INTRODUCTION

Devices with significant computational power and capabilities can now be easily carried on our bodies .Their small size typically leads to limited interaction space. Since we cannot simply make buttons and screens larger without losing the primary benefit of small size, we consider alternative approaches that enhance interactions with small mobile systems

One option is to opportunistically appropriate surface area from the environment for interactive purposes. For example we can use a a small mobile device to turn tables on which it rests into a gestural finger input canvas. However, tables are not always present, and in a mobile context, users are unlikely to want to carry appropriated surfaces with them . However, there is one surface that has been previous overlooked as an input canvas, and one that happens to always travel with us: our skin. Appropriating the human body as an input device is appealing not only because we have roughly two square meters of external surface area, but also because much of it is easily accessible by our hands.

Furthermore, proprioception – our sense of how our body is configured in three-dimensional space – allows us to accurately interact with our bodies in an eyes-free manner. For example, we can readily flick each of our fingers, touch the tip of our nose, and clap our hands together without visual assistance. Few external input devices can claim this accurate, eyes-free input characteristic and provide such a large interaction area.

A touch screen is an electronic visual display that can detect the presence and location of a touch within the display area. The term generally refers to touching the display of the device with a finger or hand.

Skinput is a collaboration between Chris Harrison at Carnegie Mellon University and Dan Morris and Desney Tan at Microsoft's research lab in Redmond, Washington.As the researchers explain, the motivation for Skinput comes from the increasingly small interactive spaces on today's pocket-sized mobile devices.

Skinput Technology use our skin as a medium for controlling a computer or other gadgets. By using sensors placed on the arm, every touch on every part will be able to control many things. Sensor that is able to distinguish a touch hard on every point so that differences can be

used to distinguish the desired control. Skinput – a method that allows the body to be appropriated for finger input using a novel, non-invasive, wearable bio-acoustic sensor.

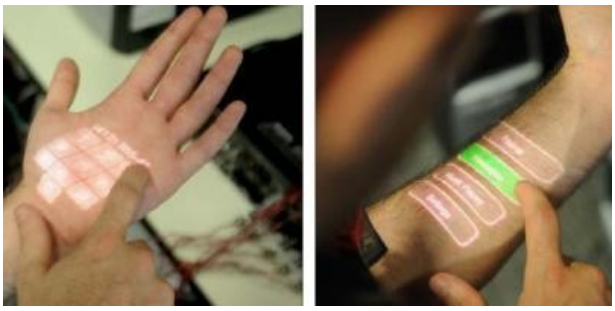
SKINPUT TURNS OUR BODY INTO TOUCHSCREEN INTERFACE

Skinput uses a series of sensors to track where a user taps on his arm. Previous attempts at using projected interfaces used motion-tracking to determine where a person taps. Skinput uses a different and novel technique: It "listens" to the vibrations in our body.Tapping on different parts of your arm creates different kinds of vibrations depending on the amount and shape of bones, tendons and muscle in that specific area. Skinput sensors can track those vibrations using an armband and discern where the user tapped.

The arm band is a crude prototype.The next generation could be made considerably smaller – likely easily fitting into a wristwatch.From there it's fairly simple to associate those tappable areas with different commands in an interface, just as different keystrokes and mouse clicks perform different functions on a computer.

When coupled with a small projector, Skinput can simulate a menu interface like the ones used in other kinds of electronics. Tapping on different areas of the arm and hand allow users to scroll through menus and select options. Skinput could also be used without a visual interface . Different areas on the arm and fingers simulate common commands for these tasks, and a user could tap them without even needing to look.

Figure : Skin as a touchscreen interface



The next generation of miniature projectors will be small enough to fit in a wristwatch, making Skinput a complete and portable system that could be hooked up to any compatible electronics no matter where the user goes.

Skinput, and similar sensor devices could have applications beyond simple menu screens.One of the developers said that Skinput-like interface allowed him to play Guitar Hero, a popular music game, without the requisite plastic guitar controller.Despite working in vastly different ways the system focus on letting users play games with their on bodies without the need for accessories and game controllers.

The researchers have shown that Skinput can allow users to simply tap their **skin** in order to control audio devices, play games, make phone calls, and navigate hierarchical browsing systems.In Skinput, a keyboard, menu, or other graphics are beamed onto a user's palm and forearm from a pico projector embedded in an armband. An acoustic detector in the armband then determines which part of the display is activated by the user's touch. As the researchers explain, variations in **bone density**, size, and mass, as well as filtering effects from soft tissues and joints, mean different skin locations are acoustically distinct.Their software matches sound frequencies to specific skin locations, allowing the system to determine which “skin button” the user pressed.

Currently, the acoustic detector can detect five skin locations with an accuracy of 95.5%, which corresponds to a sufficient versatility for many mobile applications. The prototype system then uses wireless technology like Bluetooth to transmit the commands to the device being controlled, such as a phone, iPod, or computer. Twenty volunteers who have tested the system have provided positive feedback on the ease of navigation.The researchers say the system also works well when the user is walking or running.

It is an interesting idea to use human body as an input device. This idea will minimize and create effectiveness in using spaces. This way what we need is just all the possible skin in our body to be used as the input device, from head until the tip toe.

SKINPUT CAN USE SOUND TO TURN OUR BODY INTO AN INPUT DEVICE

The user needs to wear an armband, which contains a very small projector that projects a menu or keypad onto a person's hand or forearm. The armband also contains an acoustic sensor. The acoustic sensor is used because when you tap different parts of your body, it makes unique sounds based on the area's bone density, soft tissue, joints and other factors.

The software in Skinput is able to analyze the sound frequencies picked up by the acoustic sensor and then determine which button the user has just tapped. Wireless Bluetooth technology then transmits the information to the device. So if you tapped out a phone number, the wireless technology would send that data to your phone to make the call.The developer have achieved accuracies ranging from 81.5 to 96.8 percent and enough buttons to control many devices.

The Skinput doesn't require any markers to be worn and it is more suitable for persons with sight impairments, since it is much easier to operate it.

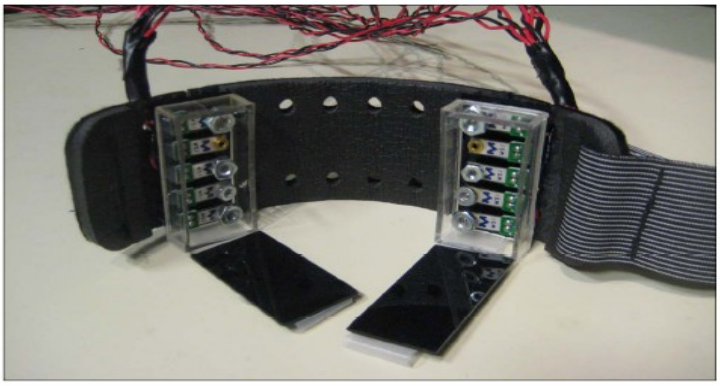
WORKING WITH SKINPUT

Skinput is a technology that appropriates the human body for acoustic transmission, allowing the skin to be used as an input surface. The location of finger taps on the arm and hand is resolved by analyzing mechanical vibrations that propagate through the body. These signals are

collected using a novel array of sensors worn as an armband. This approach provides an always available , naturally portable and on-body finger input system.

To expand the range of sensing modalities for always available input systems, we introduce Skinput, a novel input technique that allows the skin to be used as a finger input surface. In our prototype system, we choose to focus on the arm (although the technique could be applied elsewhere) .This is an attractive area to appropriate as it provides considerable surface area for interaction , including a contiguous and flat area for projection.Furthermore, the forearm and hands contain a complex assemblage of bones that increases acoustic distinctiveness of different locations. To capture this acoustic information, we developed a wearable armband that is non-invasive and easily removable.

Figure 1



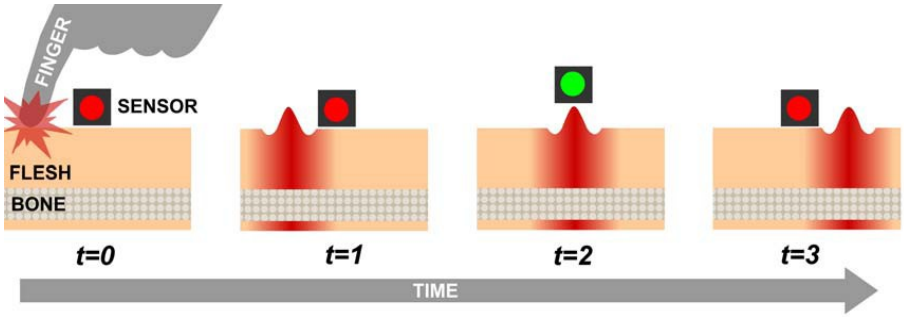
A wearable, bio-acoustic sensing array built into an armband. Sensing elements detect vibrations transmitted through the body. The two sensor packages shown above each contain five, specially weighted, cantilevered piezo films, responsive to a particular frequency range

BIO-ACOUSTICS

When a finger taps the skin, several distinct forms of acoustic energy are produced. Some energy is radiated into the air as sound waves; this energy is not captured by the Skinput system.

Among the acoustic energy transmitted through the arm, the most readily visible are transverse waves, created by the displacement of the skin from a finger impact (Figure 2).

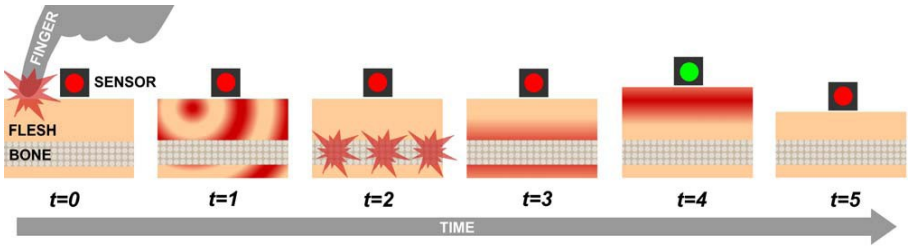
Figure 2



Transverse wave propagation: Finger impacts displace the skin, creating transverse waves (ripples). The sensor is activated as the wave passes underneath it.

When shot with a high-speed camera, these appear as ripples, which propagate outward from the point of contact.The amplitude of these ripples is correlated to both the tapping force and to the volume and compliance of soft tissues under the impact area. In general,tapping on sof treg-ions of the arm creates higher amplitude transverse waves than tapping on boney areas which have negligible compliance. In addition to the energy that propagates on the surface of the arm, some energy is transmitted inward, toward the skeleton(Figure 3)

Figure 3



Longitudinal wave propagation*:* Finger impacts create longitudinal (compressive) waves that cause internal skeletal structures to vibrate. This, in turn, creates longitudinal waves that emanate outwards from the bone (along its entire length) toward the skin**.**

These longitudinal (compressive) waves travel through the soft tissues of the arm, exciting the bone,which is much less deformable then the soft tissue but can respond to mechanical excitation by rotating and translating as a rigid body. This excitation vibrates soft tissues surrounding the entire length of the bone, resulting in new longitudinal waves that

propagate outward to the skin. We highlight these two separate forms of conduction – transverse waves moving directly along the arm surface, and longitudinal waves moving into and out of the bone through soft tissues – because these mechanisms carry energy at different frequencies and over different distances.Higher frequencies propagate more readily through bone than through soft tissue, and bone conduction carries energy over larger distances than soft tissue conduction. While we do not explicitly model the specific mechanisms of conduction, or depend on these mechanisms for our analysis, we do believe the success of our technique depends on the complex acoustic patterns that result from mixtures of these modalities.

Similarly joints play an important role in making tapped locations acoustically distinct. Bones are held together by ligaments, and joints often include additional biological structures such as fluid cavities. This makes joints behave as acoustic filters. In some cases, these may simply dampen acoustics; in other cases, these will selectively attenuate specific frequencies, creating location specific acoustic signatures.

SENSING

To capture the rich variety of acoustic information we evaluated many sensing technologies, including bone conduction microphones, conventional microphones coupled with stethoscopes , piezo contact microphones and accelerometers. However, these transducers were engineered for very different applications than measuring acoustics transmitted through the human body. Most of the mechanical sensors are engineered to provide relatively flat response curves over the range of frequencies that is relevant to our signal. This is a desirable property for most applications where a faithful representation of an input signal – uncolored by the properties of the transducer – is desired. However, because only a specific set of frequencies is conducted through the arm in response to tap input, a flat response curve leads to the capture of irrelevant frequencies and thus to a high signal- to-noise ratio. While bone conduction microphones might seem a suitable choice for Skinput, these devices are typically engineered for capturing human voice, and filter out energy below the range of human speech (whose lowest frequency is around 85Hz). Thus most sensors in this category were not especially sensitive to lower-frequency signals (e.g., 25Hz.)To overcome these challenges, we moved away from a single sensing element with a flat response curve, to an array of highly tuned vibration sensors. Specifically, we employ small piezo film.By adding small weights to the end

of the cantilever, we are able to alter the resonant frequency, allowing the sensing element to be responsive to a unique, narrow, low-frequency band of the acoustic spectrum. Adding more mass lowers the range of excitation to which a sensor responds .

Additionally, the cantilevered sensors were naturally insensitive to forces parallel to the skin (e.g., shearing motions caused by stretching). Thus, the skin stretch induced by many routine movements (e.g., reaching for a doorknob)tends to be attenuated. However, the sensors are highly responsive to motion perpendicular to the skin plane – perfect for capturing transverse surface waves (Figure 2) and longitudinal waves emanating from interior structures (Figure 3). Finally, our sensor design is relatively inexpensive and can be manufactured in a very small form factor , rendering it suitable for inclusion in future mobile devices(e.g., an arm-mounted audio player).

ARMBAND PROTOTYPE

Our final prototype, shown in Figures 1 and 5, features two arrays of five sensing elements, incorporated into an armband form factor. The decision to have two sensor packages was motivated by our focus on the arm for input. When placed on the upper arm (above the elbow), we hoped to collect acoustic information from the fleshy bicep area in addition to the firmer area on the underside of the arm, with better acoustic coupling to the Humerus, the main bone that runs from shoulder to elbow. When the sensor was placed below the elbow, on the forearm, one package was located near the Radius, the bone that runs from the lateral side of the elbow to the thumb side of the wrist, and the other near the Ulna, which runs parallel to this on the medial side of the arm closest to the body.

Figure 5 Prototype armband

Each location thus provided slightly different acoustic coverage and information helpful in disambiguating input location.We tuned the upper sensor package to be more sensitive to lower frequency signals, as these were more prevalent in fleshier areas. Conversely, we tuned the lower sensor array to be sensitive to higher frequencies, in order to better capture signals transmitted though (denser) bones.

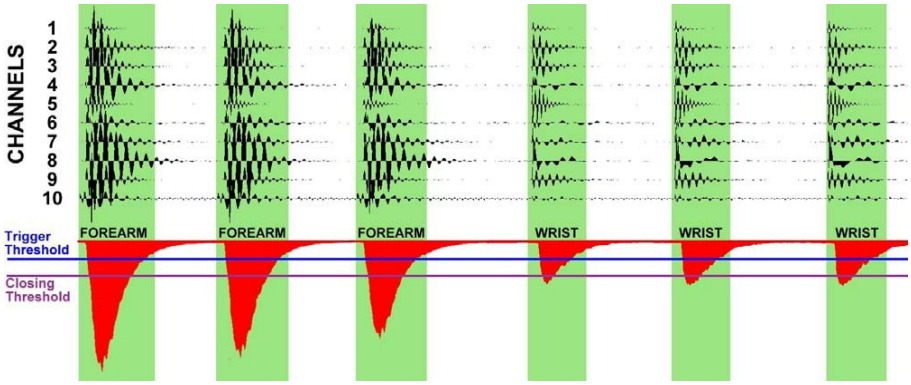
PROCESSING

In our prototype system, we employ a Mackie Onyx 1200F audio interface to digitally capture data from the ten sensors. This was connected via Fire wire to a conventional desktop computer, where a thin client written in C interfaced with the device using the Audio Stream Input/ Output (ASIO) protocol. Each channel was sampled at 5.5kHz, a sampling rate that would be considered too low for speech or environmental audio, but was able to represent the relevant spectrum of frequencies transmitted through the arm. This reduced sample rate (and consequently low processing bandwidth) makes our technique readily portable to embedded processors.

Data was then sent from our thin client over a local socket to our primary application, written in Java. This program performed three key functions. First, it provided a live visualization of the data from our ten sensors, which was useful in identifying acoustic features (Figure 6Second, it segmented inputs from the data stream into independent instances). (taps). Third, it classified these input instances.

The audio stream was segmented into individual taps using an absolute exponential average of all ten channels (Figure 6, red waveform). When an intensity threshold was exceeded (Figure 6, upper blue line), the program recorded the timestamp as a potential start of a tap. If the intensity did not fall below a second, independent "closing" threshold (Figure 6, lower purple line) between 100ms and 700ms after the onset crossing (a duration we found to be the common for finger impacts), the event was discarded. If start and end crossings were detected that satisfied these criteria, the acoustic data in that period (plus a 60ms buffer on either end) was considered an input event (Figure 6, ver tical green regions).

Figure 6



Although simple, this heuristic prove to be highly robust, mainly due to the extreme noise suppression provided by our sensing approach.After an input has been segmented, the waveforms are analyzed .The highly discrete nature of taps (i.e. point impacts)meant acoustic signals were not particularly expressive over time.Signals simply diminished in intensity overtime. Thus, features are computed over the entire input window and do not capture any temporal dynamics.We employ a brute force machine learning approach, computing features in total, many of which are derived

combinatorially.

These features are passed to a Support Vector Machine (SVM) classifier . Our software uses the implementation provided in the Weka machine learning toolkit. Other, more sophisticated classification techniques and features could be employed.Before the SVM can classify input instances, it must first be trained to the user and the sensor position. This stage requires the collection of several examples for each input location of interest. When using Skinput to recognize live input, the same acoustic features are computed on-the fly for each segmented input. These are fed into the trained SVM for classification. We use an event model in our software – once an input is classified, an event associated with that location is instantiated. Any interactive features bound to that event are fired.We readily achieve interactive speeds.

EXPERIMENT

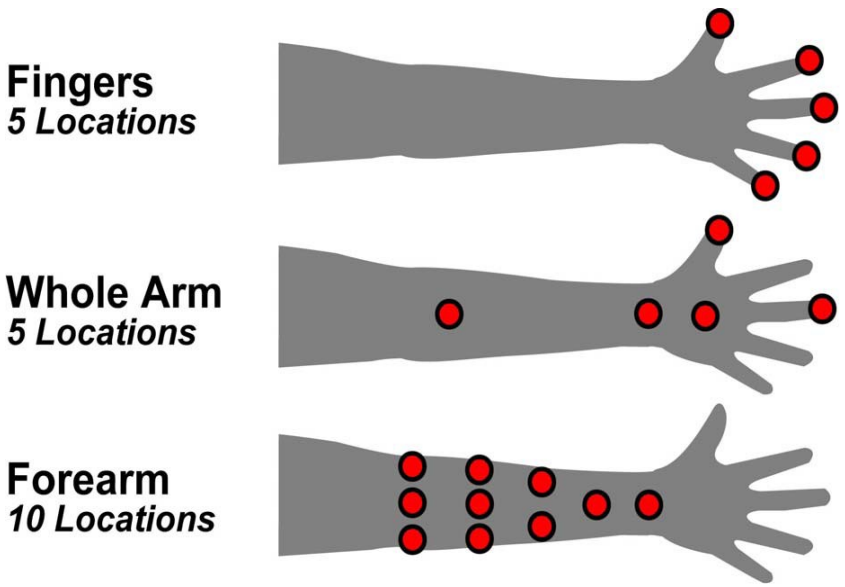
PARTICIPANTS

To evaluate the performance of the system,the developers recruited 13 participants (7 female) from the Greater Seattle area. These participants represented a diverse cross-section of potential ages and body types. Ages ranged from 20 to 56 (mean 38.3), and computed body mass indexes (BMIs) ranged from 20.5 (normal) to 31.9 (obese).

EXPERIMENTAL CONDITIONS

The team selected three input groupings from the multitude of possible location combinations to test.These groupings, illustrated in Figure 7, are of particular interest with respect to interface design, and at the same time, push the limits of our sensing capability. From these three groupings they derived five different experimental conditions, described below.

Figure 7 The three input location sets evaluated in the study



FINGERS (FIVE LOCATIONS)

The fingers offer interesting affordances that make them compelling to appropriate for input. Foremost, they provide clearly discrete interaction points, which are even already well-named (e.g., ring finger). In addition to five finger tips, there are 14 knuckles (five major, nine minor), which, taken together, could offer 19 readily identifiable input locations on the fingers alone. Second, we have exceptional finger-to-finger dexterity, as demonstrated when we count by tapping on our fingers. Finally, the fingers are linearly ordered, which is potentially useful for interfaces like number entry, magnitude control (e.g., volume), and menu selection. At the same time, fingers are among the most uniform appendages on the body, with all but the thumb sharing a similar skeletal and muscular structure. This drastically reduces acoustic variation and makes differentiating among them difficult. Additionally, acoustic information must cross as many as five (finger and wrist) joints to reach the forearm, which further dampens signals. For this experimental condition,they thus decided to place the sensor arrays on the forearm, just below the elbow.

Despite these difficulties there may have measureable acoustic differences among fingers, which is primarily related to finger length and thickness, interactions with the complex structure of the wrist bones, and variations in the acoustic transmission properties of the muscles extending from the fingers to the forearm.

WHOLE ARM (FIVE LOCATIONS)

Another gesture set investigated the use of five input locations on the forearm and hand: arm, wrist, palm, thumb and middle finger (Figure 7, “Whole Arm”).They selected these locations for two important reasons. First, they are distinct and named parts of the body (e.g., “wrist”). This allowed participants to accurately tap these locations without training or markings. Additionally, these locations proved to be acoustically distinct during piloting, with the large spatial spread of input points offering further variation.

The team used these locations in three different conditions. One condition placed the sensor above the elbow, while another placed it below. This was incorporated into the experiment to measure the accuracy loss across this significant articulation point (the elbow). Additionally, participants repeated the lower placement condition in an eyes-free context: participants were told to close their eyes and face forward, both for training and testing. This

condition was included togauge how well users could target on-body input locations in an eyes-free context.

FOREARM (TEN LOCATIONS)

This experimental condition used ten locations on just the forearm (Figure 6, "Forearm").Not only was this a very high density of input locations (unlike the whole-arm condition), but it also relied on an input surface (the forearm) with a high degree of physical uniformity (unlike, e.g., the hand). This location was compelling due to its large and flat surface area, as well as its immediate accessibility, both visually and for finger input. Simultaneously, this makes for an ideal projection surface for dynamic interfaces. To maximize the surface area for input, they placed the sensor above the elbow, leaving the entire forearm free. Rather than naming the input locations, as was done in the previously described conditions, they employed small, coloured stickers to mark input targets. This was both to reduce confusion (since locations on the forearm do not have common names) and to increase input consistency. They consider the forearm is ideal for projected interface elements; the stickers served as low-tech placeholders for projected buttons.

DESIGN AND SETUP

They employed a within-subjects design, with each participant performing tasks in each of the five conditions in randomized order: five fingers with sensors below elbow; five points on the whole arm with the sensors above the elbow; the same points with sensors below the elbow, both sighted and blind; and ten marked points on the forearm with the sensors above the elbow. Participants were seated in a conventional office chair, in front of a desktop computer that presented stimuli. For conditions with sensors below the elbow, they placed the armband 3cm away from the elbow, with one sensor package near the radius and the other near the ulna. For conditions with the sensors above the elbow, they placed the armband 7cm above the elbow, such that one sensor package rested on the biceps. Right-handed participants had the armband placed on the left arm, which allowed them to use their dominant hand for finger input. For the one left-handed participant, we flipped the setup, which had no apparent effect on the operation of the system. Tightness of the armband was adjusted to be firm, but comfortable. While

performing tasks, participants could place their elbow on the desk tucked against their body, or on the chair's adjustable armrest; most chose the latter.

PROCEDURE

For each condition, the experimenter walked through the input locations to be tested and demonstrated finger taps on each. Participants practiced duplicating these motions for approximately one minute with each gesture set. This allowed participants to familiarize themselves with our naming conventions and to practice tapping their arm and hands with a finger on the opposite hand .It also allowed to convey the appropriate tap force to participants, who often initially tapped unnecessarily hard.

To train the system, participants were instructed to comfortably tap each location ten times, with a finger of their choosing. This constituted one training round. In total, three rounds of training data were collected per input location set.An exception to this procedure was in the case of the ten forearm locations, where only two rounds were collected to save time (20 examples per location, 200 data points total). Total training time for each experimental condition was approximately three minutes.

They used the training data to build an SVM classifier. During the subsequent testing phase, they presented participants with simple text stimuli (e.g. "tap your wrist"), which instructed them where to tap. The order of stimuli was randomized, with each location appearing ten times in total. The system performed real-time segmentation and classification, and provided immediate feedback to the participant (e.g. "you tapped your wrist").They provided feedback so that participants could see where the system was making errors (as they would if using a real application). If an input was not segmented (i.e. the tap was too quiet), participants could see this and would simply tap again. Overall,segmentation error rates were negligible in all conditions, and not included in further analysis.

SUPPLEMENTAL EXPERIMENTS

The team conducted a series of smaller, targeted experiments to explore the feasibility of this approach for other applications.In the first additional experiment, which tested performanceof the system while users walked and jogged, they recruited one male (age 23) and one female (age 26) for a single-purpose experiment. For the rest of the experiments, they recruited seven new participants (3 female, mean age 26.9) from within their institution. In all cases, the sensor armband was placed just below the elbow. Similar to the previous experiment, each additional experiment consisted of a training phase, where participants provided between 10 and 20 examples for each input type, and a testing phase, in which participants were prompted to provide a particular input (ten times per input type). As before, input order was randomized; segmentation and classification were performed in real-time.

WALKING AND JOGGING

Acoustically-driven input techniques are often sensitive to environmental noise. In regard to bio-acoustic sensing, with sensors coupled to the body, noise created during other motions is particularly troublesome, and walking and jogging represent perhaps the most common types of whole-body motion. This experiment explored the accuracy of our system in these scenarios.Each participant trained and tested the system while walking and jogging on a treadmill. Three input locations wereused to evaluate accuracy: arm, wrist, and palm.Additionally,the rate of false positives (i.e., the system believed there was input when in fact there was not) and true positives (i.e., the system was able to correctly segment an intended input) was captured.

The testing phase took roughly three minutes to complete (four trials total: two participants, two conditions). The male walked at 2.3 mph and jogged at 4.3 mph; the female at 1.9 and 3.1 mph, respectively. In both walking trials, the system never produced a false positive input. Meanwhile, true positive accuracy was 100%. Classification accuracy for the inputs (e.g., a wrist tap was recognized as a wrist tap) was 100% for the male and 86.7% for the female (chance=33%).In the jogging trials, the system had four false-positive input events (two per participant) over six minutes of continuous jogging. True-positive accuracy, as with walking, was 100%. Considering that jogging is perhaps the hardest input filtering and segmentation test, we view this result as extremely positive. Classification accuracy, however, decreased to 83.3% and 60.0% for the male and female participants respectively (chance=33%).

Although the noise generated from the jogging almost certainly degraded the signal (and in turn, lowered classification accuracy), the chief cause for this decrease was the quality of the training data. Participants only provided ten examples for each of three tested input locations. The training examples were collected while participants were jogging. Thus, the resulting training data

was not only highly variable, but also sparse – neither of which is conducive to accurate machine learning classification.More rigorous collection of training data could yield even stronger results.

SINGLE-HANDED GESTURES

There are a range of gestures that can be performed with just the fingers of one hand.This work did not evaluate classification accuracy.The team conducted three independent tests to explore one handed gestures. The first had participants tap their index,middle, ring and pinky fingers against their thumb (akin to a pinching gesture) ten times each. Our system was able to identify the four input types with an overall accuracy of 89.6% .They ran an identical experiment using flicks instead of taps (i.e., using the thumb as a catch, then rapidly flicking the fingers forward). This yielded an impressive 96.8% accuracy in the testing phase.

This motivated them to run a third and independent experiment that combined taps and flicks into a single gesture set.Participants re-trained the system, and completed an independent testing round. Even with eight input classes in very close spatial proximity, the system was able to achieve a remarkable 87.3% accuracy.This result is comparable to the aforementioned ten location forearm experiment (which achieved 81.5% accuracy), lending credence to the possibility of having ten ormore functions on the hand alone. Furthermore, proprioception of our fingers on a single hand is quite accurate, suggesting a mechanism for high-accuracy, eyes-free input.

SURFACE AND OBJECT RECOGNITION

The system had some ability to identify the type of material on which the user was operating. Using a similar setup to the main experiment, asked participants to tap their index finger against

1) a finger on their other hand,

2) a paper pad approximately80 pages thick and

3) an LCD screen

Results show that system can identify the contacted object with about 87.1% accuracy. This capability was never considered when designing the system, so superior acoustic features may exist. Even as accuracy stands there are several interesting applications that could take advantage of this functionality, including workstations or devices composed of different interactive surfaces, or recognition of different objects grasped in the environment.

IDENTIFICATION OF FINGER TAP TYPE

Users can “tap” surfaces with their fingers in several distinct waysOne can use the tip of their finger (potentially even their finger nail) or the pad (flat, bottom)of their finger. The former tends to be quite boney, while the latter more fleshy. It is also possible to use the knuckles.To evaluate approach’s ability to distinguish these input types,the team had participants tap on a table situated in front of them in three ways (ten times each): finger tip, finger pad, and major knuckle.

A classifier trained on this data yielded an average accuracy of 89.5% during the testing period.This ability has several potential uses.The mostcnotable is the ability for interactive touch surfaces to distinguishcdifferent types of finger contacts (which are indistinguishable)c Interaction could be that “double-knocking” on ancitem opens it, while a “pad-tap” activates an options menu.

SEGMENTING FINGER INPUT

A pragmatic concern regarding the appropriation of fingertips for input was that other routine tasks would generate false positives. For example, typing on a keyboard strikes the finger tips in a very similar

manner to the finger-tip input.Thus the team set out to explore whether finger-to-finger input sounded sufficiently distinct such that other actions could be disregarded. As an initial assessment the team asked participants to tap their index finger 20 times with a finger on their other hand, and 20 times on the surface of a table in front of them. This data was used to train the classifier. This training phase was followed by a testing phase, which yielded a participant wide average accuracy of 94.3%

FEATURES

ALWAYS AVAILABLE INPUT

The primary goal of Skinput is to provide an always available mobile input system – that is, an input system that does not require a user to carry or pick up a device. A number of alternative approaches have been proposed that operate in this space. Techniques based on computer vision are popular.These, however, are computationally expensive and error prone in mobile scenarios. Speech input is a logical choice for always-available input, but is limited in its precision in unpredictable acoustic environments, and suffers from privacy and scalability issues in shared environments.

Other approaches have taken the form of wearable computing. This typically involves a physical input device built in a form considered to be part of one's clothing.A smart fabric"system that embeds sensors and conductors into fabric may be possible, but taking this approach to always-available input necessitates embedding technology in all clothing, which would be prohibitively complex and expensive.The SixthSense project proposes a mobile, always available input/output capability by combining projected information with a color-marker-based vision tracking system. This approach is feasible, but suffers from serious occlusion and accuracy limitations.In Skinput we are using the combination of on-body sensing with on-body projection.

BIO-SENSING

Skinput leverages the natural acoustic conduction properties of the human body to provide an input system, and is thus related the use of biological signals for computer input. Signals traditionally used for diagnostic medicine, such as heart rate and skin resistance, have been appropriated for assessing a user's emotional state.These features are generally subconsciously driven and cannot be controlled with sufficient precision for direct input.There has been less work relating to the intersection of finger input and biological signals. Researchers

have harnessed the electrical signals generated by muscle activation during normal hand movement through electromyography (EMG).

At present, however, this approach typically requires expensive amplification systems and the application of conductive gel for effective signal acquisition, which would limit the acceptability of this approach for most users.The input technology most related to our own is that of who placed contact microphones on a user's wrist to assess finger movement. Moreover techniques required the placement of sensors near the area of interaction (e.g., the wrist), increasing the degree of invasiveness and visibility. Finally, bone conduction microphones and headphones – now common consumer technologies - represent an additional bio-sensing technology that is relevant to the skin input mechanism.These leverage the fact that sound frequencies relevant to human speech propagate well through bone. Bone conduction microphones are typically worn near the ear, where they can sense vibrations propagating from the mouth during speech. Bone conduction headphones send sound through the bones of the skull and jaw directly to the inner ear, bypassing transmission of sound through the air and outer ear, leaving an unobstructed path for environmental sounds.

ACOUSTIC INPUT

Our approach of skinput mechanism is also inspired by systems that leverage acoustic transmission through (non-body) input surfaces.We measure the arrival time of a sound at multiple sensors to locate hand taps on a glass window.We can use a similar approach to localize a ball hitting a table, for computer augmentation of a real-world game. Both of these systems use acoustic time-of-flight for localization, which we explored, but found to be insufficiently robust on the human body, leading to the fingerprinting approach.

DISADVANTAGES

- Many people would not wear a very big band around their arm for the day just to have this product and especially for the seniors it just creates a big inconvenience
- Skinput does not answer the incoming calls so we still have to reach in our pocket, find our phone and answer it
- Individuals with visible disabilities such as amputated arms or the blind cannot use this product
- Not enough research has been conducted on this product to test the possible diseases one can get from using this product
- Using the Skinput on the road is a reason for deviating individual's attention that results in accident and harm other drivers and himself
- Workers will ignore their workplace dress code in order to use the Skinput so that this technology only works on direct skin exposure

CONCLUSION

Skinput appropriating the human body as an input surface with the help of a novel, wearable bio-acoustic sensing array that we built into an armband in order to detect and localize finger taps on the forearm and hand. Results from the experiments have shown that the system performs very well for a series of gestures, even when the body is in motion which provides hope to further explore in future work with a rich design space.Touchscreens may be popular both in science fiction and real life as the symbol of next-gen technology, but an innovation called Skinput suggests the true interface of the future might be us.

REFERENCES

- www.wikipedia.com

- Skinput: Appropriating the Body as an Input Surface Chris Harrison , Desney Tan, Dan Morris

- research.microsoft.com