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Human Skin as an Input Surface

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***Abstract*-— In this paper, an attempt has been made to utilize the natural acoustic and mechanical wave conduction property of human skin along with simple technological tools to achieve high accuracy for classification of taps done onto the skin so, that it may be use in future to create interactive interface technologies. Previous work in this field employed very expensive and sophisticated vibration detection approach which was not preferable for layman use both due to its physical size and cost. We in this paper try to re duce both these important parameters by employing accelerometers instead of vibration sensors.**

***Keyword*: MEMS , MPU 6050, SVM.**

I. EXISTING SYSTEM

Piezoelectric materials produce an electrical charge when stressed mechanically and when an electric field is applied, it produces a mechanical strain. Under such a case, these materials are said to act in a "direct" manner. It is this effect which is used in sensors like piezoelectric accelerometers.[1]. The accelerometer used in this paper is MPU-6050. It senses the vibrations on the skin and converts them into electrical signals. These signals are then fed to MATLAB through Arduino UNO board for further processing. It is quite evident from the mechanism that such piezoelectric materials can have many applications in the field of structural dynamics. Moreover, they are extensively used because of its being sturdy, lightweight and inexpensive. They are also in the formation of microelectromechanical systems varying from simple shapes like rectangular to complex shapes.[1]. The fundamental advantage of using them is that they can be easily integrated with silicon wafers to obtain a monolithic system with the implementation of the sensor elements and the electronics on the same substrate.[2] .

The, MPU 6050 uses piezoelectricity to measure the acceleration, although it can also be measured by capacitive and piezo resistive method depending upon the inherent limitations and advantages.[1-3][2]. It has a 3-axis gyroscope and a 3-axis accelerometer on the same silicon die. It is capable of accessing sensors like external magnetometers through an auxiliary master I2C bus.

The paper presents a novel utility of MPU 6050 that can be used to control electronic gadgets with great ease, thus making it a successful technology in the market. Skin is used as an input to the touch done mechanically. It is so because it is the largest sense organ and in being so it can easily detect the vibrations of the touch. The system developed is economical and once programmed properly becomes very handy to be used. The implementation of this mechanism in real life can thus be a cutting-edge development that will pave its way to the diverse fields like medicine, engineering, robotics etc.

The paper is organized as follows: Section II & III provides a brief overview of micro electromechanical systems and MPU6050 respectively. Section IV gives references about the types of readily available inputs. Section V gives a detailed overview of biosensing property of skin. Section VI gives an overview of sensor placement. Section VII describes the experimental procedure. Section VIII gives the results of performed experiment. Conclusion and future work is provided in section IX.

II. MICRO-ELECTROMECHANICAL-SYSTEMS

In the late 80s with the emergence of the micromachining technology micron-sized sensors and actuators came into being. Micro- electromechanical-systems(MEMS) are thus formed by integrating a signal conditioning and processing circuitry using micro transducers to perform real-time distributed control.[3]. Over the recent ten years, micromachining technology has become available in order to fabricate micron-sized mechanical parts. Micro machines have versatile applications in many disciplines like biology, medicine, optics, aerospace, and mechanical and electrical engineering.[3]. The benefits of this ever growing field is not limited to providing miniature transducers for sensing and actuation in a domain that we could not examine in the past, but it also allows us to venture into a cutting-edge research area where surface effects dominate most of the phenomena.[3].

Inertial sensors that are based on MEMS technology are fast becoming ubiquitous as it is being used in many types of consumer electronics products, like smart phones, tablets, gaming systems, toys, and even power tools and wearable sensors. MEMS-based motion tracking enhances the user interface by allowing response to user motions. This is nowadays one of the most standard features of many smartphones.[4].

III. MPU6050

Nowadays, a "must-have" function that is being adopted by smartphone and tablet manufacturers is Motion Interface which adds enormous value to the end user experience. Gesture commands for applications and phone control, enhanced gaming, augmented reality, panoramic photo capture and viewing, and pedestrian and vehicle navigation are some of the many applications of Motion Interface in smartphones. Motion Tracking technology has an ability to precisely and accurately track user motions that convert handsets and tablets into powerful 3D intelligent devices. It can be used in many applications like health and fitness monitoring, location-based services to name a few. There are certain key requirements for Motion Interface enabled devices like small package size, low Consumption of power, high accuracy and repeatability and high shock tolerance.

The MPU-6050 parts are the world‟s first Motion Tracking devices designed for the low power, low cost, and high-performance requirements of smartphones, tablets and wearable sensors. The MPU-6050 incorporates InvenSense‟s Motion Fusion and run-time calibration firmware which allows manufacturers to eliminate the costly and complex selection, qualification, and system level integration of discrete devices in motion-enabled products, guaranteeing that sensor fusion algorithms and calibration procedures deliver optimal performance for consumers. The MPU-6050 devices have a combination of a 3-axis gyroscope and a 3-axis accelerometer on the same silicon die, along with an onboard Digital Motion Processor (DMP), which processes complex 6-axis MotionFusion algorithms. An added feature of this device is that it can access external magnetometers or other sensors through an auxiliary master I²C bus, that allows the devices to gather a full set of sensor data without any intervention from the system processor. The devices are offered in a 4 mm x 4 mm x 0.9 mm QFN package. [5].

IV. TYPES OF INPUTS

Keypads and voice-based devices tend to provide high relative input bandwidths. Gesture-based devices, however, tend to have lower bandwidths. Access time is quite large for touch based devices, whereas gesture devices are usually persistent, making their access times low to non-existent. There are following types of inputs available:

Accelerometer-Based: Use telemetry data from accelerometers to classify gestures.[5][6].

Glove-Based: Use embedded strain gauges to measure finger orientation.[11][6].

Buttons and Keypads: Including mini-qwerty keypads common on mobile phones.[3][6], as well as mobile chording keypads, which are one-hand portable keyboards that provide fairly high data rates.[7][6].

Devices with a few buttons (eg some GPS receivers) can also be classified in this category, though their input rates are typically lower.

Touch and Stylus: Use a touchscreen to recognize pen stroke gestures.[14][6].

Vision: Use a camera to process signals from the environment. Examples would include the WristCam .[9,12][6].

Voice: Use audio speech recognition to provide input to the system.[6, 8][6].

V. BIOSENSING

Our device has been affiliated with the previous works in the use of biological signals for computer input thus can leverage the natural acoustic conduction properties of human body to provide input system.[7,8,9]. Further, bone conduction microphones and headphones – now common consumer technologies - represent an additional bio-sensing technology which are in accordant with the present work. These aid the phenomenon of human speech propagation through the bone in accordance with the sound frequencies. Bone conduction microphones are customarily worn near the ear, where they can sense vibrations propagating from the mouth and larynx during speech. Bone conduction headphones send sound through the bones of the skull and jaw directly to the inner ear, bypassing transmission of sound

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Fig.1: Boney region

Fig.2: Fleshy region

through the air and outer ear, leaving an unobstructed path for environmental sounds.[10].
When the user taps on the forearm, mechanical waves are generated onto the skin and the waves propagates via two types of medium, soft fleshy region and boney region. Soft fleshy medium which offers more attenuation to the waves and when the medium consist of bone which is relatively rigid than the fleshy medium and thus offer less attenuation, that is why when the user tap below the wrist region of the forearm as shown in Fig.1 the waves propagates through the bone and when the user taps above the antecubital region as shown in Fig.2. The waves propagate through soft fleshy region. The amplitude detected by the sensor is less for below the wrist region as compared to the fleshy part below the antecubital because the distance between the sensor and the wrist is greater than compared to the fleshy part below the antecubital, even when the attenuation offered by bone is less than that of flesh.

VI. SENSOR PLACEMENT

When a user taps on their skin, transfer of mechanical energy takes place. Most part of this mechanical energy is converted into sound energy and the rest is absorbed by skin. It propagates through it in form of waves (both transverse waves and longitudinal waves).[6]. For highest accuracy detection it is crucial to place the sensor at an appropriate location.
As sound waves propagates through a medium it suffers from attenuation due to the physical properties of the medium. The attenuation is inversely proportional to the stiffness of the material and that is the reason why sound suffer less attenuation through bones than soft tissues. It is therefore crucial to pre determine a mounting location with little to none skin movement. [6]. After testing several locations on our arm it was observed that the antecubital (front of elbow) region is the appropriate location for sensor placement. We then employed 2 MPU6050 sensors to detect tap vibrations with highest possible accuracy, one being placed below and above the antecubital. The sensor above antecubital region detects the waves propagating through soft tissue while the sensor below the antecubital detects waves propagating through bones.

VII. EXPERIMENTAL PROCEDURE

We have identified three points on the skin(forearm) A,B,& C as shown in the Fig.3. The objective is to detect these three points when touched. To evaluate the performance of the proposed system a large number of data is collected. The data is collected by tapping on these points. A program is written in MATLAB to classify these points.
After affixing the sensor at appropriate arm location the next step is the collection of acceleration values resulting after tapping on the forearm. The MPU 6050 senses the taps as acceleration values along the z axis. These acceleration values are converted from analog to digital format by an inbuilt 16bit ADC present inside MPU 6050.[5]. These digital values of acceleration are mapped onto a specified numeric value range via Arduino Uno java software. Then, the acceleration values can be easily monitored on serial monitor of this software.
Data is collected in MATLAB file via a simple MATLAB code in a specified size double data array format. The data collected is known as data sets. The size of a data set could be varied as per requirement. The accuracy of the achieved trained model is directly proportional to the size of data set.
It is not possible to allot alphabetic features to data set. To overcome this, it is advised to convert data set into table data type for further processing. Further processing can be achieved by employing the array to table conversion command. The data set in table data type format is now suitable for feature allocation and further processing.
After a suitable number of features is allotted (3 in our experiment), the dataset could be used to obtain trained

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model to classify new data sets based on the pattern by which features are allotted to the training dataset. Next step is the formation of trained model. For this we utilize the MATLAB"s classification learner tool. This interactive classification learner tools includes a variety of advanced classifiers e.g. trees, support vector machines, nearest neighbor classifier which are based on complex classification algorithms that are beyond the scope of this paper. Tree classifier or Decision tree learning is a method commonly used in data mining. [11]. The different types of tree classifiers are shown in Table.I with their respective accuracies obtained by simulation.

Support Vector Machine(SVM) constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. It is due to these hyperplanes that it becomes the most advanced classifying tool available today.[12]. The different types of SVM present are shown in the Table.I with their respective accuracies.

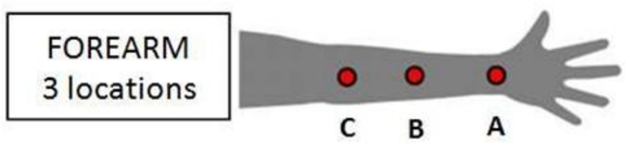

Fig.3: points taken on the forearm to perform the experiment.

TABLE.I: Types and sub-types of classifiers with their respective accuracies.

TYPE OF CLASSIFIER	SUB-TYPE OF CLASSIFIER	ACCURACIES (PERCENTAGE)
DECISION TREE CLASSIFIER	SIMPLE TREE	57.7
	MEDIUM TREE	61.6
	COMPLEX TREE	58.6
SUPPORT VECTOR MACHINES	LINEAR SVM	60.1
	QUADRATIC SVM	61.3
	CUBIC SVM	61.0
	FINE GAUSSIAN SVM	**68.2**
	MEDIUM GAUSSIAN SVM	61.6
	COARSE GAUSSIAN SVM	60.4
NEAREST NEIGHBOR CLASSIFIER	FINE KNN	62.5
	MEDIUM KNN	62.2
	COARSE KNN	57.4
	COSINE KNN	57.1
	CUBIC KNN	60.4
	WEIGHTED KNN	64.6

In pattern recognition, the k-nearest neighbors algorithm (k-NN) is a non-parametric method used for classification and regression [13].

Both for classification and regression, it can be useful to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where d is the distance to the neighbor. [13]. Types of KNN classifiers used in this paper are as shown in the Table.I with their respective accuracies.

In this paper, we have implemented all of the above classifiers practically and the best accuracy of trained model is achieved by implementing Fine Gaussian SVM classifiers. This tools also allows the user to extract the best fit model (model with highest classification accuracy) onto the workspace that can be easily utilized for further feature prediction on fresh data sets.

The classification learner tool presents the data set in the form of a scatter plot as shown in Fig.4, it shows the ROC curve of trained model in Fig.5.

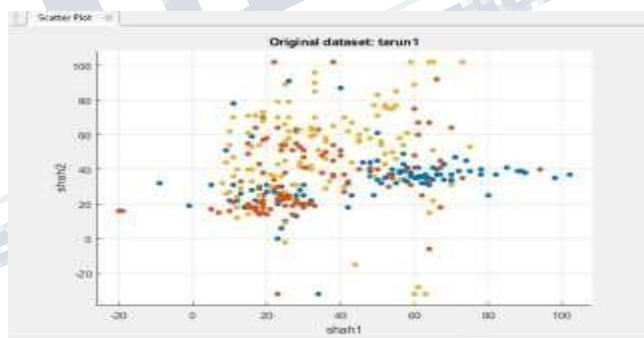

Fig.4: Scatter plot of data set

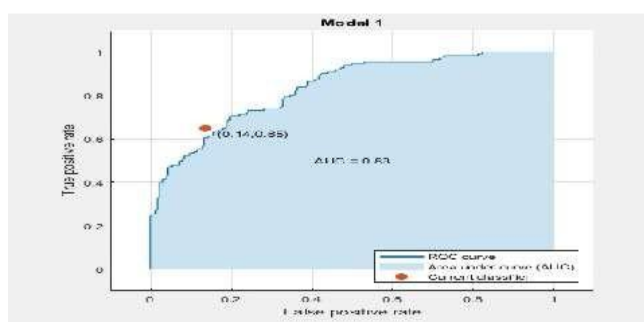

Fig.5: Region Of Convergence (R. O. C) of a trained model

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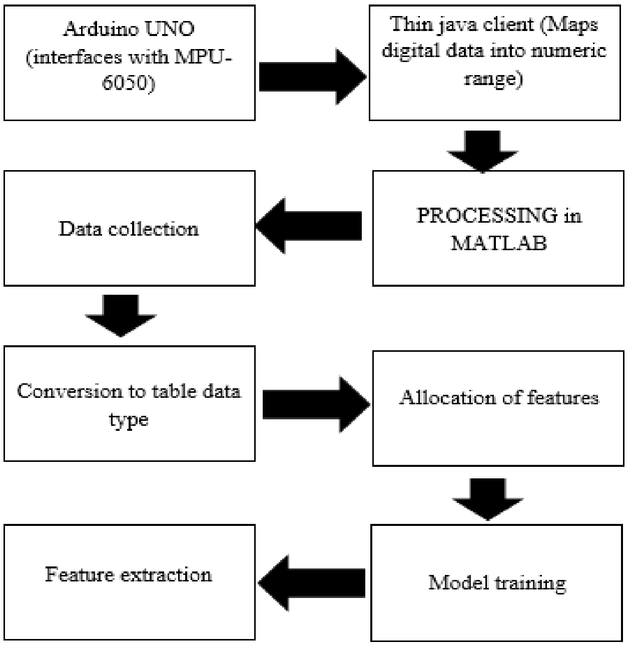

Fig.6: Block diagram depicting the complete process being followed

It utilizes a five folds validation technique (In this technique data is divided into five folds and accuracy is estimated on each fold separately) leading to increased efficiency of trained model and reduced overfitting of dataset during training. After the training is finished the model with highest accuracy is exported onto the workspace. In our experiment the highest accuracy was achieved by fine Gaussian SVM, as shown in Table I.

VIII. RESULT

After thoroughly experimenting with our device we came to the conjecture that when three features are allotted to a dataset of 333*3 size array and model was trained. After training the highest theoretical accuracy achieved using classification learner tool was 68.02%, and then, we tried to predict the features of a new data set and observed that out of 111 times when feature „A" was allotted our model was able to detect it
70 times thus achieving a practical accuracy of 63.03%. similarly, in the case of the accuracies of feature „B" and „C" were 53.15 and 66.67% respectively. The detailed observation is shown in the Table.II.

TABLE.II : Experimental results

NO. OF TAPS ON EACH POINT	111	111	111
ALLOTED FEATURE	A	B	C
NO. OF TIMES POINT „A" PREDICTED	70	24	17
NO. OF TIMES POINT „B" PREDICTED	33	59	20
NO. OF TIMES POINT „C" PREDICTED	8	28	74
ACCURACY (percentage)	63.063	53.15	66.67

IX. CONCLUSION & FUTURE WORK

In this paper, we have presented our approach to felicitous the human body as an input surface. We have construe an innovative, cost effective input method that at present stage has limited accuracy but in future with more effort can be readily employed in wide range of applications. These include single-handed gestures, taps with different parts of the finger, and differentiating between materials and objects. Previous work in this field requires complex and expensive circuitry for detection of taps and analog to digital conversion but using MPU-6050 and Arduino with its in-build 16 bit analog to digital converter has reduced the cost of technology drastically.

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