Botential: Localizing On-Body Gestures by Measuring Electrical Signatures on the Human Skin

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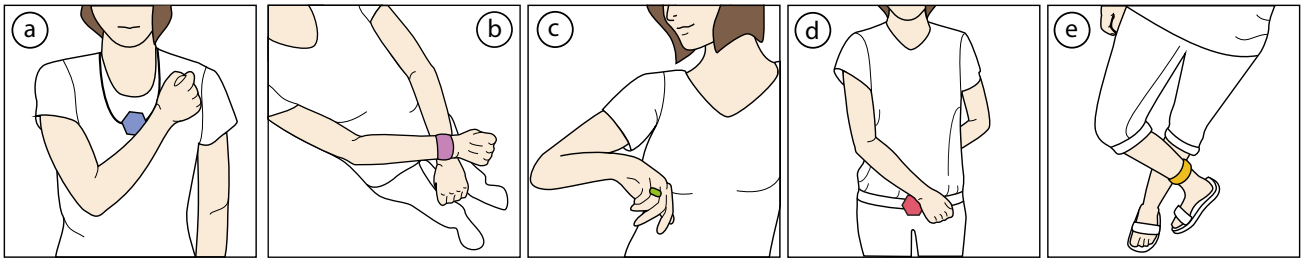

Figure 1. *Botential* leverages the entire human body as an interactive surface, while enabling the identification of tap gesture locations on different body parts and a hovering through the clothes. It is conceivable to integrate this technology with various wearable objects, such as a) Necklace b) Bracelet c) Ring d) Belt and e) Legband.

ABSTRACT
We present *Botential*, an on-body interaction method for a wearable input device that can identify the location of on-body tapping gestures, using the entire human body as an interactive surface to expand the usually limited interaction space in the context of mobility. When the sensor is being touched, *Botential* identifies a body part's unique electric signature, which depends on its physiological and anatomical compositions. This input method exhibits a number of advantages over previous approaches, which include: 1) utilizing the existing signal the human body already emits, to accomplish input with various body parts, 2) the ability to also sense soft and long touches, 3) an increased sensing range that covers the whole body, and 4) the ability to detect taps and hovering through clothes.

Author Keywords
Embodied Interaction; On-Body Interaction; User Interface; Hands-free; Eyes-free; EMG; Capacitive Sensing.

ACM Classification Keywords
H.5.2 [Information interfaces and presentation (e.g., HCI)]: User Interfaces — Input devices and strategies.

INTRODUCTION
A number of previous research [17,19,24] have demonstrated the advantages of leveraging our own body as input device for human-computer interaction, which is defined as On-Body Interaction [18]. While mobile devices usually have a very limited interaction space, using our body as an interactive surface has the advantages of being more accessible, offering a relatively larger input footprint (up to two m^2 of interaction space [5, 29]), and the ability to support eyes-free interaction based on proprioception [23], i.e. the sense of our own body's configuration in space. Researchers have proposed a number of approaches to sense on-body inputs from a distance, such as using optical tracking [14,17], or by having the sensing device in direct contact or connection with the body parts, as in Skinput [19] or Touché [33]. Each of the above approaches has its own advantages but also some constraints. For example, optical tracking is affected by lighting conditions, and acoustic sensing has difficulties in detecting soft and thus silent touches. Capacitive sensing has been used to detect different types of touch events, but not to reliably distinguish the different parts of our body.

In this paper, we propose *Botential* (*Body Potential*), a novel interaction technique that senses electrical capacitances and potentials of different body areas when being in touch with the input device. This alternative way of sensing can complement previous approaches and improve mobile interaction. Instead of using the human body as an interrupter [3] or receptor [8], we treat it as an emitter and enable for the following benefits:

- Identifying the location of taps on the entire body without driving an electrical current through the body.
- The ability to sense soft and long touches and an increased sensing range per sensor unit.
- Supporting a number of techniques for eyes- and hands-free interaction to allow different tapping and hovering gestures even through clothes.

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In the following sections we explain the theoretical background of the electrical properties of human cells, methods of measurement, and our developed prototype. To gain insights, on how such system performs in terms of accuracy, we furthermore conducted an evaluation with 10 users. Besides the technical contribution, we envision an interaction concept, conduct a field study, and discuss how this concept could possibly be applied and embedded into wearable devices to enable eyes- & hands-free interaction.

BOTENTIAL

Botential leverages a unique electrical signature, measured on the bare skin, to provide concrete information on which part of the human body is being touched with the sensor.

As a proof of concept, *Botential* is realized using a simple off-the-shelf EMG prototype sensor to measure tiny voltage on the skin caused by the negative potential of cells, which slightly varies across body parts. Due to the prototypical nature of this sensor, we additionally require the support of a capacitive sensor (CS). Frequency based capacitive sensing provide additional information on the virtual capacitance of the skin and the underlying tissues. Nevertheless, with a high quality clinical EMG device there would not be the need for capacitive sensing, as both the resolution and reliability of the system can be significantly enhanced.

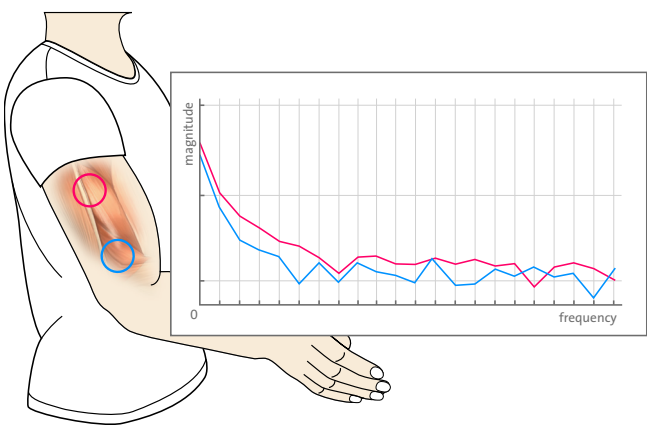

Figure 2. Illustrating the measured signal spectrum at specific areas. The red/blue lines in the graph represent the signal measured from the red/blue areas.

Background and Theory

In contrast to nonliving objects, in living animal and plant cells we can commonly find electric potentials caused by an imbalance of ions between the two sides of a cell membrane [21]. Literature defines two types of electric potentials that can be detected in our body: the relatively static membrane potential called the *resting potential* (or resting voltage), and the specific dynamic electrochemical phenomena called *action potential*, which occurs in excitable cells, such as neurons, muscles, and some secretory cells in glands [12]. While action potential occurs when tensing a muscle, the resting potential is always present and can be also found in any other tissue. Furthermore, it has 2 important properties:

1. *Resting potential is different at each part of our body.* For example, the resting membrane potential for skeletal muscle cells is approximately -95 mV and for smooth muscle cells is -60 mV; our neurons have a resting potential of -60 to -70 mV [21]. The differences in the body's anatomical and physiological structure result in unique resting potentials in almost every part of our body, as illustrated in Figure 2.
2. *The magnitude of resting potential is relatively stable over time and against stimulation, since it is determined by the cells' static properties* [21]. When an excitable cell is activated, e.g. when contracting a muscle, it quickly accumulates a positive action potential. It can increase up to 100 mV, and then discharges in a few milliseconds. This is followed by a very low fluctuation (~1 mV [36]) of the resting potential.

Sensing Methods

Electromyography (EMG) is a common way to measure such electrical potentials. There are two fundamental measurement techniques: the invasive setup with needle electrodes and the non-invasive setup that directly places the sensors in contact with the bare skin. Particularly when measuring in a non-invasive way on the surface of the skin, the measured signal could contain strong noise accumulated during the propagation of the actual signal through different tissues in the body. The noise received by the EMG sensor can be typically caused by *Causative Factors*, *Intermediate Factors* and *Deterministic Factors* [26]. For us the causative factors are more relevant, because they directly affect the signal, and can be further divided into *Extrinsic Factors* (e.g. type of contact to the skin, such as through tiny hair/dirt, or the shape, surface, orientation of the electrodes, etc.) and *Intrinsic Factors* (e.g. anatomical, physiological, and biomechanical factors such as Microvibrations [31] or properties of muscle fibers in terms of thickness, type, temperature, etc.) [11].

As mentioned, most of the human body's cells have an excess of electrons and thus a negative electrical potential / charge to the outside. The ability to store this electrical power can be described as a *capacitance* or as *body capacitance* when referring to the overall capacitance of the human body. The capacitances vary between 50 – 150 pF depending on the individual body parts [34]. This capacitance can also be measured invasive or on the skin at different body parts, which is called *Capacitive Sensing (CS)*. In general, we distinguish between three sensor setups for capacitive sensing: *Transmit Mode*, *Loading Mode* and *Shunt Mode* [35], which differ in physical arrangement, number of electrodes, and their function allocation.

Determining *action potential* of a muscle, usually requires at least two measuring electrodes (e.g. EMG_{mid} and EMG_{end}), attached to two different spots over a certain muscle or muscle group. Furthermore a reference electrode (e.g. EMG_{ref}) is required to be attached to a different spot, which

should not be affected by any muscle activity. As part of the measurement principle, the sensor always detects the potential difference between the reference electrode and the measuring electrode. The resulting difference between the gathered signals of two measuring electrodes indicates the action potential. This can be used to accomplish a gesture control, such as proposed by Saponas et al. [32] who use the sensor on a fixed muscle group to detect action potential at certain areas around the arm and to thus interpret finger gestures.

Previous research for muscle-computer interaction typically uses EMG to detect action potentials of muscle cells. This technology can also be used to measure *resting potential* in almost all types of cells, including locations with few muscle cells (e.g. belly). However, pure resting potential of individual body tissue is very difficult to measure without using specialized tools (i.e. Potentiometric Probes [13]) that are intrusive. What can be realistically measured in an interaction setting is a combination of the overall resting potential for all body tissues in a non-intrusive way on the skin at a particular location, plus some noise. While noise is usually undesirable, colored noise also can provide important information that helps localization, if it is somehow significant across body parts' surfaces.

Electrode Arrangement

Compared to the common sensing approaches, we can also re-orient the measuring electrode (facing the air) and make it touchable by any body part. In this arrangement only the reference electrode is still needed to be permanently in contact with the body. Regarding the measuring electrodes, we actually only require one, or arrange both closely next to each other (Figure 3). This way we achieve a contact area, which collects the unique electrical signature of the body part that is touching it.

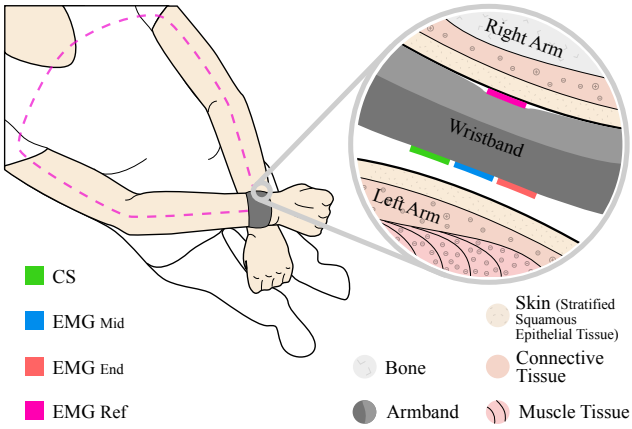

Figure 3. The *Botential* setup: the measuring electrodes are re-orientated and act as a touch point.

IMPLEMENTATION

In order to demonstrate the feasibility of our proposed concept, we built a proof-of-concept wearable input device (Figure 4), which we envision to be integrated into everyday wearable accessories as illustrated in Figure 1.

Prototype

The prototype basically consists of four components: a portable EMG sensor module (Muscle (EMG) Sensor v2 from Advancer Technologies[1]), a voltage divider circuit (consisting of a 22pF capacitor and a 10MΩ resistor) and an astable multivibrator to enable for a Capacitive Sensing in loading mode, a microcontroller (an Arduino Pro Mini) to pre-process and transform the signal, and a Bluetooth modem (HC-06) to enable wireless communication with a computer, where the data is displayed, processed, and classified. Two conventional 9V batteries and a 3.7V LiPo battery power the prototype. The hardware is mounted on a Velcro tape and thus allows the user to wear the device as a leg, wrist or armband.

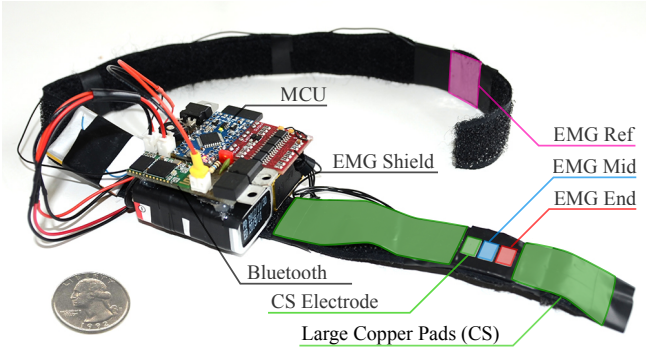

Figure 4. *Botential* mounted on a band: the EMG mid / end and the CS electrode are surrounded by copper pads which are hidden under black isolation tape and enable hovering.

The EMG sensor module has three electrodes, from which the reference electrode (REF, size: 20 x 20 mm - mounted on the inside of the band) is always in contact with the skin (e.g. with the exterior side of the hand when worn as a wristband). The other two electrodes (size: 10 x 4 mm each with a distance of 1 mm), which are labeled as MID and END, are integrated on the outside part of the band, to allow for proper contact with a desired body part.

To gain additional information on which body part is being touched, we put another electrode next to the MID EMG electrode to enable capacitive sensing. These electrodes represent the actual contact area that can be touched with a desired body part. Around the contact area, large copper pads (size: 20 x 35mm + 20 x 70 mm) are embedded to enable the sensing of an approaching body part and touching through clothes.

Signal

While a professional needle EMG would be able to provide a frequency-based signal, containing a summation of resting potentials, we are unable to measure such clear signal on the surface of the skin. Instead, we measure a noisy signal, which is a superposition of resting potentials from different

[1] *http://www.advancertechnologies.com/p/muscle-sensor-v3.html* [last accessed 26/01/2015]

fibers plus different noise caused by Extrinsic Factors, which we include as a feature in our electrical signature. These factors are crucial, since the characteristic of the surface that touches the sensor instrumentally determines the measured signal and thus the detected body part.

In contrast to a clinical EMG sensor, the EMG sensor used in our prototype has limited capabilities due to the hardware components, which already rectify, smooth and normalize the gathered signal. This loss in information only enables to behold the amplitude and not the whole frequency spectrum of the actual signal. To compensate that we also use a capacitive sensing in loading mode to enrich the electrical signature with further frequency information and thus extend the set of features. Signals from both EMG and capacitive sensors are then merged together (Figure 5). After this early sensor fusion, we broadcast the computed signal via a serial Bluetooth connection to a computer, where a Fast Fourier Transformation (FFT) is applied on the fused signal.

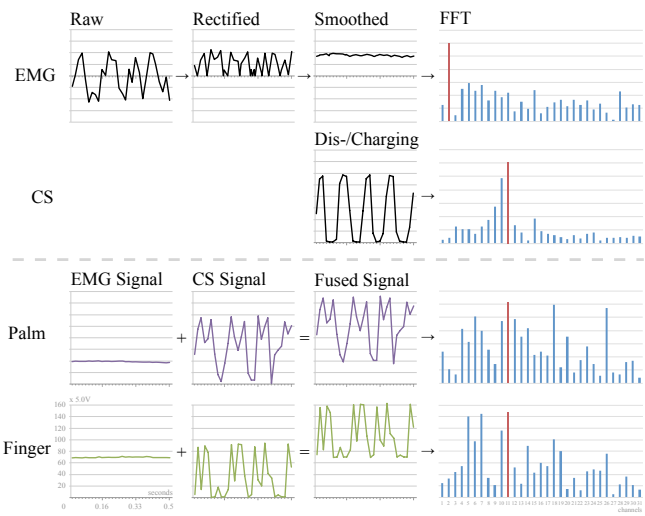

Figure 5. The gathered raw data of the EMG & CS are being fused and afterwards treaded with an FFT. Features used for touch recognition are extracted from the FFT.

Furthermore, the capacitive sensing (with the integrated copper plates in the armband), also enables a precise detection of a hovering state within the distance of 4 cm, which is achieved by sending electric pulses to the copper plates and measuring the time of charging and discharging.

Recognition

Before we can recognize the body part that is being touched with the sensor, we need to first conduct a *Training Phase*, in which the user is required to record samples of each body part. After completing such process, we can enter the *Recognition Phase*, in which body parts can be detected based on the known electrical signatures gathered in the previous training phase. The recognition can be performed *Online* in real-time, which requires a classification to perform quickly with sufficient high recognition rates, since computational resources are limited. Alternatively, we can process the gathered data *Offline*, which has the advantages of being independent from just-in-time decisions and limited computational or time resources. For evaluation we followed this approach to post process and analyze the data.

Online

During the *Training Phase*, the user needs to use the sensor to touch the desired body parts. Then, the EMG sensor data and the capacitive sensing data are recorded over duration of about 2.5 seconds with a sampling rate of 100 Hz, to create an FFT with [0,127] channels out of one instance with a window size of 256 values. During the *Prediction Phase*, the live data stream is constantly compared with saved patterns from the training phase while applying a "Fast Correlation-Based Feature"-like algorithm [15] to find similarities. While tapping can always be detected immediately, the identification of a body part takes ~500ms but can last up to ~2.5s in this setup. Nevertheless, there is a trade-off between speed and accuracy in recognition.

Offline

Based on the experience of our previous test, in the *Training Phase* we now reduced the window size down to 64 values to create a quicker FFT with [0,31] channels. We recorded each training set (which is a position on a body part) with a sampling rate of 60 Hz over duration of about 11 seconds, to separate 10 instances. Broader window sizes, more instances or higher sampling rates did not provide better results. To not lose information, we waived on applying any filters and then defined 6 features, which provided high separation sharpness on the raw data:

- **Signal Energy**

$$P_{Signal} = \frac{1}{N}\sum_{n=-1}^{n=1} |\, x_n(f)|^2$$

- **Number of Mean-Crossings**

$$MCR = \frac{1}{T-1}\sum_{t=1}^{T-1} \| \{A_{Window} - A_{Mean}\}$$

- **Summed Second highest Amplitude**

$$2ndA = \sum_{n=-1}^{n=1} |\, max_2(A_{Window})|$$

- **Summed Third highest Amplitude**

$$3rdA = \sum_{n=-1}^{n=1} |\, max_3(A_{Window})|$$

- **Summed Delta of highest Frequency in Noise Area**

$$\Delta HighestNoiseAmp = \sum_{n=-1}^{n=1} |\, \partial_{\max\,(A_{Noise})}(f)|$$

- **Signal-to-Noise Ratio**

$$SNR = 10log_{10}\left(\frac{P_{Signal}}{P_{Noise}}\right)$$

The recognition is detailed in the following section.

EVALUATION

To discover the system's capabilities, we sequentially conducted several tests in which we investigated the cross-user compatibility of the system (**T1**), the distinguishability between 8 different body parts (**T2**), the resolution of each body part in a range of 1.5, 3, 5, 7, 9 cm (**T3**) and the recall accuracy overtime (**T4**).

Participants

We recruited 10 participants (1 female) with an age of 24-33 (M=27.2). Their height was 1.72-1.98m. All participants were within +/- 10% of their body-mass index and thus optimal for our evaluation to ensure a possibly higher comparability. Among all participants, one participant rejected measurements to be performed on her thigh. T4 was performed with only one participant.

Procedure and Task

For the evaluation, we first marked the recording areas on the user's body parts, as shown in Figure 6. Then, we mounted the contact electrodes on a separate Velcro tape, which was long enough to be fixed tightly to the user's body, to avoid potential irregularities due to the shifting of the sensor. The user was instructed to sit still and not tensing any muscles. Even if some spots are different for each user, such as the finger already ends at 70mm, we decided to still measure the 90mm spot – in this case, on the hand palm. For each user we recorded the raw data in a CSV file and concurrently generated an ARF feature file.

Figure 6. Tested areas: (1) calf, (2) finger, (3) upper arm, (4) palm, (5) back of the hand, (6) forearm, (7) thigh & (8) belly.

Classification

To determine a classifier we analyzed the feature files with the Weka data mining tool v3.7.11 [16]. For each user we compared all 8 body parts against each other with 5 state-of-the-art classifiers, which we found suitable (**Figure 7**). To understand the classifiers theoretical performance level, we applied a 10-fold cross validation, but which did not yield any statistical differences as shown by an ANOVA for correlated samples ($F_{4,36}$ = 1; p=.42). To achieve a more realistic impression on the recall rate, we furthermore applied a leave-one-out method, but which did not show any differences either ($F_{4,36}$ = 1.29; p=.29). Also the Weka's percentage split of 66% did not yield any significant differences ($F_{4,36}$ = 2.21; p=.09). Based on the performances we chose the Bayes Net because of its slightly lower standard deviation & comparably high mean.

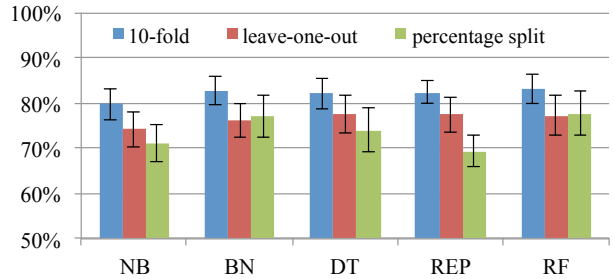

Figure 7. Classifier performance of Naïve Bayes (NB), Bayes Net (BN), Decision Table (DT), REP Tree (REP) and Random Forrest (RF). Error bars are .95 confidence intervals

T1: Cross-User Compatibility

Different users demonstrate different physiological properties, including thick / thin / dry / oily skin, more / less evolved muscles or fat and water sedimentations. Our data also confirmed that it is not possible to train a generic classifier that works for all users. A leave-k_{User}-out (k=5) cross validation with a Bayes Net classifier results in an overall recall rate of 16.1%, due to massive confusions. Therefore, it seems very unlikely that data from one user could be used for another user. It suggests that the system indeed needs to be trained using personal data for each user.

T2: Identification of Body Parts

To achieve an overall impression on the recall accuracy of the identification of body parts, we generated a leave-$k_{Instance}$-out (k=5) cross validation with the Bayes Net classifier for each user, since a cross-user compatibility is not given. The training and test sets have been separated out of the 10 collected instances. The results for all users are summed up together in Table 1 below.

a	b	c	d	e	f	g	h	< classified as
82%	-	10%	-	-	-	1%	7%	**a** = calf
-	93%	-	2%	-	3%	-	-	**b** = finger
9%	-	69%	1%	12%	3%	5%	1%	**c** = upper arm
-	3%	2%	82%	-	5%	8%	-	**d** = palm
1%	8%	9%	3%	73%	4%	-	-	**e** = hand back
1%	-	5%	7%	3%	80%	-	-	**f** = forearm
10%	1%	8%	14%	-	6%	54%	7%	**g** = thigh
6%	13%	-	-	-	4%	12%	59%	**h** = belly

Table 1. The Confusion Matrix shows all identified instances in percentage (rounded) per body part.

While the upper arm, belly and the thigh have been confused more often; the finger, palm, calf and the forearm seem to be reliably recognizable. Discarding problematic locations, such as the belly and thigh, would even further improve the overall recognition rates.

T3: Resolution within Body Parts

To ascertain the resolution of each body part, we assume the ideal case that only 2 spots are being trained. Because we had 5 distances of 15, 30, 50, 70, and 90 mm from our reference point, we had to generate 395 confusion matrices (400-5 on the thigh since one participant did not agree to be measured on her thigh) in which we were comparing a Bayes Net with a percentage split (33%) algorithm to find

out about possible confusions. A leave-one-out algorithm would require 3950 matrices that are beyond practicality. The accuracy of each matrix has been summed up below.

15	30	50	70	90	< distance
78.5%	86.3%	86.5%	95.4%	**95.9%**	calf
92.3%	94%	99.2%	**100%**	**100%**	finger
91.4%	96.5%	95.4%	**99.2%**	95.7%	upper arm
95.4%	95.4%	**100%**	94.9%	95.7%	palm
96.2%	96.2%	93.8%	97.7%	**100%**	hand back
87.7%	94.6%	94.6%	93.8%	**96.6%**	forearm
77.9%	83.8%	**96.6%**	94.9%	91.5%	thigh
85.6%	**86.5%**	86.2%	76.1%	77.8%	belly

Table 2. Resolution of body parts: The percentage values are the probability for our system to distinguish two points for the given distance and body part.

When only comparing 2 trained spots at a single body part, the distinguishability is quite clear. In a more realistic context with multiple locations on multiple body parts, the recognition accuracy may not be as high as shown in Table 2, which is a best-case scenario. However, given the relatively heterogeneous structure of our hand, it is still possible to distinguish spots by a distance of only 15 mm on the palm. Although resting potentials, capacitances and the surfaces vary in most parts of our body; they are less differentiable for more homogeneous body parts, such as belly, calf and thigh. Our tests indicate that the distinguishability within a body part is affected by the degree of homogeneity of the underlying body structure.

T4: Recall Accuracy Over Time

While performing tests over time, we found out that the electrical signature tends to vary slightly. A complete study on this phenomenon would require more precise apparatus, such as clinical EMGs, and would be very complex in terms of logistics. Nonetheless, to gain an impression on how the system theoretically performs over time, we recorded data of all body parts for one test subject over two days at random time points. For a first analysis (**Figure 8** – *red line*), we took the initial recorded signature as a reference pattern and compared all later recordings with a 10-fold cross validation (Bayes Net classifier) against it.

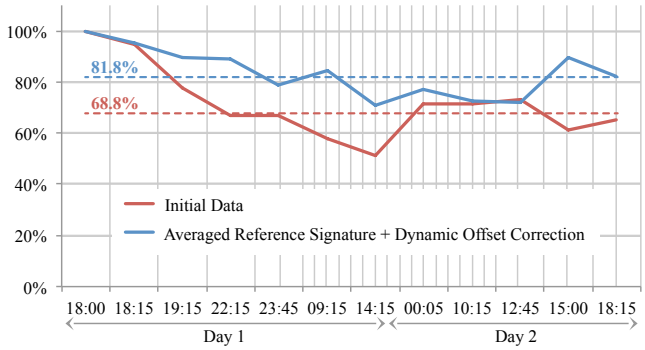

Figure 8. The curve extending over two days (note: x-Axis is not linear). We conducted a 10-fold cross validation with the Bayes Net classifier over the data set. Overall accuracy: initial data (red - 68.8%) and corrected (blue - 81.8%)

The accuracy (**Figure 8** – *red line*) decreases quickly after a few hours to an average of 68.8%. We suspect that mainly sweating but also microvibrations [31], environmental temperature, and the way the sensor is being placed on the skin have an impact on the measured electrical signature. While we could see some unknown variation to occur, we could also determine an offset change of the signal energy.

To ensure an accurate recognition of all body parts over time, the profiling of a person needs to take multiple references points (e.g. from the morning / lunch / and evening). Furthermore we can make use of an additional reference sensor, which provides us the current skin resistance, to calculate a dynamic signal offset correction. By applying this last correction, we were able to achieve a recall accuracy of 81.8% (**Figure 8** – *blue line*) for our data, which is a more acceptable accuracy. Another improvement that could be done would be to measure the temperature of the electrode, which has an impact on its current conductivity.

WEARABLE INTERACTION WITH *BOTENTIAL*

The ability to detect input gestures on various body parts allows *Botential* to support a variety of quick interactions in mobile context, which demand little user attention. Such interactions are defined as "microinteractions" by Ashbrook [2]. Interacting with *Botential* can be performed eyes-freely or hands-freely due to proprioception. Making use of such technology, users can achieve hands-free interaction either with their forearm or leg if their hands are occupied with activities, such as carrying groceries or riding a bike. Interaction with *Botential* can be performed by either touching the wearable device with various body parts (such as placing the finger, palm, or wrist on a necklace) or moving the wearable device to contact the various body parts (such as moving a ring on the finger to touch the arm, chest, or the leg). Below, we detail how *Botential* can be integrated into five common wearable objects to enhance such mobile interactions (Figure 1).

a) Torso (Necklace): Botential can be worn as a necklace (Figure 1-a). In this configuration, the wearer can interact by touching the device with the fingers or sliding the palm on its surface. Considering a scenario where the wearer is in a meeting or having dinner, a tap on the necklace with the hand could reject a call, while a sliding with the forearm could send the caller a predefined "I'm busy" message.

b) Wrist (Wristband or Watch): Integrating a *Botential* unit in a wristband (Figure 1-b) enables two different interaction styles: directly interacting on the wristband with the other arm or tapping, sliding, and hovering above other body parts (e.g., the belly). This method still supports hands-free interaction, which is desirable when holding things in the hands. The user can assign different functions to different body parts. For example, while jogging, the user could invoke the play/pause music command by tapping, or change the volume by sliding on

the belly. Since the arm is the most agile part, putting the device on it ensures access to many distinct body parts.

c) Finger (Ring): Integrating *Botential* into a ring (Figure 1-c) allows a wide variety of subtle gestures. Since the hand is a highly agile part of the body, it is possible for a user to tap on almost any body part, except the back, which is hard to reach. Since touching body parts with our hands can be performed eyes-freely, this kind of interaction would be very useful in scenarios where visual attention is already committed to real world tasks, but hands are not occupied.

d) Waist (Belt Buckle or side of the belt): Attaching the device to a belt (Figure 1-d) enables similar interactions as those on the torso. Mounting the device on the hip also makes it possible to interact with the whole forearm without the need to wear a device on the arm itself. This can be useful in everyday situations when carrying heavy grocery bags, and a binary input, through a tap with the forearm on a belt, is sufficient.

e) Leg/Foot (Legband or Shoe/Sock): Attaching the device as a legband at the thigh enables a user to slide or tap with the hand or wrist on the upper leg. Attaching it to the lower leg or to the shoe/sock enables natural leg gestures (Figure 1-e), where the user can slide, hover, or tap using one leg on the other. Leg gestures can be executed in a subtle way and are also useful when both hands are occupied, for example, when holding on to the handgrips in a bus or a train, or when typing on a keyboard. In these situations, it is easy to use tap gestures for discrete commands and to slide one leg on the other.

Technological Advantages and Limitations

Botential significantly enhances the ability to sense soft, hard and long touches. The pressure applied to the sensor on the skin does not affect the signal, unless it is really squeezed or almost not touching the skin. The system is also robust against commonly environmental influences, such as vibrations while driving or varying lighting conditions. While technology is evolving, such sensor type unit can be easily embedded into a wearable device. When integrated into a wearable object, the system can be used to interact on a large body area, as long as the sensor can reach it. For example, wearing *Botential* on the forearm, wrist, or hand allows interaction with most body parts, except where limited by the user's range of motion (e.g. the ability to reach a certain area on the back). Additionally the detection of the hovering state enriches the type of interaction one can perform with the body. Although the current implementation only provides information about distance and no indication of the body part being hovered, hovering can be used as an additional design channel to create a buffer state between no action and committed action.

Like any other technology, *Botential* has its own constraints. First, to correctly identify the body part being tapped, the electrodes need to be in direct contact with the skin. Secondly, the measurement on the skin is influenced by intrinsic factors [26], such as blood flow or sweat, which typically affects electrical resistance. However, this can be mitigated with additional sensors that monitor the skin resistance and make appropriate adjustments to the system. External influences, such as electrical surface charging of the skin, such as when being in an electrostatic environment (e.g. server room or fluffy carpet) can affect the signal. Also excessively heavy touches and abrupt movements can make the signal hard to interpret. While variation of the signal over time may seem impractical, we want to emphasize the fact that we still found great similarities in the signal after two days without any recalibrating and a future intelligent system would have the ability to learn and recalibrate itself while being used. Moreover, the accuracy of detection dramatically increases as the number of assigned body locations decreases.

Discussion

Embodied Interaction [10], such as on-body interaction [18] is an interesting approach to meld human and computer together. Leveraging the human skin has several advantages, such as a stretchable, large and heterogeneous surface of about two square meters [5,29]. Nevertheless, it is arguable whether interaction on the body is *suitable and socially acceptable*. Especially when interacting in public with conspicuous gestures, social awkwardness might be pronounced [30]. However, this may change as making a call by talking to thin air with a Bluetooth headset also became socially acceptable over the past years. Still, touching different locations on the body has mental associations, which differs by culture backgrounds and disables specific body parts to be used as interaction interfaces, such as the collarbone [25] or breast.

Multi-user input on the skin of another person is also an interesting scenario to investigate, which conveys rich emotional connections and meanings [20]. It is to assume, that personal interaction, which is usually accomplished with personal devices (e.g. a smartphones), could be enriched with interaction of one's own skin, rather than using somebody else's skin. Nevertheless, having additional input space available on one's body, might change the perception and probably decrease the aversion of being touched by acquaintances. When offering multi user input, we also have to think on how to design rules to regulate interaction for certain user groups such as strangers.

Thirdly, it is still unclear how *Botential* should be used on the full-body scale, whereby most of the body parts are often occluded with clothes. As already stated, we envisioned *Botential* to be integrated into several everyday wearables. However, we think integrating in a wristband is most beneficial to extend current devices. This would enable the user to interact on each body part reachable with their hand, but especially the forearm and hand, which are the most preferred locations for on-body interaction as found out in a rigorous study by Weigel et al. [38].

BOTENTIAL FIELD STUDY

Designing novel interfaces is facing several challenges; an important one is creating interaction concepts that are neither uncomfortable nor socially awkward to the user. Social awkwardness can quickly occur while performing circuitous gestures or touching specific body parts in certain context. Previous research has revealed that tapping on the belt [30] or the wrist [25] tends to be more acceptable than a touch close to the face.

To verify *Botential*'s ability to complement current input modalities for mobile scenarios, we ran a study to compare two different approaches: using *Botential* to perform on-body gestures vs. the default interaction method of Google Glass, by touching its frame. We recruited 40 participants (14 females, aged 18-52, M=27.2). Participants had to wear a Google-Glass-like device running a photo application. To interact with it, 20 participants used the interactive frame and the other 20 used the *Botential* worn on the wrist.

We let the participants familiarize with the application and explained to them how to take pictures (by *tapping* on their body or on the frame), switch to picture display mode (with a *long tap*), and how to browse through pictures (by *sliding* on the frame or *tapping/double tapping* with *Botential*) with the assigned input device. Participants then had to fill out a custom questionnaire, in which we asked them to rate on a Likert Scale from 1 to 5 whether it would make them feel awkward to interact with either the frame or *Botential*.

Because both input interfaces follow a slightly different interaction strategy, it is interesting to find out whether the two groups also perceive the task differently. Therefore we additionally measured the NASA Task Load Index of each participant. The NASA TLX results did not yield any significant difference between the two input devices for any of the 6 criterions (p>.05), thus both groups experienced the performed task quite similar in terms of Mental, Physical and Temporal Demand, Performance, Effort and Level of Frustration, which indicates the comparison to be valid.

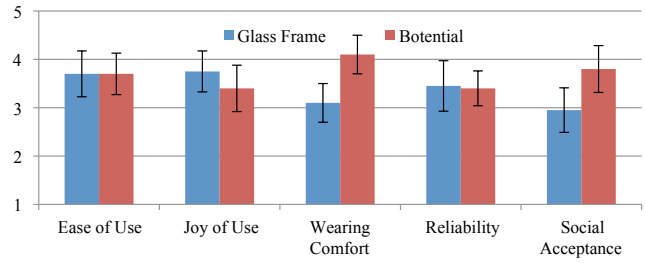

Figure 9. Results of the Custom Questionnaire. Error bars are .95 confidence intervals

As seen on Figure 9, our results suggest that users felt interacting with *Botential* ($M_{\text{Botential}}$=3.8/5) was significantly more acceptable (confirmed by a Mann Whitney test; U=285, n_1=n_2=20, p=.01) than interacting with the frame (M_{Frame}=2.95/5). The study confirms that lifting the arm towards the head and exerting pressure on a glass frame is being significantly (M_{Frame}=3.1/5, $M_{\text{Botential}}$=4.1/5, U=309, n_1=n_2=20, p<.001) perceived as more unpleasant than a subtle and natural gesture such as tapping the wrist, belly or touching the side of the leg. Furthermore, participants also suggested these discreet gestures to be suitable to be performed during conversations and other social occasions.

Outlook

Wearable devices such as Google Glass are becoming increasingly available to the general public. The major difference between HMDs and current mobile devices is the always-available visual output that allows users to perform quick tasks while on the go. The interaction paradigm on such products usually relies on either speech input, which might not work in noisy areas, or on simple gestures on the device's frame. In scenarios such as important business meetings, voice input or interacting on the glass frame can be less desirable. Alternatively for these cases, a subtle touch on the side of the leg can be much less obvious and more socially acceptable. We envision *Botential* also to be integrated into smartwatch wristbands, such as from Apple Watch, which would complement these devices with a broader input space and alternative input paradigms.

RELATED WORK

Researchers have developed various ways to enable interaction with our own body and to make it suitable for mobile interaction. To better understand the unique properties of each technique, we summarize some recent work in this area in Table 3.

	Technology	Interaction Style	Eyes-Free	Hands - Used
OmniTouch [17]	Projector+D.C	Contact	N	1
Imaginary I. [14]	IR Camera	In air	N	2
Cohn et al. [7]	Electric Field	In air	Y	0
Botential	EMG + Capacitive S.	Hovering + Contact	Y	0
Skinput [19]	Projector+Piezo	Contact	Y	1
Humantenna [8]	Electromagnet.	In air	Y	1
WristFlex [9]	FSRs	In air	Y	1
Touché [33]	Capacitive S.	Contact	Y	1
Saponas et al.[32]	EMG	In air	Y	1
ShoeSense [4]	Depth Camera	In air	Y	1

Table 3. Overview of Related Work. Hands-Used is the minimal number of hands needed to interact. A hand is considered not being used if the user can interact while holding an object. Interaction Style: interaction is based on tapping or hovering above a body part or on gestures in air.

Optical Tracking is a widely used technology but can be easily undermined by light conditions. Imaginary Interfaces [14] uses a small IR camera to detect hand and finger gestures, but it fails under certain light conditions. Depth cameras (Kinect) can be mounted on the human body to detect hand and finger gestures as presented in ShoeSense [4] or OmniTouch [17]. However, these setups cannot track the whole body. Using proximity sensors, such as demonstrated in SenSkin [24], is affected by the same issues as it is facing the problem of occlusion.

Capacitive Sensing is a reliable way to detect touches on surfaces. Touché [33] presents a method known as Swept Frequency Capacitive Sensing, which measures the impedance with respect to the frequency while driving a high frequency AC signal through the body. Such technique could in theory be expanded to the whole human body. However, A wearable interaction concept and how to reliably identify taps on different body parts is not being demonstrated. Interactive clothing has been proposed and used to detect interaction as in Pinstripe [22]. This technology consumes little power and allows for fabrication in high density and flexible material. However, expanding this to all clothes requires a big sensor network.

Resistive Sensing is one of the oldest but still relevant methods for sensing input. Recently, WristFlex [9] presented how to incorporate FSRs in a wristband to classify hand and finger gestures. Also it can be utilized to detect mechanical deformations and touch events on the skin with printed tattoos [39] or an additional artificial skin [37]. Still, expanding this technology to the whole body might not be realistic, as it can be obtrusive and entails a possibly high acceptance threshold for users.

Bio Acoustic Sensing with Piezo Films is presented by Skinput [19], which allows detection of hitting the forearm or hand based on the produced sound transmitted through bone conduction. Soft or long taps are not feasible to be detected. While the signal attenuates with distance, scaling this to the entire body would require many sensors.

Accelerometers and Gyroscopes have been used by many researchers such as Aylward and Paradiso [1] and Rekimoto [27, 28]. This sensing allows for tracking of in-air gestures. The drawback is that an algorithm is required to constantly run to distinguish between wanted movement and unconscious movement when performing everyday tasks.

Still a very uncommon way to detect body gestures is to utilize *Environmental Electromagnetic Radiation* as demonstrated in Human Antenna [8] or to use *Static Electric Field Sensing* as presented by Cohn et al. [7].

Measuring a *Magnetic Field* would be another method, which has recently been explored for finger gestures. Nenya [3] detects the movement of a ring mounted with a magnet around its wearer's finger. The drawback with this technology is that it is limited physically to a specific radius. How to enable a more complex input with this technology in a 3D space is demonstrated in uTrack [6].

Electromyography (EMG) is a technology that can detect muscle tension through an increase in action potential. Saponas et al. [32] demonstrated its use for detecting finger gestures. In that particular case, many EMG electrodes must be fixed tightly on a certain area, such as around the arm. To measure very clean signals, the electrodes should be invasive. Depending on the number and nature of electrodes, heavy classification algorithms may be required.

CONCLUSION

In *Botential*, we proposed a novel proof-of-concept to enable hands-free and eyes-free mobile input that uses the human body as an extended input space. By sensing electrical signatures on the skin we utilize the existing signal the human body already emits, which is different from previous approaches and nicely complements those. While not just detecting the presence of a touch, but also recognizing a number of locations on the body, designers can assign different meanings to localized areas, which significantly increases the number of commands one can associate with on-body interaction. In addition to using an EMG sensor, our prototype also incorporates capacitive sensing to improve recognition and to enable the detection of hovering events, although detecting the exact location of the hovering event is not currently supported. While our study revealed electrical signatures to be user dependent and to slightly vary over time, broader studies with clinical EMG devices and a larger population are required to decrypt the human property of electrical potential and capacitance measurable on the skin.

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