A

Seminar report

On

Skinput Technology

Submitted in partial fulfillment of the requirement for the award of degree of ECE

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Preface

I have made this report file on the topic **Skinput Technology** ; I have tried my best to elucidate all the relevant detail to the topic to be included in the report. While in the beginning I have tried to give a general view about this topic.

My efforts and wholehearted co-corporation of each and everyone has ended on a successful note. I express my sincere gratitude to …………..who assisting me throughout the preparation of this topic. I thank him for providing me the reinforcement, confidence and most importantly the track for the topic whenever I needed it.

ABSTRACT

Skinput is a technology that appropriates the human body for acoustic transmission, allowing the skin to be used as an input surface. In particular, 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. The capabilities, accuracy and limitations of this technique are assessed through a two-part, twenty-participant user study.

INTRODUCTION

Devices with significant computational power and capabilities can now be easily carried on our bodies. However, their small size typically leads to limited interaction space and consequently diminishes their usability and functionality. 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 a technique that allows a small mobile device to turn tables on which it rests into a gestural finger input canvas. However, tables are not always present, and are not usable in a mobile context,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 (e.g., arms, upper legs, torso).

Skinput is a method that allows the body to be appropriated for finger input using a novel, non-invasive, wearable bio-acoustic sensor

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.

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.

HARDWARE ARCHITECTURE

To expand the range of sensing modalities for always available input systems, a novel input technique that allows the skin to be used as a finger input surface is described in this paper and is named as Skinput. In this prototype system, the focus is 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 (discussed subsequently).

Furthermore, the forearm and hands contain a complex assemblage of bones that increases acoustic distinctiveness of different locations. To capture this acoustic information a wearable armband that is non-invasive and easily removable is developed. In this section, the mechanical phenomenon that enables Skinput is discussed, with a specific focus on the mechanical properties of the arm. The Skinput sensor and the processing techniques used to segment, analyze, and classify bio-acoustic signals are studied in this section.

Major Components are

- Bio-Acoustics
- Sensing
- Armband Prototype
- Processing

APPLICATIONS

A method for controlling an iPod with skin-touch based input to select music tracks while jogging.

- It turns the fingers into a controller for the game of Tetris.
- It may be used for dialing your phone on your arm.

SKINPUT

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 (discussed subsequently). Further more, 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 In this section, we discuss the mechanical phenomena that enables *Skinput*, with a specific focus on the mechanical properties of the arm. Then we will describe the *Skinput* sensor and the processing techniques we use to segment, analyze, and classify bio-acoustic signals.

1.1. 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). 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 soft regions of the arm creates higher amplitude transverse waves than tapping on boney areas (e.g., wrist, palm, fingers), 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. 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. Roughly speaking, 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, we also believe that 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.

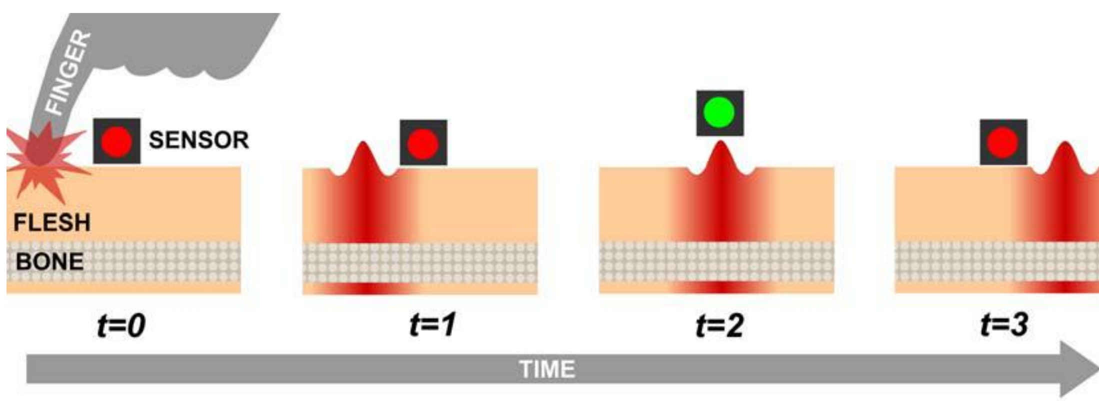


Figure 2. Transverse wave propagation: Finger impacts displace the skin, creating transverse waves (ripples). The sensor is activated as the wave passes underneath it.

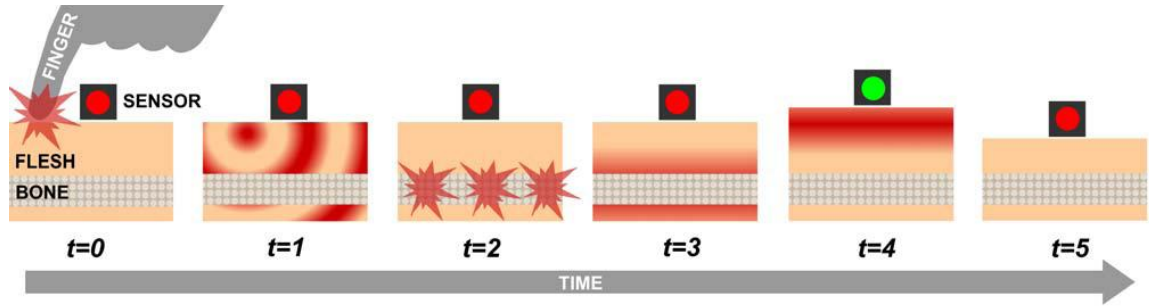
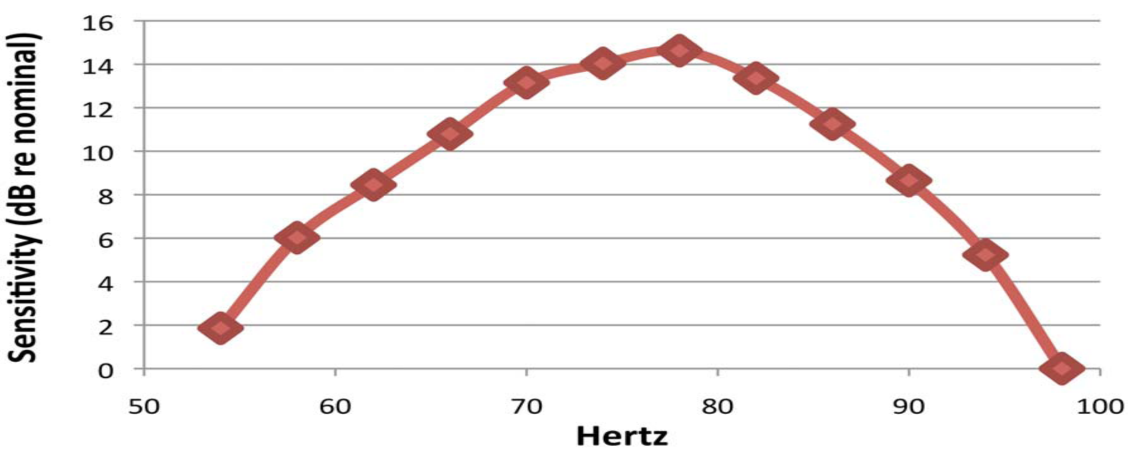


Figure 3. Longitudinal wave propagation: Finger impacts create longitudinal (compressive) waves that cause internal skeletal structures to vibrate. This, in turn, creates longitudinal waves that emanate outwards from the bone (along its entire length) toward the skin.

1.2. SENSING

To capture the rich variety of acoustic information described in the previous section, we evaluated many sensing technologies, including bone conduction microphones, conventional microphones coupled with stethoscopes, piezo contact microphones, and accelerometers. Ho wever, these transducers were engineered for very different applications than measuring acoustics transmitted through the human body. As such, we found them to be lacking in several significant ways. Foremost, most 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), which we found in our empirical pilot studies to be vital in characterizing finger taps. 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, cantilevered piezo films (MiniSense100, Measurement Specialties, Inc.). 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 aunique, narrow, low-frequency band of the acoustic spectrum. Adding more mass lowers the range of excitation to which a sensor responds; we weighted each element such that it aligned with particular frequencies that pilot studies showed to be useful in characterizing bio-acoustic input. Figure 4 shows the response curve for one of our sensors, tuned to a resonant frequency of 78Hz.



The curve shows a ~14dB drop-off ±20Hz away from the resonant frequency. Additionally, the cantilevered sensors were naturally insensitive to forces parallel to the skin (e.g., shearing motionscaused 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 (e.g., MEMS), rendering it suitable for inclusion in future mobile devices (e.g., an arm-mounted audio player).

1.3. 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. In particular, 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. Each location thus provided slightly different acoustic coverage and information, helpful in disambiguating input location. Based on pilot data collection, we selected a different set of resonant frequencies for each sensor package (Table 1). 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.

1.4. PROCESSING

In our prototype system, we employ a Mackie Onyx 1200F audio interface to digitally capture data from the ten sensors (http://mackie.com). This was connected via Firewire 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. For example, the ATmega168 processor employed by the Arduino platform can sample analog readings at 77kHz with no loss of precision, and could therefore provide the full sampling power required for *Skinput* (55kHz total). 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 6). Second, 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 (Figure6, 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, vertical green regions). Although simple, this heuristic proved to be highly robust, mainly

due to the extreme noise suppression rovided by our sensing approach.

Upper Array	25 Hz 27 Hz 30 Hz 38 Hz 78 Hz
Lower Array	25 Hz 27 Hz 40 Hz 44 Hz 64 Hz

Table 1. Resonant frequencies of individual elements in the two sensor packages.

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 (unlike gestures, e.g., clenching of the hand). 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 186 features in total, many of which are derived combinatorially. For gross information, we include the average amplitude, standard deviation and total (absolute) energy of the waveforms in each channel (30 features). From these, we calculate all average amplitude ratios between channel pairs (45 features). We also include an average of these ratios (1 feature). We calculate a 256-point FFT for all ten channels, although only the lower ten values are used (representing the acoustic power from 0Hz to 193Hz), yielding 100 features. These are normalized by the highest-amplitude FFT value found on any channel. We also include the center of mass of the power spectrum within the same 0Hz to 193Hz range for each channel, a rough estimation of the fundamental frequency of the signal displacing each sensor (10 features). Subsequent feature selection established the all-pairs amplitude ratios and certain bands of the FFT to be the most predictive features. These 186 features are passed to a Support Vector Machine (SVM) classifier.

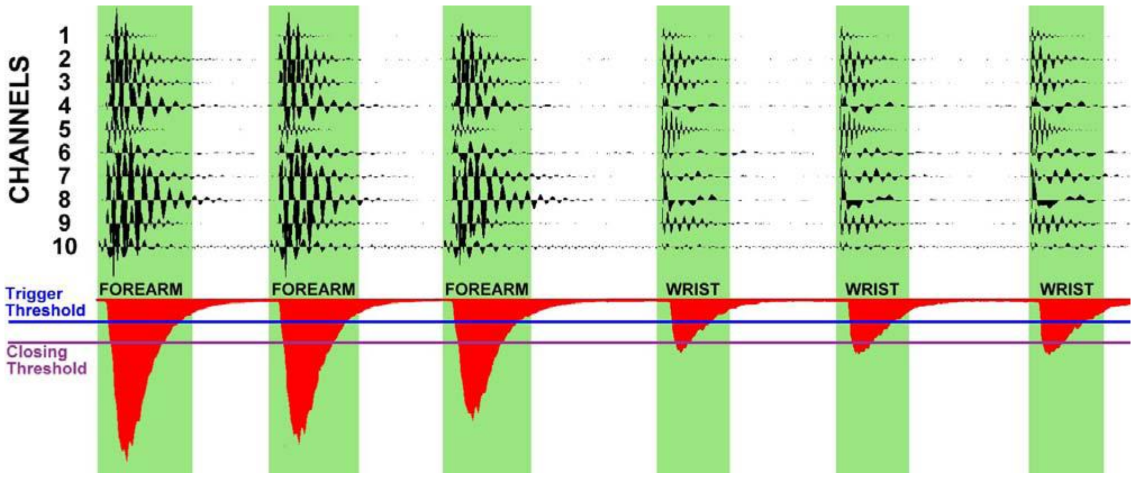


Figure 6: Ten channels of acoustic data generated by three finger taps on the forearm, followed by three taps on the wrist. The exponential average of the channels is shown in red. Segmented input windows are highlighted in green. Note how different sensing elements are actuated by the two locations.

A full description of VMs is beyond the scope of this paper (see [4] for a tutorial). Our software uses the implementation provided in the Weka machine learning toolkit [28]. It should be noted, however, that other, more sophisticated classification techniques and features could be employed. Thus, the results presented in this paper should be considered a baseline. 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 186 acoustic features are computed on-thefly 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. As can be seen in our video, we readily achieve interactive speeds.

Advantages:

1. Don’t need any Keyboard.
2. Don’t need any Keyword.
3. Provide interactive play expertise.
4. Provide straightforward navigation by providing giant buttons.
5. Arm acts as an Instrument.
6. Respond to numerous Hand Gestures.
7. Easy to access in absence of Mobile.

Disadvantages:

1. Visibility downside to the person having tattoos on its skin.
2. It will cause the folks to be socially distracted.
3. Provide solely five buttons.
4. Body mass index can scale back the accuracy.
5. Arm band is large.

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Pico-Projector in Mobile devices

By this technology, 5 skin location detection are distributed with accuracy of over ninety fifth. It’s the technology that’s not affected together with your movement as if you’re moving or walking, you’ll be able to use it with identical potency.

Operation

Skinput has been publicly demonstrated as an armband, which sits on the biceps. This prototype contains ten small cantilevered Piezo elements configured to be highly resonant, sensitive to frequencies between 25 and 78 Hz. This configuration acts like a mechanical Fast Fourier transform and provides extreme out-of-band noise suppression, allowing the system to function even while the user is in motion. From the upper arm, the sensors can localize finger taps provided to any part of the arm, all the way down to the finger tips, with accuracies in excess of 90% (as high as 96% for five input locations).[5] Classification is driven by a support vector machine using a series of time-independent acoustic features that act like a fingerprint. Like speech recognition systems, the Skinput recognition engine must be trained on the "sound" of each input location before use. After training, locations can be bound to interactive functions, such as pause/play song, increase/decrease music volume, speed dial, and menu navigation.

Conclusion

In this paper, the approach is to appropriate the human body as an input surface. A novel, wearable bio-acoustic sensing array built into an armband in order to detect and localize finger taps on the forearm and hand is developed. Results from experiments have shown that the system performs very well for a series of gestures, even when the body is in motion.

Additionally, presented initial results demonstrating other potential uses of the approach, which are hoped to further explore in future work. These include single-handed gestures and taps with different parts of the finger.

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