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# PROPOSED NEW TECHNIQUE FOR EVALUATION OF SKIN AS TOUCH SCREEN IN COMPUTER ENGINEERING

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## ABSTRACT

In this paper the work has been done on the sensitivity of human skin in such a manner that it can be used as a touch screen. In this work human skin will be used as a touch screen as in mobiles, laptops, tablets and all other electronic gadgets. If user find them getting annoyed at the tiny touch screens on today's mobile devices, they might be interested in a "new" yet overlooked input surface. A new skin-based interface called Skinput allows users to use their own hands and arms as touch screens by detecting the various ultralow-frequency sounds produced when tapping different parts of the skin. Latest tools available are used to simulate the results.

**Keywords**: Skinput, Bio-acoustics, Pico Projector, Acoustic Detector, Armband Prototype & Audio Interfaces.

## INTRODUCTION

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 [1]. As shown in figure 1, 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 [2]. Their software matches sound frequencies to specific skin locations, allowing the system to determine which "skin button" the user pressed.

**FIGURE:-1**

Figue 2 shows the 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 [2].

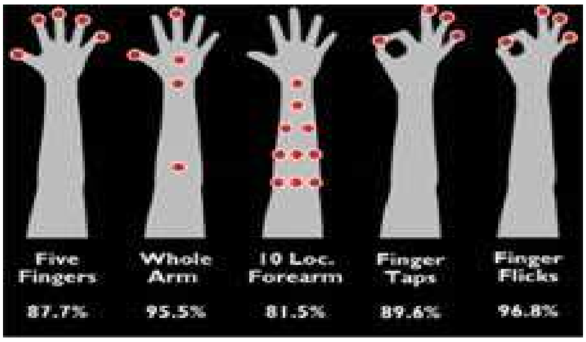


**FIGURE:-2**

RELATED WORK

Skinput is an amazing Bluetooth-enabled device being developed by scientists from Carnegie Mellon and Microsoft that allows users to use their skin as a touchscreen to control your phone, MP3 player or gaming console.It works by using a bio-acoustic sensing technique that allows your body to be used as an input surface. When your finger taps your skin, the impact creates acoustic signals that can be measured by the device [4][7]. To capture these signals, scientists have developed a bio-acoustic sensing array which listens for impacts and classifies them [3].

BIO-ACOUSTICS

In this section, the mechanical phenomenon that enables *Skinput*, with a specific focus on the mechanical properties of the arm is demonstrated. Then the *Skin put* sensor and the processing techniques that are used to segment, analyze, and classify bio-acoustic signals are discussed [12][8]. 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. In figure 3(a) 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. When shot with a high-speed camera, these appear as ripples, which propagate outward from the point of contact. In figure 3(b),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[14][13]. 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.

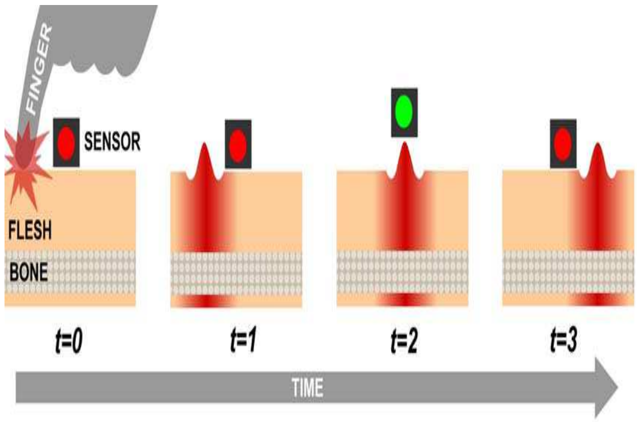


**FIGURE:-3(A):-** Transverse wave proporgation:Finger impact displaces the skin,creating the transverse waves.

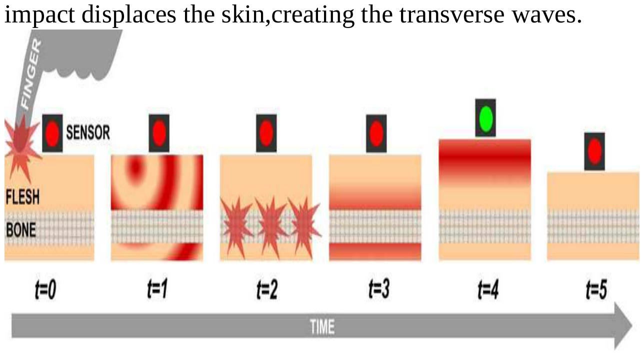


**FIGURE 3(B):-** Longitudinal wave propogation:Finger impact creates longitudinal waves that cause internal skeleton structures to vibrate.

**SENSING**

To capture the rich variety of acoustic information described in the previous section, many sensing technologies were evaluated, including bone conduction microphones, conventional microphones coupled with stethoscopes, piezo contact microphones , and accelerometers[15]. However, these transducers were engineered for very different applications than measuring acoustics transmitted through the human body. As such,it was found that they were lacking in several significant ways[16]. Foremost, most mechanical sensors are engineered to provide relatively flat response curves over the range of frequencies that is relevant to the 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[9][10]. 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.

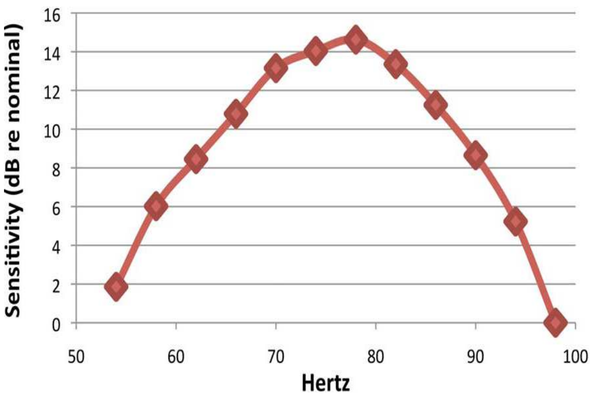


**FIGURE 4:-** Response curve between sensitivity and frequency for the sensing element that resonates at 78 Hz.

In figure 4, the curve shows a~14dB drop-off ±20Hz away from the resonant frequency [17].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 [18]. However, the sensors are highly responsive to motion perpendicular to the skin plane – perfect for capturing transverse surface waves and longitudinal waves emanating from interior structures[11][13]. Finally, this 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).

## ARMBAND PROTOTYPE

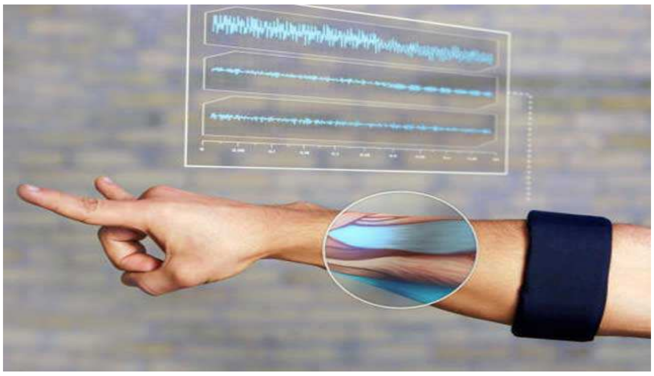

**FIGURE 5(A)**

The final prototype, features two arrays of five sensing elements, incorporated into an armband form factor. The decision to have two sensor packages was motivated by focus on the arm for input[19]. In particular, when placed on the upper arm (above the elbow), it was 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.

**FIGURE 5(B):-** Armband prototype

## PROCESSING

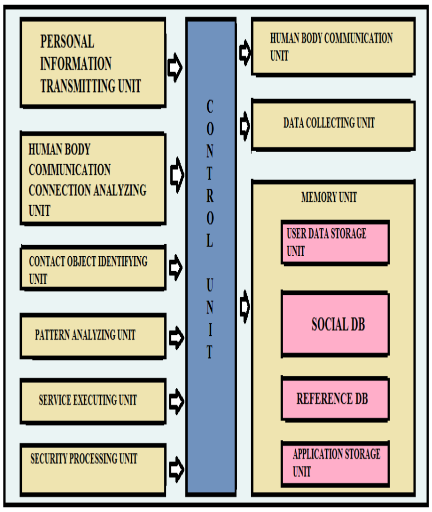


**FIGURE 6:-**

**PROCESSING**

In this figure 6.it classifies the input instances. The audio stream was segmented into individual taps using an absolute exponential average of all ten channels. When an intensity threshold was exceed the program recorded the timestamp as a potential start of a tap [20]. If the intensity did not fall below a second, independent "closing" threshold 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 bufferon either end) was considered an input event.The figure 7 shows channels of acoustic data generated by finger taps.

**Upper Array –**
25 Hz 27 Hz 30 Hz 38 Hz 78 Hz

**Lower Array –**
25 Hz 27 Hz 40 Hz 44 Hz 64 Hz

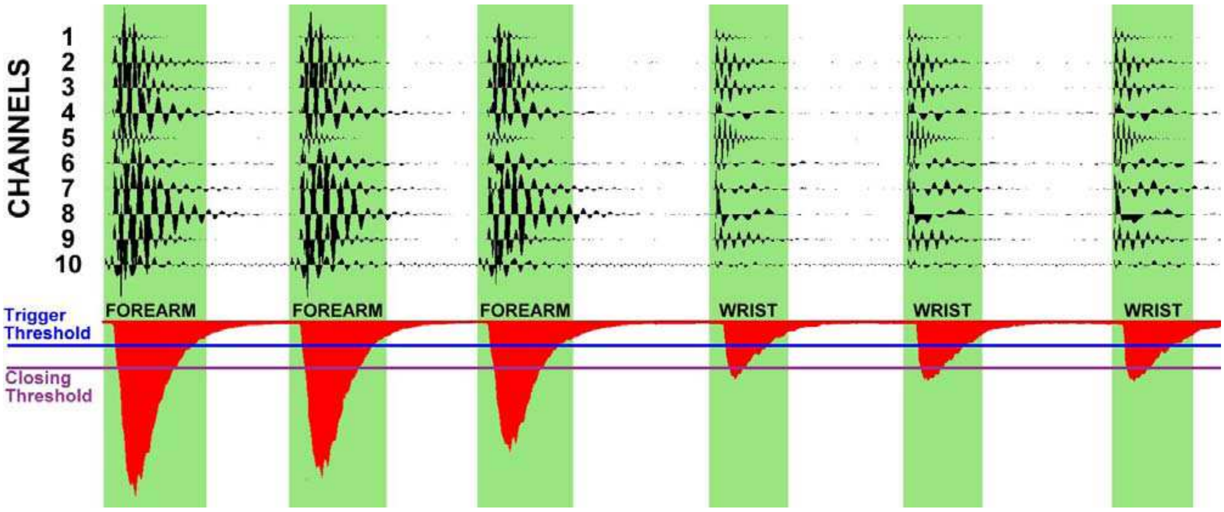


**FIGURE 7:-** Ten channels of acoustic data generated by three finger taps on the forearm,followed by three taps on the wrist.
RED - Exponential average of the channels.
GREEN- Input windows

**FUTURE SCOPE**

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. The researchers say the system also works well when the user is walking or running. As the researchers explain, the motivation for Skinput comes from the increasingly small interactive spaces on today's pocket-sized mobile devices.

**CONCLUSIONS**

In this paper, the work has been done to appropriating the human body as an input surface. The work has been done to describe a novel, wearable bio-acoustic sensing array that has built into an armband in order to detect and localize finger taps on the forearm and hand. Results from our experiments have shown that this system performs very well for a series of gestures, even when the body is in motion. Additionally, work has been done to present initial results demonstrating other potential uses of our approach, which we hope to further explore in future work. These include single-handed gestures, taps with different parts of the finger, and differentiating between materials and objects.This concludes with descriptions of several prototype applications that demonstrate the rich design space it believes *Skinput* enables.

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