zPatch: Hybrid Resistive/Capacitive eTextile Input

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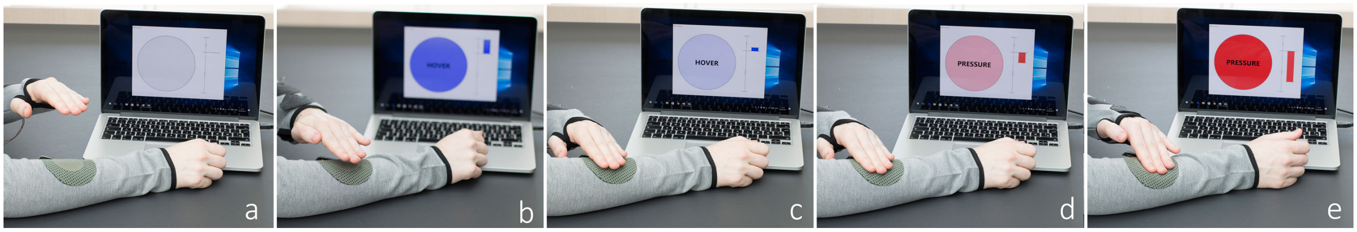

Figure 1 – Hand approaching and pressing a zPatch: (a) initially, the patch does not detect the hand, (b, c) as the hand approaches the sensor, hover is detected, (d, e) once the hand touches the sensor, the exerted pressure is reported.

ABSTRACT

We present zPatch: an eTextile patch for hover, touch, and pressure input, using both resistive and capacitive sensing. zPatches are made by layering a piezo-resistive material between silver-plated ripstop, and embedding it in non-conductive fabric to form a patch. zPatches can be easily ironed onto most fabrics, in any location, enabling easy prototyping or ad hoc modifications of existing garments. We provide open-source resources for building and programming zPatches and present measures of the achievable sensing resolution of a zPatch. A pressure based targeting task demonstrated users could reliably hit pressure targets at up to 13 levels, given appropriate feedback. We demonstrate that the hybrid sensing approach reduces false activations and helps distinguish between gestures. Finally, we present example applications in which we use zPatches for controlling a music player, text entry and gaming input.

Author Keywords

Hybrid Sensing, eTextile, On Body Input

ACM Classification Keywords

Human-centered computing~Human computer interaction (HCI) • Human-centered computing~User interface toolkits

INTRODUCTION

On-body input sensing has received much attention in HCI. For example, wearable sensors have been presented for mobile gesture input [34] and on-skin tracking has expanded the interaction space of smartwatches beyond the device [18]. These input techniques and technologies typically focus on lateral interaction across the body: Though taps, swipes and multi-touch may be used, it is their spatial distribution across the surface plane that received the most attention.

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When interacting on the body, pressure and touch-dynamics are especially interesting, as we perceive the interaction both with the active hand and the passive body part that is being touched [22]. The way in which we might interact with our body is also very likely to be more complex [42] than could be detected by a simple touch-position sensor.

We have therefore designed zPatches: small fabric sensor patches that can be sewn or ironed onto existing clothing. zPatches are designed to maximize sensing capabilities to capture the dynamics of on-body touch interaction. zPatches use a hybrid sensing approach: capacitive sensing enables the measurement of approach behavior and hover interactions, while resistive sensing provides robustness and high-resolution pressure measurements.

zPatches are designed to be simple to manufacture and deploy. This simplicity does not come at the cost of sensor performance: using both sensing modalities of a zPatches provides it with the ability to distinguish between different input gestures. Additionally their hybrid sensing approach can be used to reduce false activation problems [14] typically associated with fabric sensors.

zPatches are not only easy to build, but also simple to deploy. They can be sewn or ironed onto garments, allowing for individual customization. They can also be attached with safety pins for fast prototyping.

We make the following contributions: (1) a simple workflow as well as instructions and open source code for novices and experts to create similar textile sensors; (2) evaluations of the fidelity zPatch and a demonstrate of how hybrid sensing can reduce unintentional activation and improve gesture classification; and (3) example applications of zPatches, including a music player, text entry, and gaming.

RELATED WORK

We present an eTextile sensor that enables proximity-, touch-, and pressure-based input on the body. While touch, proximity [16] and pressure [31] have been explored in rigid devices, our primary interest is to develop a platform that allows for their transfer on to the body. Our research draws upon in eTextile sensing and craft, and is inspired by our proprioceptive, kinesthetic and tactile perception.

Haptic Physiology

Our body provides us with a rich feedback channel for touch interactions. We can sense the location of a touch within around 2mm for the hands and face and around 10mm on most other parts of the body [22,43]. The tactile sensitivity of the skin has been measured to be around 0.07g for the face and hands, ~0.4g for the arms, and ~1g for the legs [1]. We present a system focusing on the latter feedback channel. Additionally, we benefit from the proprioceptive resolution of our body in understanding how our limbs are arranged relative to each other [19]. This may be of advantage for on-body hover interactions.

On-Body Sensing in HCI

Much of the existing on-body input research has focused on interacting around smartwatches (e.g.,[20]) as they provide both close-by visual feedback and a convenient housing for sensors. Prototypes have demonstrated the feasibility of IR sensors [18,24,36], capacitive touch [23], magnetic techniques [10], as well as approaches that send electrical [45] or ultrasonic [21] signals through the body for on-body input around smartwatches.

Further work has explored camera-based tracking for interaction [35,40]. Harrison demonstrated a device that allowed tapping input on the skin [12] and using computer vision expanded this work for general on-body input [11].

Others have moved interfaces even closer to the body by integrating sensing capabilities in make-up [7], beauty products [39], or temporary tattoos [38]. The latter were also explored by Weigel et al. [41], who demonstrated a series of applications for thin devices worn on the skin.

Our work situates itself in yet another approach to on body input: integrating sensing capabilities in the textiles of our clothing.

eTextile Sensors

Clothing provides a convenient location for sensor placement. This has led to the integration of various sensors into fabric, including stretch [37], biometric [25], touch [26,30], pressure [6], and even optical sensors [13]. Most eTextile approaches however are based around either capacitive or resistive sensing.

Capacitive eTextiles

A fabric keypad was one of the earliest demonstrations of capacitive eTextiles [26]. GesturePad presented a similar concept to demonstrate capacitive sensing around the body [32]. More recently, with Project Jacquard, conductive threads have been woven into textiles [30], enabling mass manufacturing of capacitive sensors. Indeed, this technique has already been used in a first product, in the form of a Levi's Jacket [47].

While these systems can be used to detect hover or near-sensor in-air gestures, they are primarily used for touch detection. A notable exception is work by Cheng et al. [3] which measures changes in the capacitance of the human body to infer the user's movements. We expand upon this work by exploring gestural input above the sensor.

Resistive eTextiles

More recently, pressure sensitive fabrics have also gained attention. For example, Roh et al., Donneaud et al., and Zhou et al. have explored pressure sensitive textiles, but primarily on rigid surfaces [5,33,46]. Although their sensing abilities are promising, research has shown the performance of users interacting with sensors worn on the body to be half as fast than on a rigid surface. Users cited task completion strategies that included 'holding ones breath' [14].

Parzer et al. demonstrate a general purpose elastic textile sensor for input on furniture, and show its applicability to the body [27]. Wearable pressure sensors have also been explicitly designed for on-body gesture input on the arm [34] thigh [14]. Here, however, pressure was used to infer touch position. Yoon et al. present a finger-worn textile used for gesture detection. Parzer et al. [28] also expand on the typical gesture vocabulary by adding fabric-deformation gestures. Continuous pressure as an input modality for eTextiles on the body has, however, received comparatively little attention. We add to this work by exploring this pressure dimension.

Robust and Hybrid Sensing

We use the term 'hybrid sensing' to describe sensors that combine two distinct information channels. This can provide additional information about dynamics of movements, or improve the robustness of the sensor [8]. Such a hybrid textile was presented by Wicaksono and Paradiso [44]. Using seven functional and two layers of non-functional fabric, they measure up to four modalities simultaneously.

Hybrid sensing was also used in iSkin to distinguish between two levels of pressure input [41]. A similar approach was used in the 'one button recognizer' to distinguish between different people based on button-push-dynamics [29]. Hybrid sensing has applications beyond improving input-resolution – an alternative use was presented by Freed and Wessel who demonstrated that hybrid sensing could improve robustness to electrode deterioration [8].

Robustness is a limitation of current fabric sensors. For example, Heller et al. [14] demonstrated that task completion time doubled when a soft sensor was moved from a flat surface on to the body. Heller and others also presented systems such as Pinstripe [17] and Grabrics [2] which bypass this problem by requiring explicit pinch or rub gestures.

Hybrid sensing helps us address the robustness problem noted by Heller [14]. Hybrid sensing also enables us to infer additional information about the input gesture, similar to the work by Pohl et al. [29] and as suggested by Cheng et al.[4]. Finally hybrid sensing enables combined touch and hover interactions [16] using zPatch.

WHAT IS A ZPATCH?

A zPatch is a thin, soft, iron-on textile patch, similar to patches used to cover a torn garment or show off one's favorite band (Figure 2). zPatches provide users with an input channel to control an app on their phone or a remote IoT device with their day-to-day clothing. We envision a user might buy a 10 pack of zPatches and iron them on their jacket, backpack, or jeans. The user would then train it to detect a set of gestures of their choosing. This supports novices to effortlessly augment their clothing and customize their input methods.

zPatches can either have a single sensor (as seen in Figure 2) or a sensor cluster (Figure 6, Figure 12c). A single sensor zPatch already supports a rich set of interactions. It provides capacitive proximity and resistive pressure sensing, with which complex gestures can be built through temporal patterns of interaction.

A zPatch with a cluster of sensors (Figure 6, Figure 12c), or multiple zPatches placed in proximity of each other (Figure 12a, b), provide a three-dimensional interaction space – adding the opportunity of spatial interaction in the x and y dimension in addition to the temporal patterns of approach behavior and pressure.

Benefits of zPatch design over Similar Sensors

a) Low Complexity

zPatches use two analog input pins and require no additional hardware. Thus, the mechanical and electrical complexity is low. This enables easy incorporation of zPatches into garments and simple interfacing to existing microcontroller platforms.

The manufacturing technique used for zPatches is less complex than yarn-based approaches, such as Jacquard [30], but can still be used to achieve professional-standard results [9]. Compared to Wicaksono's eTextile keyboard [44], the approach presented in this paper uses 3 functional fabric layers instead of 7, increasing its robustness and making it easier for novices to replicate.

b) Resolution in the Z Axis

Various pressure based textile sensors exist in the research [14,27,34] and DIY community [5,15]. These sensors are typically used to infer the location of pressure events. zPatches do not provide position information, however, unlike most existing solutions they are optimized for interaction along the z Axis.

c) Continuous Hybrid sensing in a Soft Circuit

Freed et al. [8] and Pohl et al. [29] presented rigid hybrid sensors that capture continuous input. Unlike their implementations our sensors are soft and can easily be integrated into garments. The on-skin sensors by Weigel et al. provide a similar soft form factor, however they do not offer the continuous proximity and pressure sensing of zPatch.

Figure 2 - A pack of zPatches with regular Denim patches in the background.

d) Improved resistivity to noise and improved gesture detection through Hybrid Sensing

Hybrid sensing provides the potential for discarding many forms of false activation. Typically, one would expect input from the two data sources to be correlated (Figure 3, compare also Figure 9). If they are not correlated, one might discard such activation as noise: for example, if one bumps into an object the resistive sensor is triggered, but without finding the expected approach behavior in the capacitive readings.

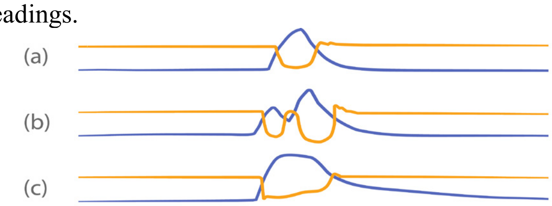

Figure 3 – Typical readings for (a) single-tap, (b) double-tap, (c) slow release. Resistive measures are yellow, capacitive blue.

While correlated, the two signals measure different things: Capacitive sensing captures the release and approach behavior, while pressure sensing provides an accurate measure once the sensor is touched. When attempting to distinguish between different input methods, this can be of advantage (Figure 3). For example, a regular tap (Figure 3a) can be distinguished from a tap where the finger lingers after the action is completed (Figure 3c). Actions with a temporal pattern (such as a double tap) can easily be identified on both sensing channels (Figure 3b).

BUILDING ZPATCH

The design of zPatches and the code used are open source. Here we present a quick overview. In depth documentation can be found online. Links to step by step instruction and code are available on the projects GitHub repo[1]

[1] https://github.com/fkeel/zPatch

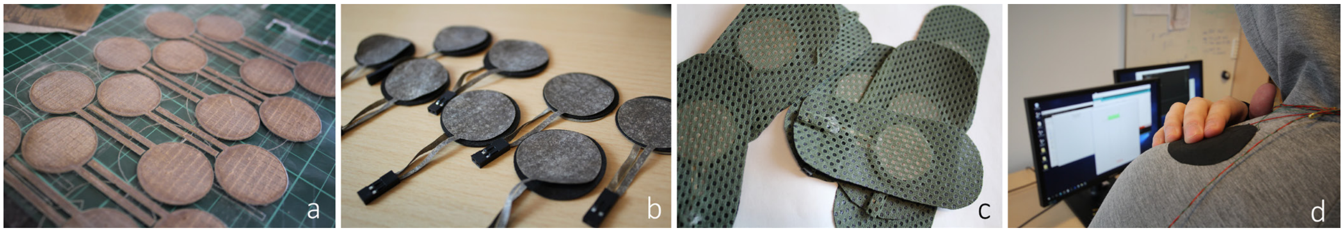

Figure 4 – (a) Laser-cut conductive fabric, (b) assembling the sensor, (c) fusing the textile to form a zPatch, (d) zPatch in Action.

Materials

zPatches are designed with simplicity and versatility in mind. They are simple to construct using a layering technique (as seen in Figure 4a-c).

zPatches use 3 materials (Figure 4a-c and Figure 5): The center layer of a sensor consists of non-woven resistive fabric by Eeonyx (20kΩ/□). Mechanically it behaves similarly to very dense felt. Electrically it is piezo-resistive: when compressed, its resistance decreases.

Figure 5 – Cross Section of zPatch

The resistive material is sandwiched between two conductors made of ‘Bremen’ ripstop by Statex, a silver-plated polyamide fabric with < 0.3Ω/□ surface resistivity. The conductive fabric is crimped to standard headers.

For mechanical stability, these three layers are encased in non-conductive textiles. Any non-conductive textile can be chosen, allowing the sensors to be tailored to the target garment. To optimize our sensors, we chose a very thin polyester mesh as the top layer (visible in Figure 5c). The mesh allows direct contact between finger and conductive material. This improves the robustness of touch sensing, and allows visual inspection of the underlying electrodes. The sensors also work with non-mesh material. We chose a relatively strong cotton fabric as a backing, to provide structural support and to lift the sensor off underlying skin.

The individual layers are heat-bonded: A sheet of double-sided fabric glue (interfacing) is placed between the layers one wishes to fuse, and subsequently heated and compressed using a household iron. Note that there should be no glue between the resistive and conductive materials, because this degrades the sensor performance.

Process

Sensor layouts can be designed in any vector-based application (we used Adobe Illustrator). Those designs are laser-cut on an Epilog Helix 60Watt laser cutter (Figure 4a). The Eeonyx resistive material was directly placed in the laser-cutter without any special preparations and cut at 50% speed, 9% power and 5000Hz.

The conductive ripstop was first fused to a layer of double sided interfacing which is fused to wax paper. The wax paper was then glued to an acrylic sheet. This made the conductive material act rigid, dispersing worries of the airflow in the laser-cutter moving it while it is being cut. Here, we set the power of the laser-cutter to slightly engrave the acrylic underneath (50% speed, 20% power, 5000Hz).

Once cut the conductive material can be simply peeled off the acrylic. The laser-cutting process has the additional benefit that it seals all the cuts, preventing the fabric from fraying. This makes the fabric easier to work with than it would be if cut by a knife or scissors. Once all materials are cut, crimp connectors are added, the materials are fused together, layer by layer using double sided interfacing.

Configuring the microcontroller

zPatches have two symmetrical connectors – the orientation with which they are attached to a microcontroller is irrelevant, if both are connected to analog input pins. zPatches work by taking advantage of the multiple ways a microcontroller pin can be configured. The pins are configured to measure capacitance[2] and resistance alternatingly. Code examples ready to upload to an Arduino can be found on our GitHub page[1].

Multi-Sensor Synergies

zPatch configurations with more than two electrodes are also possible. In fact, combinations allow for increasing the spatial resolution beyond their sum: Figure 6a and 12c shows a layout in which four electrodes allow us to infer pressure from nine locations, based on common activation.

Flexibility with pin-configurations allows us to minimize complexity of such sensors. For example, the four electrodes shown in Figure 6a, can be pulled low sequentially and the voltage can be measured by a shared electrode at the bottom. In the depicted setup (also seen in Figure 12c),

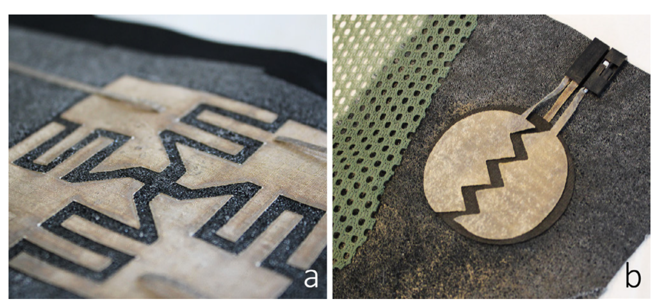

Figure 6 – (a) 4 sensors used to generate 9 touchpads as used in our text-input demo and (b) differential pressure sensor as used for our music-player demo.

[2] Code adapted from http://playground.arduino.cc/Code/ADCTouch

pressure can be measured at nine locations with a single analog input – however as all electrodes are electrically connected they act as a single capacitive sensor.

The layout in Figure 6b (also seen in Figures 12a and 12b) enables differential pressure sensing. By connecting the two visible electrodes to +5v and GND and reading from the bottom electrode, we measure 2.5v. If a finger is placed in the center of the zPatch, that voltage does not change (though we can detect the finger's presence through the capacitive readings. If the finger is rolled towards the positive or negative electrode the measured voltage will rise or sink accordingly.

EVALUATING ZPATCH

We conduct a range of evaluations of zPatch. First, we report on the sensing resolution of zPatches. Consequently, we report initial findings of a targeting task. We demonstrate that, with this resolution, we can support multi-item menu selection with pressure alone. Finally, we demonstrate that hybrid sensing improves the performance of a Random Forest algorithm for gesture classification and false positive reduction.

Sensor Performance

Resistive Sensing

We placed weights on our sensor to better understand how it reacts to pressure changes. We found the sensor could detect pressure of < 1.38 Pascal (5g with 3.5cm^2 area). We incremented the weights until 829 Pascal (3kg with 3.5cm^2 area) and found that between ~10 Pascal and ~275 Pascal the change in weight had an exponential relation to the change in resistance (R^2 = 0.95). Readings were inconsistent below, and flattened out above this range.

Capacitive Sensing

We placed and calibrated a zPatch in 3 positions relative to a user, to measure the signal response to the user's open palm. The zPatch was taped directly on the user's left arm (Figure 7, blue), attached to the left arm of a hoodie worn by that user (Figure 7, orange) and placed on a table in front of the user (Figure 7, green). We fixed the position of the left arm and varied the position of the right palm with a plexiglass spacer. Once the sensor was placed in its intended position we set the current capacitive reading as its baseline. We then measured the signal when the right palm was 0.2, 0.5, 1, 1.5, 2, 3, 4, 5, 10 and 20cm away from the zPatch. Figure 7 shows 50 samples of each combination of position and distance. The samples represent change in capacitance from the baseline.

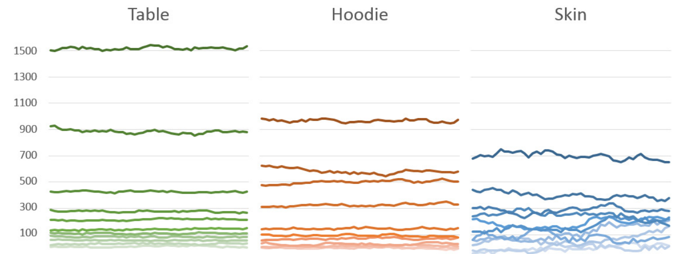

Figure 7 – 50 sample measures at 0.2 (darkest), 0.5, 1, 1.5, 2, 3, 4, 5, 10 and 20cm (lightest). Y axis is the change in capacitance, as measured using the code we provide.

Our measurements show that proximity to the skin impedes the sensing capabilities of the sensor. Additionally, when placed directly on the body, the signal becomes extremely sensitive to the slightest movements of the textile relative to the body, as seen in Figure 7 on the right. The change in response based on placement makes it difficult to correctly infer proximity. The size of the sensor influences the ability to sense proximity as well - the larger the sensor area, the more sensitive it becomes. However, while the absolute readings of the capacitive sensor are inconsistent, even when placed directly on the skin, hover and approach *dynamics* are observable.

Input Performance

While we assume the primary use of capacitive sensing will be in hover detection and gesture classification, we speculate that on-body pressure input could also be used for navigating menus and target selection. We therefore present an evaluation of user input performance in a targeting task.

We recruited 11 participants (all students, 1 female. Age: M = 26.5, SD = 5.24) for a targeting task (Figure 8a). Participants wore a hooded jacket with 8 integrated sensors (stomach, wrist, biceps, sternum, shoulder, back of hand, palm, and temple). They were shown a 700 pixel vertical linear

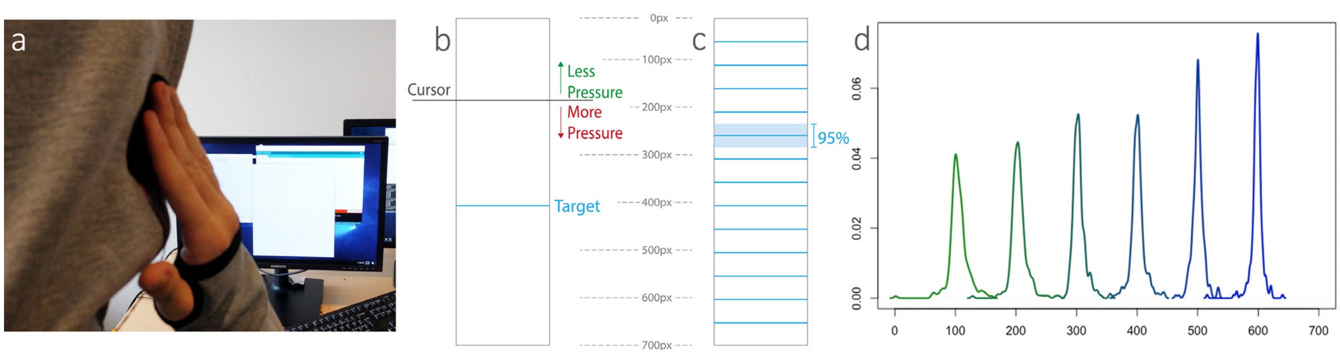

Figure 8 – (a) participant during the experiment (the UI was shown in front of them on a screen) (b), interface presented to user with single target, (c) target positions as calculated based on observed distributions (if users were to aim for the 5th target, we would expect 95% of all hits to fall within the highlighted area), (d) density plot of all observed distributions by target.

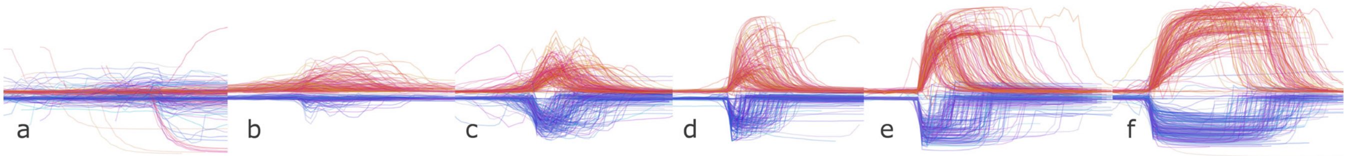

Figure 9 – Raw data sorted by class: (a) noise, (b) hover, (c) swipe, (d) gentle tap, (e) strong tap, (f) push. Reds are capacitive measures, blues are resistive measures. For visualization purposes measures are aligned so that the largest negative change in resistance lines up. Consequently, the average of the first 5 readings was set to zero, per measure type. Finally, resistive and capacitive measures were slightly vertically offset to reduce overlap. Each image shows 200 measures per sensing method.

slider. The cursor of the linear slider had its resting state at the top, and it moved towards the bottom with increasing pressure (Figure 8b). Participants were shown one-pixel targets and were instructed to move the cursor to the target as fast and precisely as possible.

We linearized the output of the sensor, and then calibrated each sensor per participant: We asked each participant to provide us with a minimum pressure (gentle touch) and their maximum comfortable pressure. These were set to the values 0 and 700. Pressure levels in between were mapped to the 700 point range proportionally, corresponding to the 700 pixels of the vertical slider. 6 targets were placed with 100 pixel distance from minimum, maximum and each other. Participants repeated each target 3 times

We collected a total of 1584 (11 *Participants* × 8 *Locations* × 6 *Targets* × 3 *Repetitions*) measures as offsets from their intended target and found that, on average, participants missed the target by 8 pixels (M = 8.95, SD = 9.56). Participants tended to overshoot (M = 9.00, SD = 9.88) more than undershoot (M = 6.55, SD = 8.38). Figure 8d shows the density functions of all trials by targets.

Based on our observed distribution of targeting offset, we calculated that we could correctly classify 95% of all trials if the targets were placed every 50 pixels (Figure 8c), 98% with a spacing of 73 pixels and 99% with targets every 85 pixels. Dividing the total pixel range by the calculated target spacing suggests that our sensor can accommodate 13, 8 or 7 targets, depending on acceptable classification error.

Our initial evaluation leaves many questions regarding the psychophysics of pressure perception and human input, as well as gender variation regarding on body interaction unanswered. While more detail is beyond the scope of this paper, we hope that future research will investigate these questions. The current study demonstrates that zPatches can be a useful tool for such explorations.

Hybrid Sensing to Improve Robustness

We imagine that if zPatches were a product, the included software might allow users to train the patch to recognize a set of gestures and how they perform them. To demonstrate that hybrid sensing can help reduce false activations and improve gesture recognition, we implemented such a system. We roughly follow an approach presented by Pohl et al. [29]. Note that we merely use machine learning as a demonstration of the benefits of hybrid sensing, the following example is by no means optimized.

Data Collection

We collected data from 10 participants. They were given a box that had a sweater tightly stuffed inside. The sweater had a zPatch attached. Participants followed instructions presented on a laptop screen. The data was collected in three phases:

1) Participants removed the sweater from the box and depending on condition either wore it or placed it on a table. During this period 'noise' was recorded. 2) Participants were then instructed to perform either a *hover*, *swipe*, *gentle tap*, *strong tap* or *push* gesture. Participants performed each gesture 10 times, whenever the screen changed color. In between these explicit inputs a random number of 2 to 4 'noise' trials were recorded. These were used to add additional variation to the 'noise' class. 3) Participants were instructed to place the sweater in the box. During this period additional 'noise' data was recorded.

This process was repeated 10 times, so that all 5 input types were performed both on the body and on the table. Participants did not receive any training or specific instructions on how to perform the gestures. Data was continuously recorded and split into 60 sample frames which were labeled according to when they were measured.

Raw Dataset

This resulted in an intentionally noise dataset containing many 'false activations' from moving the sweater. The 'hover' gesture was included to have an edge case which we anticipated to be difficult to detect. The 'swipe' gesture was included to see if lateral movement could also be captured through the approach behavior. All gestures were designed to be relatively similar – as opposed to, for example, comparing single- and double-tap.

We trimmed the dataset to 400 measures per participant, of which ~300 were 'noise' and the remaining ~100 were evenly distributed among the remaining classes. Each measurement contained 60 resistive and 60 capacitive samples. A visualization of the raw data[3] can be found in Figure 9.

Features & Final Datasets

We chose to extract 7 features describing the signal envelope: *Attack* (max change between two readings at begin of touch), *Release* (max change between two readings at end

[3] The data can be found at https://github.com/fkeel/zPatch/tree/master/data

RESISTIVE

classified as -->	Noise	Hover	Swipe	Gentle Tap	Strong Tap	Push
Noise	**2908**	27	23	11	5	6
Hover	139	**63**	0	1	0	0
Swipe	49	0	**133**	24	0	0
Gentle Tap	33	1	28	**133**	5	1
Strong Tap	10	0	2	6	**171**	12
Push	19	0	0	2	8	**179**

CAPACITIVE

	Noise	Hover	Swipe	Gentle Tap	Strong Tap	Push
Noise	**2935**	10	13	11	5	6
Hover	56	**137**	5	4	0	1
Swipe	15	3	**162**	19	5	2
Gentle Tap	13	7	19	**147**	13	2
Strong Tap	6	0	2	10	**173**	10
Push	10	0	2	4	6	**186**

HYBRID

Noise	Hover	Swipe	Gentle Tap	Strong Tap	Push	<-- classified as
2943	5	16	6	5	5	Noise
53	**144**	3	3	0	0	Hover
17	2	**173**	14	0	0	Swipe
16	3	14	**160**	5	3	Gentle Tap
6	0	2	6	**177**	10	Strong Tap
10	0	3	2	5	**188**	Push

Figure 10 – Cumulative classification results using Random Forest and 10 fold cross validation on each participant, by dataset.

of touch), *Sustain* (distance in samples between attack and Release) and *Maximum, MaxTime* (distance in samples between attack and Maximum) *Minimum* and *MinTime* (distance in samples between attack and Minimum).

We created a dataset using only resistive measures, a dataset using capacitive measures and a 'hybrid' dataset which contained both sets of features (all 'distance' measures were put in a shared frame of reference) additionally we added the difference between the resistive and capacitive measures as features.

Results

We used Random Forest in Weka (with default settings) to classify the data. We validated our approach per participant using 10 fold cross validation. The weighted F-Measures show that the resistive data performed worst followed by the capacitive data while the hybrid data performed best (see Table 1).

We were particularly interested in the effect of the datasets on the instances of false activation, specifically, noise classified as a gesture. We found the most instances of noise classified as a gesture in the resistive data (M: 7.2, SD: 3.42) followed by the capacitive data (M: 4.5, SD: 2.16). Again, the hybrid data performed best (M: 3.5, SD: 2.57). Figure 10 shows a confusion matrix of the sums of results.

To see if the results would generalize to new participants, we re-analyzed them as a whole, again using 10 fold cross validation. This time the data was split such that each fold trained on nine participants and tested on the tenth. While the results were less convincing then for the per-person training, we observed the same trends and the data generalized relatively well, weighted *F-Measure* were 0.84 for the resistive data, 0.86 for the capacitive data and 0.89 for the shared data.

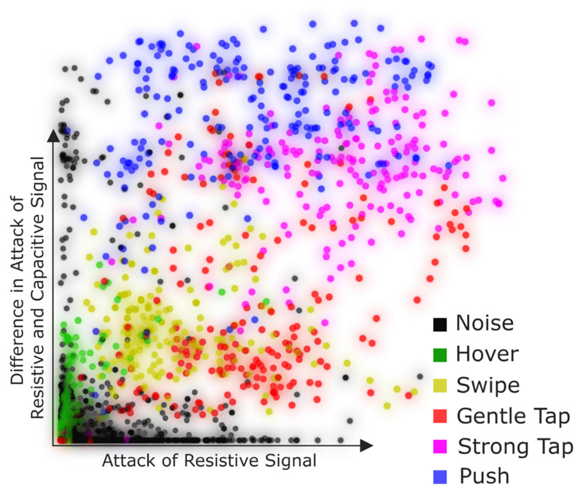

Figure 11 – Scatterplot of two features on complete dataset

	W. F-Measure		Precision		Recall	
	Mean	SD	Mean	SD	Mean	SD
Resistive	**0.89**	*0.03*	**0.89**	*0.04*	**0.90**	*0.03*
Capacitive	**0.93**	*0.01*	**0.93**	*0.01*	**0.94**	*0.01*
Shared	**0.95**	*0.02*	**0.95**	*0.02*	**0.95**	*0.02*

Table 1 – Summarized results of per person cross validation

DISCUSSION

zPatch is a hybrid sensor, providing both resistive and capacitive measures. Viewing the raw-data output we receive from either channel, the resistive readings immediately appear useful, we demonstrate participants can select from 13 pressure levels with 95% accuracy. The capacitive readings on the other hand are 'all over the place'. The extent to which their output varies based on context is a clear limitation of their utility as a continuous, absolute input channel. If we focus on discrete rather than continuous input, the situation changes. When classifying gestural input, the capacitive sensing outperforms the resistive sensing.

What we wish to demonstrate, however, is that the two approaches are complimentary and that best performance is achieved by utilizing the hybrid nature of zPatch. It should be noted that hybrid sensing not only benefits from additional data, but that the relationship between the resistive and capacitive measures provides additional information not contained in either data source. For example, using correlation based feature selection, three of the top five predictors of our 'hybrid' dataset were the *Difference in Sustain,* the *Difference in Attack* and the *Distance between Attack* of the two signals. The remaining two were *Attack* of resistive measures and *Release* of capacitive measure.

The benefit of adding the difference in signal as feature can be seen in Figure 11. While *Attack* (x-axis) is the strongest predictor of the resistive measures, it alone still does not lead to a strong result. Paired with the *Difference in Attack* (y-axis) we can see clear clustering in the data.

Figure 12 – (a, b) Audio player with gestural interface, (c) sweatband for spatial and pressure input for smartwatch, (d, e) users improvising on-body based interactions by pinning zPatches on various body locations for gaming.

APPLICATION SCENARIOS / DEMOS

We present three demos of zPatches in use. All sensors were sampled using Arduino Nanos, the data was received and processed by a C# application, and events were forwarded either to custom iOS applications or in the form of system-level input events (e.g., key presses/mouse clicks). Please refer to our Video Figure for full demonstration.

Combining Multiple Input Modalities

To demonstrate how multiple input modalities can be combined, we present a music player using two zPatches placed on a hat. Each zPatch features a differential sensor (see Figure 12a, b). Playing, pausing and stopping the currently selected song is controlled by hover gestures: to pause music (and thus hear the environment), users simply raise their hand to their ear; to resume the music, they then lower the hand again; to fully stop the music, they instead move their hand backward.

Controls for volume (front zPatch) and track selection (back zPatch), are based on pressure input. Differential pressure sensing, through rolling the finger forward or backward, allows for adjusting values: rolling the finger forward increases volume/skips to the next track, and rolling it backward does the opposite.

Interpolation & False Positive Removal

To demonstrate a) capacitive sensing for avoiding false activation, b) interpolated pressure sensing and c) item selection using pressure for navigation, we present a sweatband that can be used to provide text input for a smartwatch. The sweatband has a zPatch with a cluster of four sensors (2×2 matrix), which allows for nine discrete touch areas (i.e., buttons in a 3×3 grid) by sensing touch and pressure on different combinations of patches (see Figure 12c). We present a multi-tap[4] text entry variation: users select letters by adjusting the pressure level. The currently selected character is shown on the smartwatch. Once users are satisfied with their selection, they quickly release the pressure.

When putting on the sweatband or when the sweatband is in contact with other objects, changes in pressure are measured. We can distinguish between such pressure and intentional input through the secondary information provided by capacitive sensing - character selection is only possible when a touch is also present.

[4] https://en.wikipedia.org/wiki/Multi-tap

Easy customization

To show off the ease with which zPatches can be used to prototype interactions, we present a gaming scenario: Users can customize gaming experience by changing the location of zPatches. For example, mapping a steering mechanism to zPatches attached to a user's socks dramatically changes both the difficulty of the game and the attentional focus of the player.

We designed a system for controlling applications on a large display. We used a Unity sample (SpaceShooter[5]) to demonstrate our approach. We use three zPatches: one controlling the firing mechanism, and two for steering the spaceship left and right. Placements were chosen ad-hoc while filming. The first setup used zPatches on either shoulder (for steering left and right - see Figure 12d), and one zPatch in a sock underneath the foot to trigger firing. Another setup explored the firing mechanism attached on the chest (Figure 12e), and one zPatch for steering underneath each foot.

CONCLUSION

We presented zPatches: iron-on eTextile patches with hybrid resistive/capacitive sensors that capture multiple sensing modalities. This enables us to design general purpose sensing patches that can be used for various interaction techniques. We also demonstrated the fabrication process and strategies for combining individual sensors to create clusters with more complex functionality. We presented an evaluation showing that approach behavior can be detected even if the zPatch is placed directly on the skin and that, given appropriate feedback, pressure can be used to select from up to 13 targets using our sensor. We also show that the hybrid sensing approach improves the ability to distinguish between gestures and can reduce false activations. Finally, to demonstrate the versatility of zPatches, we presented three example applications.

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