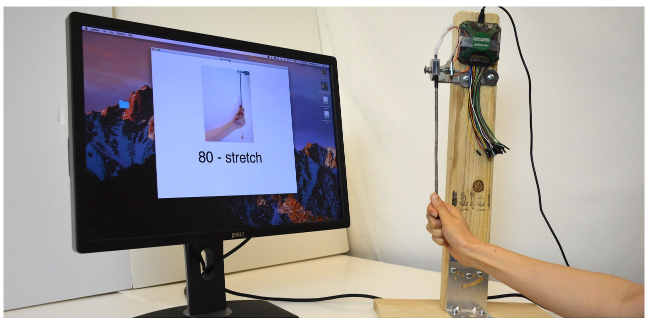

Figure 8: User interacting with Serpentine sensor on a stand

a RF-rich lab environment with the presence of 60Hz hum. The users were requested to sit in front of a monitor screen kept on a table. The sensor hung vertically on a stand as shown in Figure 8. The stand was placed on the table and was wired to the data collection system via a long cable. The cable was strapped to the back side of the stand so as to not interfere with the user while performing gestures.

Study

Our study consisted of three parts. First, we let the user explore the interaction modality by themselves, next we asked the user to perform certain predefined gestures to evaluate the system and lastly, we asked the users questions about their experience with the system and reactions to potential usage scenarios.

Part 1: Initial experience. At the beginning of the study, we gave the users a Serpentine prototype cord, but without any connections to our data processing system. We gave them a few minutes to get familiarized and interact with the cord. At this time, the users only have the knowledge that they are handling a tangible object which is flexible and stretchable. The users are unaware of the sensing or working mechanism of the sensor.

After this initial exposure, we asked the participants to:

- suggest all possible ways they could interact with this cord; and
- recommend use cases or scenarios where it would make sense to interact with this cord in their everyday lives.

We audio recorded this conversation for later analysis.

Part 2 - Interaction testing. In this part of the study, we evaluate the system with our proposed set of interactions. This helps us determine the accuracy and responsiveness of the system. We first familiarize the user with the set of interactions by showing them a pre-recorded video of a researcher performing the interactions. We then let the user try out the gestures themselves. They could do this as long as they wanted, until they felt comfortable with the different interactions. We then showed them our software set-up, in which text-labelled images (and accompanying spoken label) of an interaction are displayed and the user is asked to perform that interaction.

After familiarization, we begin data collection, consisting of a training session followed by a testing session. The training session consists of the system asking the user to perform each of the interactions 25 times, for a total of 150 data samples. The system records the sensor data for five seconds (from when the interaction direction is spoken) and later segments it using the second segmentation algorithm described earlier. The gesture display order is randomized for each user. The data saved from this session is used to train the machine learning-based gesture recognition classifier used in the testing session.

The testing session requires the user to perform each interaction 10 times, for a total of 60 data samples. The system prompts the user in the same way as during the training session. The testing system runs in realtime and looks for user input using the segmentation algorithms described earlier. For classification, we train our machine learning classifier using the training data collected in the previous session. After registering the input, the system performs classification on the input and compares the predicted result with the actual gesture. The correct or incorrect result is then displayed, with an additional visual cue to indicate whether the system recognized the correct interaction. The background becomes red for wrong classification and green for a correct recognition. During the testing session, the system also saves metrics like - classification accuracy and false positive rate. A researcher also manually recorded the false negative and false positive rate during the course of the testing session.

Part 3 - User feedback. In the last part of the study, we played a 1-minute video illustrating three applications. We then recorded a semi-structured interview to gather qualitative reactions to the Serpentine prototype, the interaction experience and reactions to the application scenarios. The interview was intended to evoke responses to the following issues:

- Interaction with the prototype in terms of intuitiveness and being natural.
- Social appropriateness and/or expressiveness of interacting with prototype.
- Comfort interacting with the prototype.
- Ease and difficulties of learning the interactions and repeating the interactions upon demand over time.
- possible sources of frustration

As a closing question, we asked participants for their overall feedback and improvements on any aspects of the system like prototype material, form factor and different interactions. After the interview the participants completed a short questionnaire similar to NASA TLX.

9 RESULTS

Quantitative Analysis

User Dependent Model. To provide realtime feedback during the testing session in the user study, we trained the machine learning classifier using only the data collected from the same user in the training session. Thus the classifier is a user-dependent model.

Overall, the realtime interaction detection accuracy of our system across 12 participants and 6 gestures was 95.7% (sd=4.10%). See Figures 9 and 10(a) for per-user accuracy statistics and the confusion matrix, respectively.

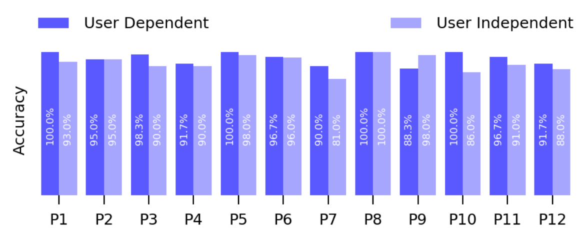

Figure 9: Accuracy per participant for Test session. Results shown here are for both a real-time user-dependent model and an off-line user-independent model.

Participants P1, P5, P8, P10 achieved 100% accuracy while participant P9 achieved the lowest accuracy at 88.3%. One of the possible reason for P9's lower accuracy could be our observation that P9 performed the Twist interaction very similar to Double Pinch, creating a confusion between these two interactions classes. Similar mix-up also happened for few other participants which likely caused Twist to have the lowest recognition precision of 88.3%. The second lowest precision was for Double Pinch at 95% which was also caused by confusion with Twist. The Pluck gesture achieved the highest accuracy at 100.0% followed by Wiggle at 97.5%.

During the testing session, we observed 13 instances of false-negatives, where the user performed their gestures either too fast or very gently than the system could detect. For these cases they were required to perform the same gesture again. Of all these false-negatives, 8 were Twirl and 5 were Twist. We did not observe false positives during this study.

User Independent Model. To see if our system could support user-independent classification, we did some offline analysis on the collected data. To build the user-independent model, we removed a participants training data and built a classifier from the remaining participant's data. To test the model, we used that participant's test data. This leave-one-participant-out testing resulted in overall average accuracy across all 12 participants and 6 gestures of 92.17% (sd=5.35%). See Figures 9 and 10(b) for per-user accuracy statistics and the confusion matrix, respectively.

The user independent modeling shows a little drop from the user-dependent model accuracy, but it is still very promising. For the user-independent scenario, P8 achieves the highest accuracy of 100% and P7 shows the lowest accuracy at 81%.

Qualitative Analysis

In this section we present the higlights from our qualitative parts of the user study.

Positive first reactions. Upon first handling the prototype, all 12 participants commented that they had an enjoyable initial experience in interacting with the prototype. They expressed their initial feelings about the prototype with keywords and phrases like : bouncy, nice elasticity, nice feeling of touch and squishiness, having a nice grip while not sticky, super fun to interact with, soft and flexible, nice feeling on skin, very versatile, nice durability for toys.

Affordances of the cord. Figure 11 illustrates many (but not all) of the suggestions the participants made about interacting with the sensor. These suggestions were made at the beginning of the study when the participants did not have any knowledge about our proposed interactions and the working mechanism of the sensor. From our proposed gesture set, Twirl, Stretch, Wiggle and Pluck were all mentioned by at least four participants. Eight participants came up with Pinch but none with Double Pinch, also none with Twist in a way we proposed. This suggests that the cord form factor does not "afford" those latter two interactions, but it does afford many other interesting interactions. Figure 11 shows number of occurrences for each interaction. It was also interesting to notice how they referred to these interactions, using terminology like "twirling hair or string", "squeezing (like pinching)" "fishing bait", "stretching a rubber

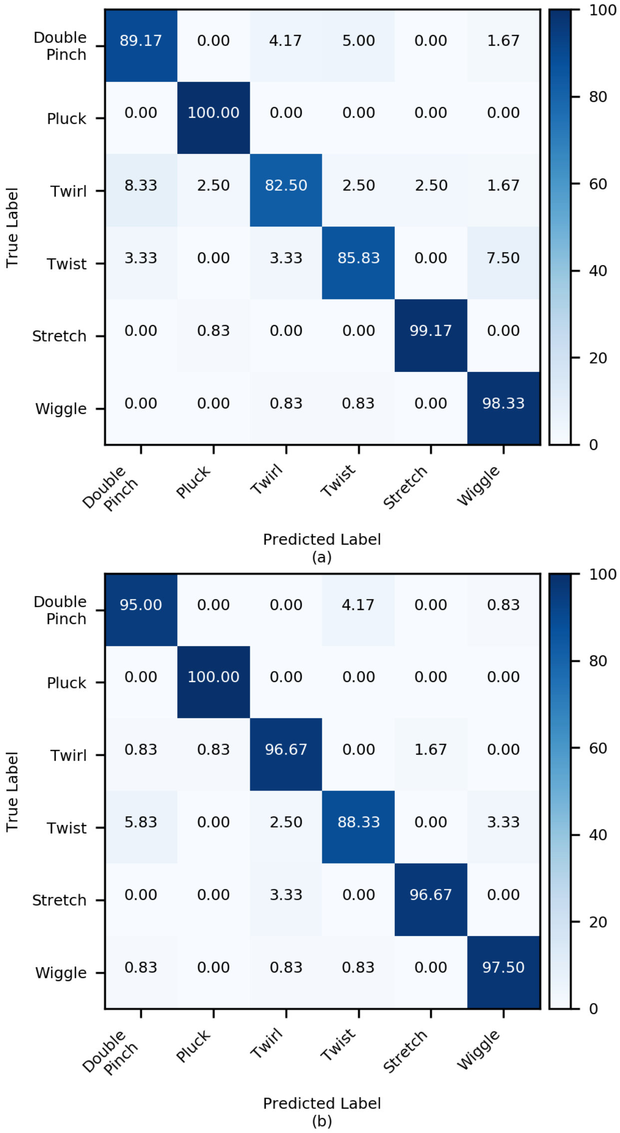

Figure 10: Confusion matrices (a) User-Independent model (b) User-Dependent model

band", "plucking string on a musical instrument or slingshot" and "fidgeting/fiddling (wiggling) hoodie band or necklace". These phrases can be used to suggest different contexts for use of Serpentine.

Social Appropriateness. Most participants found it socially appropriate to perform all interactions except Pluck and the exaggerated Wiggle when the sensor is worn on the body. Participant 6 expressed this best: "For public space, the more gentle the gesture is, the more probable using them. Double Pinch, Twist, Twirl and Stretch are subtle and unobtrusive." Participant 4 noted "unobtrusive, totally comfortable on my skin, I definitely keep fiddling with it. I won't be inhibited to do gestures like Stretch or Twirl, they are totally normal and unobtrusive."

General Impressions. We evaluated the overall impression of the interactions based on observation of participants by researchers while performing gestures, the interviews, and the questionnaire results. Overall, ordering the interactions by how natural and easy to learn were Stretch, Pluck, Twirl, Wiggle, Twist and Double Pinch, best to worst. According to all users, Stretch and Pluck were rated more pleasing and simple with minimum mental, physical and temporal workload compared to other gestures. They were both easy to learn and memorable. Participant 4 described them as "totally natural, automatic and no-brainer gestures." In addition, Stretch, Pluck, Twirl and Wiggle were all perceived as more accessible interactions than Twist and Double Pinch.

Four participants found Twist both mentally and physically demanding to perform. Participant 1 mentioned the "twisting gesture feels weird, I never do grabbing with tip of fingers. Not an intuitive gesture to me." Both Twist and Double Pinch are mostly about the contact–separation TENG operation, and they are the interactions that were most confused by our automated classifier. This may have contributed to the negative reaction to those interactions. Three participants expressed frustration while performing these two interactions and seeing them not being identified correctly. Twist and Double Pinch were both reported as most fatiguing by most participants.

While being asked to perform the interactions Twirl, Pluck and Twist, 4 participants unconsciously were performing compound gestures (e.g., Pluck-Stretch, Twirl-Stretch and Pinch-Twist). Since such compound gestures are not considered in the current implemented classification system, it caused confusion in detection, as well as frustration for users.

The user study setup was not designed to detect the intensity of interactions, for example, how hard to Pinch or how fast to Twist. It led to confusion for participants who wanted to know to know how much force is needed in performing each interaction. P2 mentioned "getting used to material and knowing how much squeezing is needed for Pinch is challenging." We discuss below the challenge and opportunity of distinguishing intensity of an interaction.

10 DISCUSSION

Does it matter that Serpentine is self-powered?

The Serpentine sensor is a self-powered sensor, but for the purpose of this paper, we only used the output signal for gesture analysis and not for power harvesting to drive any computation or communication. All of the scenarios we implemented and showed to participants required some external power source to complete the recognition and actuation. Although the energy generated from this sensor may not be sufficient for complex computation tasks, it can be used

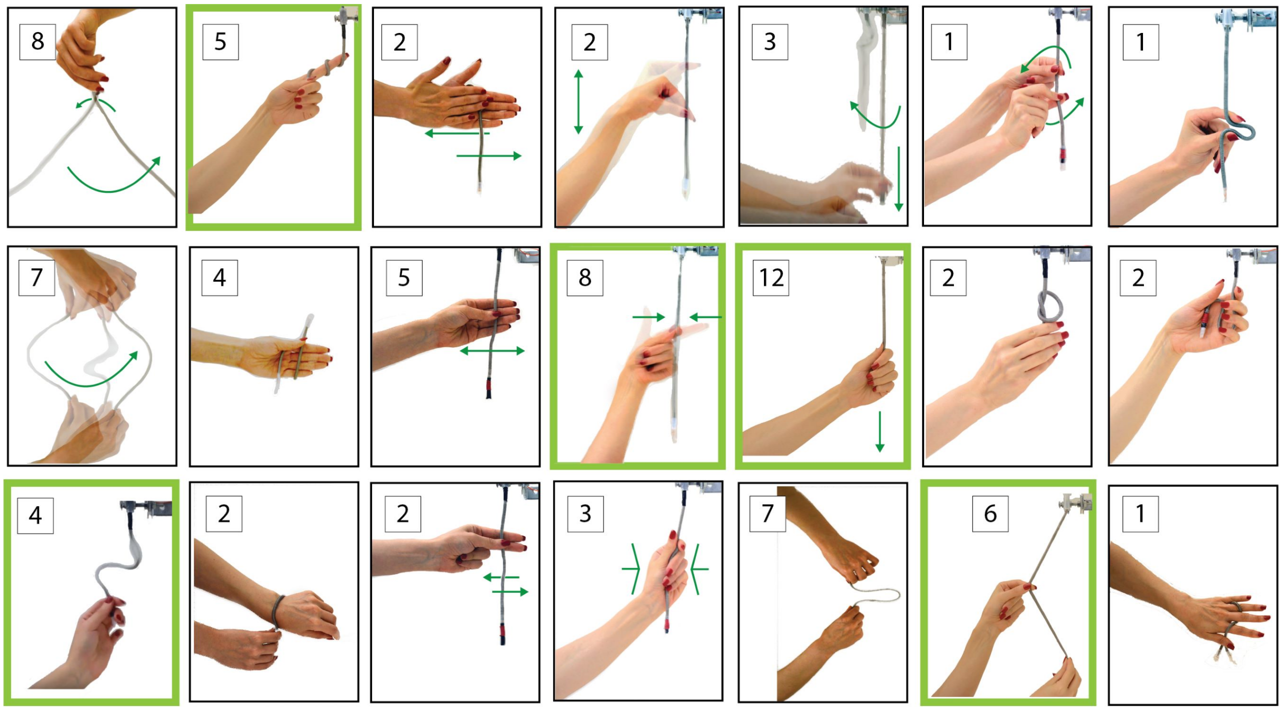

Figure 11: Various interactions suggested by the users in the beginning of the user study. A green border highlights interactions that we had implemented. Each interaction suggestion is numbered. The number in each figure shows the frequency it was suggested by 12 participants.

to relay the data wirelessly to a more complex system, thus producing a battery free input device. One way to achieve this is through analog backscatter [2, 41, 44].

The analog signal from Serpentine can be passed to the gate of a MOSFET to vary the impedance across the drain and source, where an antenna can be connected. Therefore, the analog signal will produce a variable impedance for the antenna, which in turn can modulate and reflect an incident carrier wave [9, 10]. In our initial experiment, we tested the pluck interaction by connecting Serpentine to BF1108F RF transistor and it showed promising results for backscatter communication in ISM band (915 MHz). In future we also plan to explore other transistors (like ATF-54143), to achieve communication through all proposed interactions. This communication technique allows for low power wireless communication for immobile sensor scenarios. For mobile use cases, we are exploring frequency modulation using a voltage-controlled oscillator; energy required for which, can be harvested from signal generated from Serpentine. If sensor output is encoded in frequency, the received signal will not change based on the sensor and receiver placement [36].

Interaction Design Parameters

We proposed and evaluated the recognition accuracy for six interactions with Serpentine. These six gestures only represent a small subset of all possible interactions that can be done with Serpentine. Indeed, our participants readily suggested many more interactions. The stronger contribution of Serpentine is as a platform for designers to think creatively of a broad range of natural and intuitive inputs for different situations. The potential for battery-free input allows the cord to be placed in many everyday situations.

One- or two-handed. Some interactions, like Pinch, can be performed with a single hand while other gestures, like Pluck, require two hands. Based on the application scenario, the designer can define one- or two-handed interactions. Use-cases like wearables where both hands may not be available for use at the same time can employ one-handed gestures. Scenarios like the slingshot game controller can be used with both hands. In cases where multiple Serpentine sensors can be made available, like the two strings on either side of a hoodie cap, one-handed interactions can be designed that can be performed by either hand or both simultaneously.

Configurations. Serpentine can be set up in multiple configurations when both ends are not fixed, when one end is fixed and when both ends are fixed. These configurations result in different interaction possibilities and can be chosen to suit the application setting. Some two-handed interactions can also be converted to one-handed interactions if both the ends of Serpentine are fixed.

Compound interactions. New interactions can be also developed as combinations of two or more interactions. The physical form-factor of the cord sensor affords combining gestures sequentially or in parallel. An example of a sequential compound interaction can be first stretching and then pinching. A parallel example would be stretching while pinching. During the user study, we noticed 4 participants unintentionally combining gestures like Twirl & Stretch, Pluck & Stretch, and Twist & Pinch when they were asked to perform Twirl, Pluck and Twist. Since our classification was not designed for such compound gestures at this moment, it caused some confusion in detection accuracy as well as user frustration.

Use of interaction context to reduce classification error. From our user study, we found out that certain interactions were confused by the classifier (e.g., Pinch and Twist). One reason for this is that the Twist gesture also requires the user to grasp the cord with thumb and finger, similar to a Pinch. Here, the accuracy can be improved but at the cost of eliminating simultaneous recognition of those similar interactions. In these cases, the context of interaction will need to constrain the user from performing one or the other interaction.

Intensity. The Serpentine sensor generates electrical signal proportional to net applied force on the sensor at any time. This means that along with a distinct temporal shape for the signal, the output signal may also differ in amplitude information between two different examples of the same class of interaction (i.e., a harder Pinch results in a higher amplitude of electrical signal detected). Figure 1 shows the different signals generated for increasing intensities of the same gesture. This aspect of the sensor can allow for more expressive inputs. For example, for the slingshot game controller, a harder pull can result in a longer throw.

Texture. Since Serpentine reacts to mechanical deformations, it can be covered with a tactile texture which can induce additional deformations [19, 22]. Further this texture can be made asymmetric such that a gesture in one direction can be differentiated from the same gesture in opposite direction, to distinguish, for example sliding up versus sliding down.

Stiffness versus electrical output

For Serpentine, the increase in frequency of interaction causes an increase in current, while an increase in stretch causes increased voltage. We measured the stiffness of a soft and stiff sensors through a quasi-static uniaxial tensile test (see Figure 12. The soft sensor is the one whose fabrication was described earlier and was used in our evaluation study. This sensor underwent 30000 loading cycles without any change in its sensitivity and its physical properties. The stiff sensor is made with a lower ratio of silcone:PDMS than the soft senor. Both sensors had equal initial length of 20 cm and all their design parameters except stiffness were the same. The stiff sensor tolerates a higher load, up to 26 (N) for 58 mm length extension before it breaks. The soft sensor reaches the equal extension length with less amount of force 12 about 4 (N) and does not break. The electrical outputs for each sensor are shown in Figure 13. These performance characteristics should be considered when determining what level of stiffness is desired for a given application.

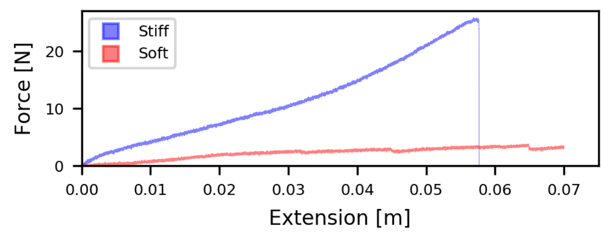

Figure 12: Elasticity measurement: Two solutions composed of different proportions of silicone elastomer to PDMS exhibit different elasticities. The Young's Modulus value (measure of elasticity/stiffness) for each is derived from the gradient of the plots in the figure above.

Limitation of Sensor and Study

There are some limitations in sensor fabrication, performance and study to consider:

First, Serpentine only generates a signal when it is undergoing manipulation. This means that only changing forces on the sensor can be recognized and not static forces. In terms of interactions, for example, the action of stretching the sensor can be detected momentarily. But if the sensor is kept in a stretched condition without any motion, it will not generate any signal output and hence the state would be undetectable. This limits the system only to interactions which involve continuous manipulation of the sensor.

Second, manual fabrication of the sensor is time-consuming and limits the scalability. However, there are solutions for automating the process in the future.

Third, in this study, we haven't gone through extensive study for sensor sensitivity versus variation of sensor length and diameter. Gomes et al. [16] has studied the influence of silicone layer thickness on the performance of PDMS-based TENGs. Dong et al. [13] with similar sensor design has conducted an extensive study on sensor characterization, durability and scalability.

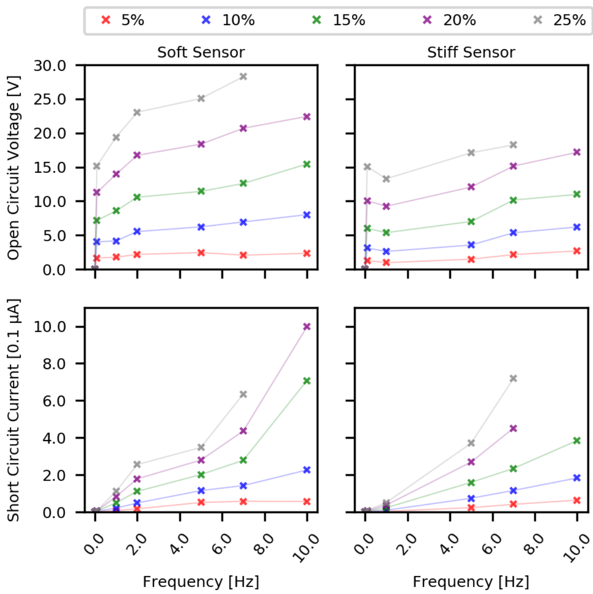

Figure 13: Comparison between soft and stiff sensors in terms of open circuit voltage and short circuit current.

Forth, for user study, the sensor hung vertically on a stand. Though appropriate for many use cases, such a set up does not simulate the wearable applications. In future, we will conduct an evaluation for false positive during on-body wear.

Future work

Increasing interactions. We presented Serpentine more as a platform for exploring and designing natural and tangible interactions that can be embedded into everyday settings. We tested a specific instance with a defined set of interactions, but as Figure 11 shows, participants suggested other natural interactions which can be more intuitive depending on the context and use cases. These and other interactions can be added to our input sensing system while our unintuitive gestures like Twist could be removed. Physical properties of sensor like stiffness could be customized to provide more affordance for radial gestures like Twist and Pinch.

Power and more fully self-sustaining solutions. Serpentine, as demonstrated, is only self-sufficient with respect to sensing. We have not explored using it as a power harvester, where the interactions generate energy to do more than the signal acquisition needed for classification. An important next step with this work is to explore ways to do either battery-free wireless communication, using techniques like analogue backscatter, or doing low power local computation on or near the Serpentine cord. The former example would result in a self-sustaining input device, and the latter in a self-sustaining computational object.

11 CONCLUSION

In this paper, we introduce Serpentine, a reversible deformable self-powered cord sensor capable of sensing natural human inputs. We outline the fabrication process of Serpentine and talk about the various design parameters. To demonstrate the novel ability of Serpentine for interaction detection, we conduct a user study with 12 participants and 6 interactions. We were able to achieve 95.7% accuracy with user-dependent and 92.17% accuracy for user-independent models. We later discussed user feedback about Serpentine and suggest design parameters for defining new interactions.

The materials used for Serpentine are relatively inexpensive, and the manufacturing process is not very complicated. This holds up the promise that self-sufficient computational materials like Serpentine could be manufactured at large-scale and low cost. These computational materials are a new way to think about the advancement of computing, marching in a different way closer to Weiser's initial vision of ubiquitous computing [48].

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