Identifying Emotional States from Touch Gestures

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***Abstract*— To date mostly everyone uses smartphone and as this trend is increasing, the next billion users are predicted to be of smartphones. Our research is to find user's emotional state from their interaction with the smartphones, without using any extra hardware, in a cost effective way. The main idea relies on the fact that user interaction is more when they are in high arousal level and the interaction is minimal when they are in low arousal level. We have proposed a model to measure the arousal level from their 2-D screen gestures and categorize the emotional states based on their activity value. Then concluding result will be based upon comparison between activity values in time intervals.**

Keywords—emotion, affective computing, mobile interaction, game play, touch.

I. INTRODUCTION

What is Emotion?

Changes in the states of organic subsystems in response to stimulus, as relevant to major concerns of the organism[2]. The basic emotional states are:

- Happy
- Sad
- Excited
- Angry
- Tender
- Scared

Affective computing is the study and development of systems and devices that can recognize, interpret, process, and simulate human emotions and affects[12]. Studies have proven that emotions can be interpreted through hand gestures[11]. Transactional Analysis plays a major role in one's communication. Analyzing the emotional state and communicating accordingly will be more effective. If the Smartphones can analyze user's emotion then we can change its interaction to adopt itself to user's emotional state for better interaction. For example, displaying advertisement based on user's emotional state, virtual reality and gaming, augmented reality apps etc. When users are in good mood they conceive more information [go]. From this research work we aim to come up with conclusion to provide better interaction to the user by analyzing their emotional state instantaneously. Learning from Nature, adaptation to changing environment leads to survival of the fittest, so taking same analogy for best Human-computer interaction, adapting the Interaction with changing emotional states will produce realistic results.

II. RELATED WORK AND LITERATURE

Don't get Emotional "conceptualize emotion as a waypoint rather than as a destination"[13] will Improve the human computer interaction by considering emotion as a factor. Emotions are classified in GEW model by Scherer[2].Two emotion models are discrete model and dimensional model. In Discrete model, universal emotional states are considered and in dimensional model, infinite emotional states are considered. Film based model is 2.6 times greater than rating based dimensional model[6]. So in our research we consider discrete model. Abstract states like Frustrated, Excited , Boredom and Relaxed are identified emotional states in What Does Touch Tell Us about Emotions in Touchscreen-Based Gameplay?[8], Identifying these states are easy for computation. Studying emotions through 2-D screen gestures and 3-D sensor is the cheapest way[9].

A. Limitations

All the previous related works were either using costly hardware, e.g., for facial or speech recognitions or were based on explicitly recording a user's emotional state first and then collecting data values. As this research field is still in its budding stage, so previous research works were foundations. This leads to limitation in developing concrete algorithms for application purpose. We aim at a natural conclusion of emotional state from using only touch behavior, so that application algorithms can be developed accordingly in various different domains as discussed in Introduction.

III. INPUT FEATURES

Users interact with their smartphone through 2-D gesture and 3-D sensors. The major 2-D gestures are:

- Click
- Long Click
- Swipe
- Scroll
- Patting

The 3-D sensors which are available in most of the smartphones are:

- Proximity sensor
- Accelerometer sensor
- Rotation
- Light sensor etc.

The 3-D sensors provides the context in which the interaction is taking place.

The properties associated with 2-D gestures are

- Size
- Velocity
- Pressure
- Direction
- Rate

The basic interaction of users is observed through their 2-D gestures, 3-D sensors and context information adds value to it. In our research, we consider 2-D screen gestures and their properties to minimize the input space, for instantaneous evaluation. Furthermore during ours research we concluded that 3-D sensors and Context information is best suited for developing applications, based on emotional states which are derived from 2-D gesture evaluation.

Android API provides GestureDetector and MotionEvent classes for sensing different touch interaction and measuring there's properties.

IV. Proposed Approach

To analyze user's emotional state we are using Geneva Emotional Wheel (GEW) [14] and partitioning the GEW into four quadrant - High Positive State, High Negative State, Low Negative State and Low Positive State as shown in Fig.1.

A. Discrete vs. Continuous Model

In Discrete model only 6 basic emotional states are considered for evaluation while in Continuous model we need to consider emotional states among dimensions. For example in Valence Arousal Dimensional model, every emotional state has two variables associated with it, namely Valence which means the positive or negative value of an emotional state, while Arousal means the degree of reactiveness to the stimuli. In Discrete model the estimation rate of final result is much more correct than Continuous model because in latter infinite pairs of co-ordinate points can be plotted which can lead to ambiguity in judgment. For example, Fear and Anger have same Arousal value. The guessing probability is less in Discrete Model and the results are more accurate. So, we will be adopting Discrete Model for evaluating Emotional States.

B. Categorizing behavior similarities for modeling:

In discrete model the six basic emotions are much more expressible using the natural language. These basic emotions are immutable throughout the evolutionary process.
The language based categorization corresponds to unique response pattern. In continuous model, different emotions having same value in a particular dimension are indistinguishable. So to create a set of emotions on the basics of behavior similarities language based basic categorization should be used.

The Emotional States are classified into four major categories based on their arousal level and their valence. Their naming follows the convention AB state where A represents the Arousal Level and B represents the Valence level. They are:

- High Positive State
- High Negative State
- Low Negative State
- Low Positive State

This abstract classification as shown in TABLE 1 by mapping emotional states can prove useful for both similar behavioral application response and developing mobile gestures conclusions for emotional states.

TABLE I. Abstract Emotional State

POSITIVE valence		NEGATIVE valence	
HIGH POSITIVE	LOW POSITIVE	HIGH NEGATIVE	LOW NEGATIVE
EXCITED	RELAXED	FRUSTRATED	BOREDOM

C. Arousal Level / Power level

In High Arousal State more pressure is applied on the screen[8] due to high interaction level or interaction rate . Pressure can be calculated using the Android API, in class Motion Event's touchEvent.getPressure() which returns float value from 0 to 1. Since it is hardware dependent, its value changes for different devices and mostly it returns either 0 or 1. If we apply more Pressure fingers flattens out and cover more size. Hence the size covered tells indirectly about the pressure applied. Instead of calculating the Pressure applied on the screen, the pixel size covered by the finger for each touch is calculated using the touchEvent.getSize() and size can be calculated on mostly all touch screen based phones , instead of pressure .

Pressure applied on the screen is directly proportional to the total pixel touched by the user and this is the relation used by

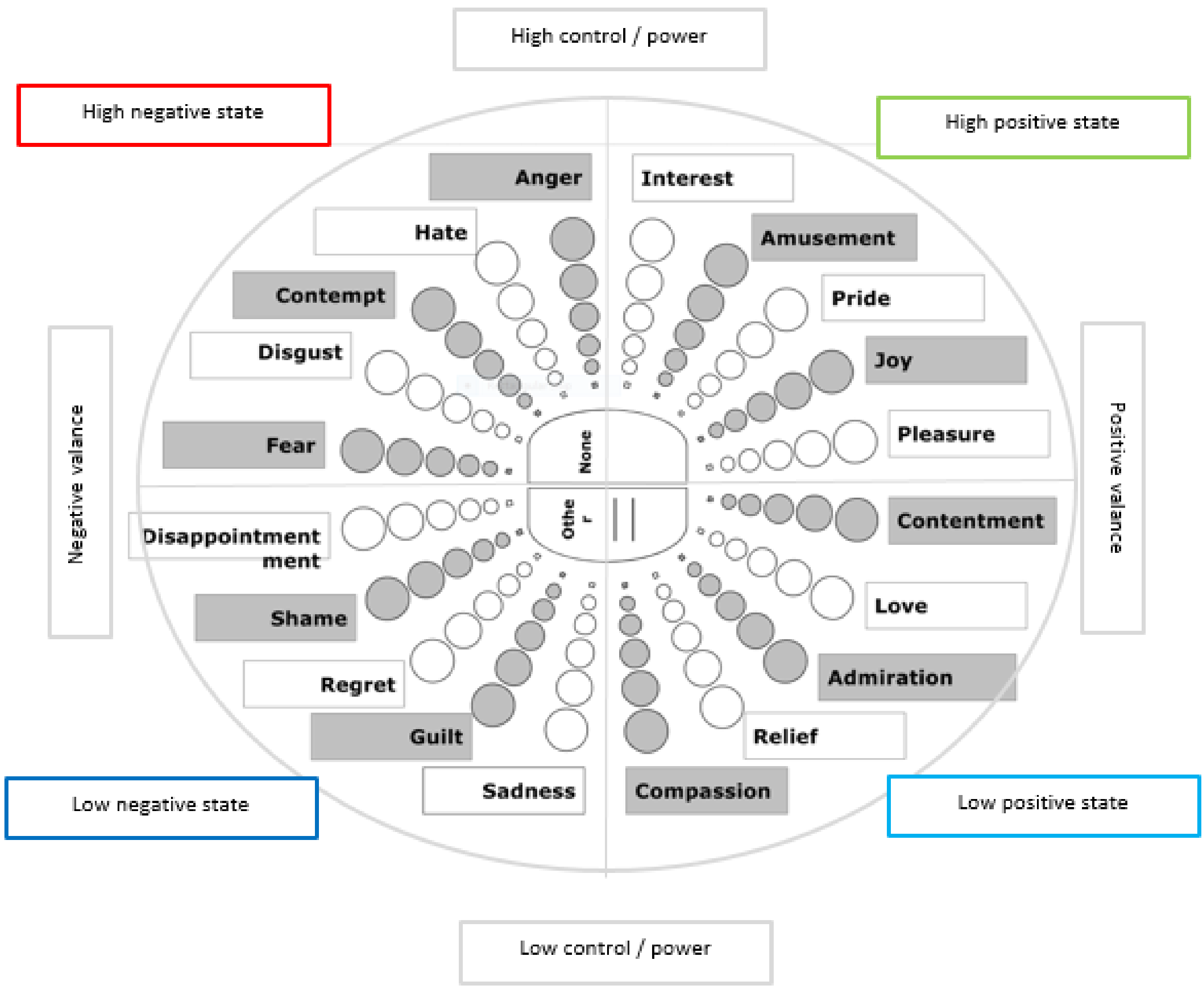

Fig.1 Partitioning Geneva Emotional Wheel (GEW) into four States

most of the cellphone vendors to provide pressure information from touch gesture's size[6].

For interval of 3 seconds each, users touch size for each event is obtained and its total size of interaction is calculated which gives the Activity Value for that particular interval. Higher the Activity Value (AV) higher the arousal level and vice versa. By comparing the Activity Value (AV) of the current interval with its previous interval, the valence level is obtained. The trend in Activity Values with time is also observed to make emotional state prediction more concrete.

Activity Value (AV) = Total size of touch interaction by the user in a particular interval (3sec).

D. Valence Level

Each Activity Value (AV) directly gives the arousal level of the activity but to find the valence level of the current interval its Activity Value (AV) is compared with its previous interval. The following hypothesis maps the cumulative Arousal and Valence combination in quadrants, as shown in Fig. 1.

Our hypothesis:

- High Negative State decreases the user's interaction and the Activity Value fluctuates in the continuous interval, with high peaks of AV in time interval. For example the frustration will be with more clicks, swipes and scrolls.
- High Positive State increases the user's interaction and the user maintains that AV .For example Excitation while typing or scrolling while reading.
- Low Negative State mostly follows the High Negative State(s) and the AV decreases monotonically or has some low AV peaks. Like boredom after frustration.

- Low Positive State mostly follows the High Positive State(s) and maintains the low AV peaks during intervals. E.g. relaxed state.

V. Implementation

A. *Trending Data Collection Methods*

- **Questionnaires** - Given a source as a stimulus, subject's emotional states is recorded in questionnaires and scaling is done based on its degree.
- **Performing Gestures** - Given an emotion state, subjects are asked to perform gestures for that.
- **Applications** - Applications recording day to day gesture activity is created and tested with the subjects.

Creating applications is more reasonable so in our implementation we created an application to collect user's touch data.

The data to test above proposed hypothesis is calculated by creating a game application "HackEmo" as shown in Fig.2, played on an android smartphone. The game is available on GitHub, link: HackEmo. It is a guessing game created to record user's info, name, age and gender and touch interaction. In this game a number will be displayed which a user has to guess, which is placed in 5 buckets randomly between buckets A- E. The game duration is 60 seconds and the users were instructed to get maximum score as possible. The users were instructed to be cautious about a penalty of -1 for each wrong answer.

The game play is as follows:

Code	Mode	Time interval (sec)
2	Random	0-15 & 31-45
0,1	Losing, Winning	16-30, 46-60

Fig.2 Guessing Game View to analyze valence level

The Mode Winning and Losing will be randomly selected for specified time intervals each time and user is not told about these Modes.User's emotional state is to always guess the right bucket every time.

Only the active time intervals were taken into consideration, i.e. when the subject was actually interacting with game continuously. In Winning mode, the user always win and in losing mode, the user always lose. The subjects were given two attempts, in the first attempt since the gameplay is new they were playing the game in low arousal level and in the second attempt their arousal level increased much to get more score. By giving two attempts, we can see the change in their arousal level.

Winning makes user excited and losing makes them frustrated. In continuous losing part of the game, the users negative valence level is analyzed and in the continuous winning part of the game, users positive valence level is analyzed.

User's activity is recorded throughout the game and their touch size is calculated and the Activity Value (AV) for each 3-seconds interval is calculated and plotted in a graphs shown in Fig 3.a,3.b where in Y-axis, each unit represents the Activity Value (AV) and in X-axis, each unit represents the an interval of 3 seconds.

VI. Result

After collecting data from subjects, the graph is analyzed during their winning part and their losing part. in both Low Arousal (Fig.3.a) and High Arousal Mode (Fig.3.b). The Emotional state and Game Mode is plotted, after generating graph, along the time intervals.

FOLLOWING RESULTS ARE DERIVED FOR EACH STATE:

- Low positive: Low Activity Value (AV) peaks are visible
- Low negative: The Activity Value (AV) atrophies to minimum value.
- High positive: The high Activity Value (AV) is maintained throughout interval
- High negative: High Activity Value (AV) peaks are visible in interaction interval.

The AV with Time and the data from graph obtained is observed. Following results are obtained:

TABLE I. Mapping AV and Emotional State

Arousal Level	Average AV	Maximum, Minimum
High Arousal	4.23	6.5 , 2.83
Low Arousal	0.94	2.1,0

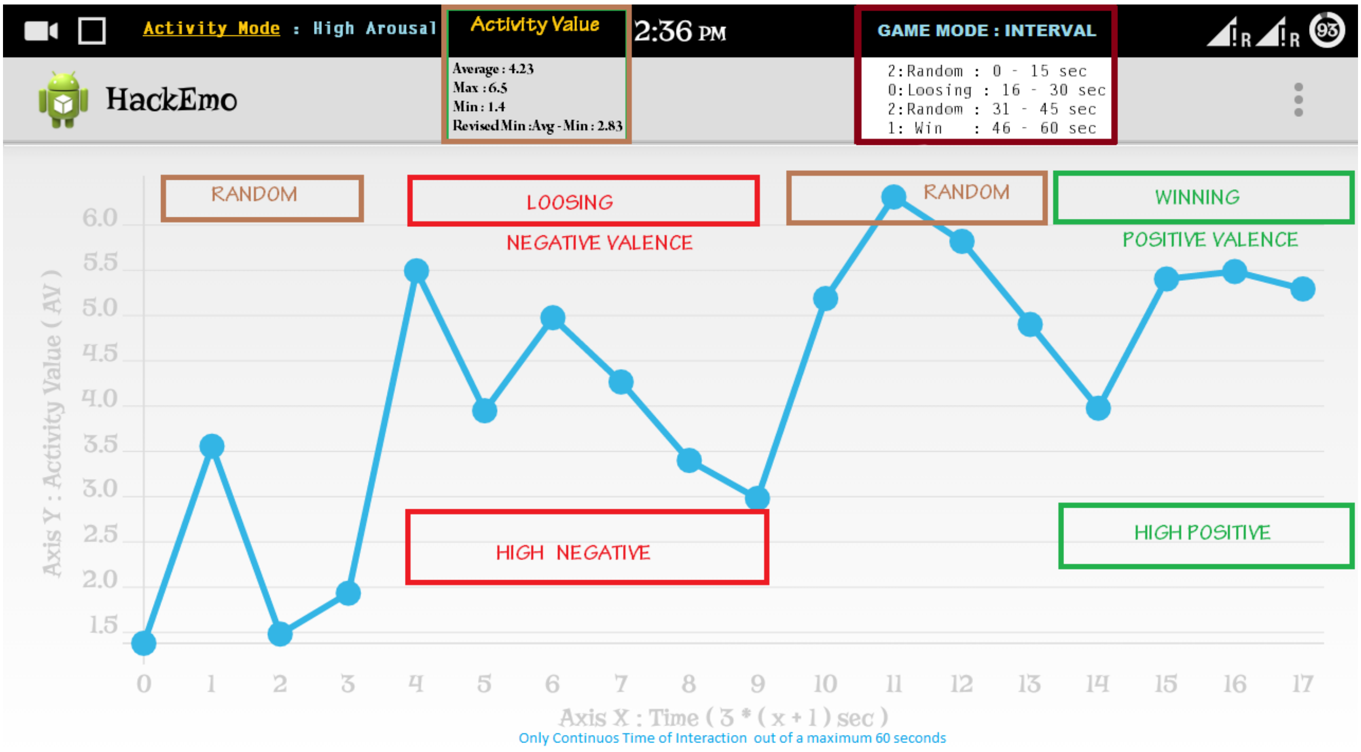

Fig.3.b Graph showing Valence level in High Arousal mode

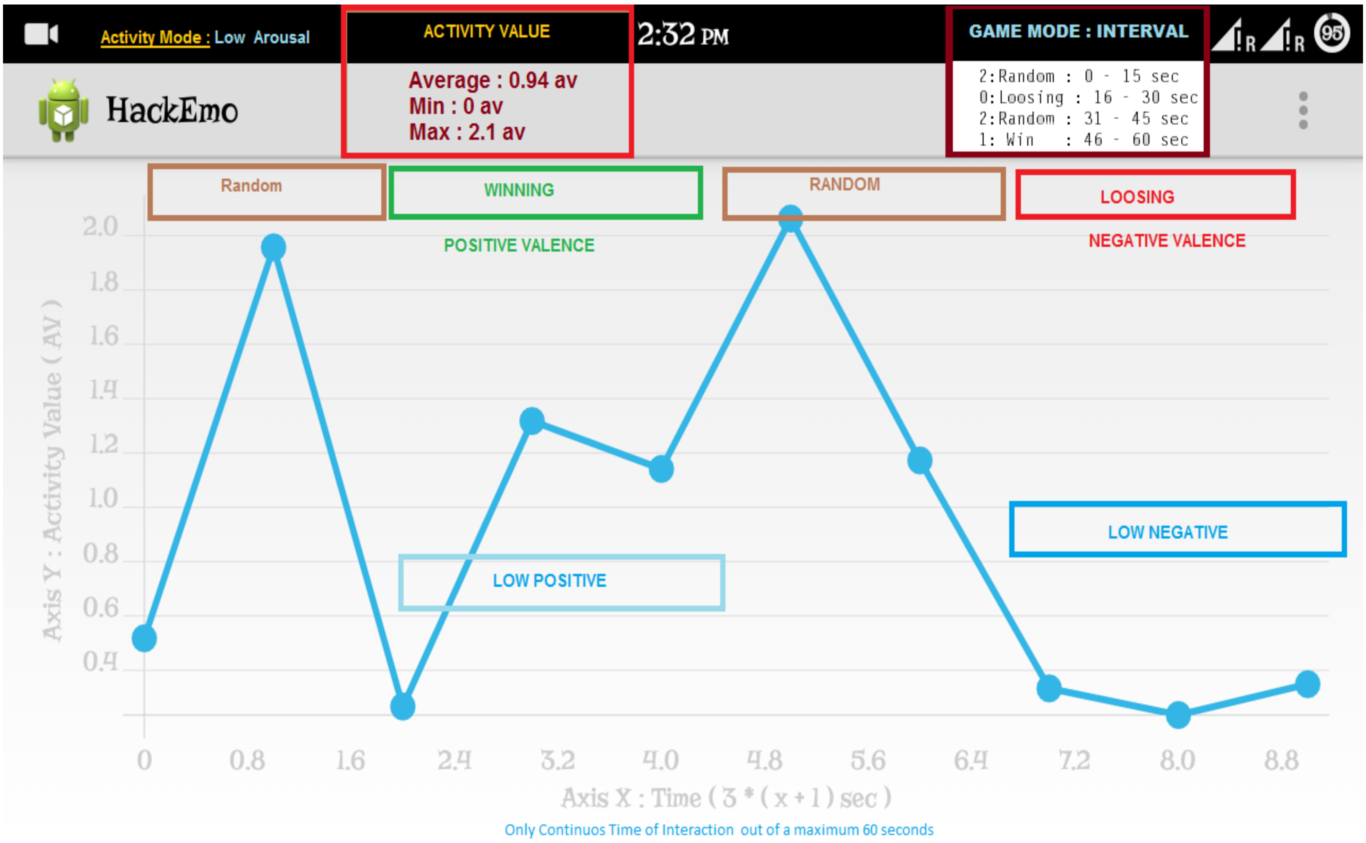

Fig.3.b Graph showing Valence level in Low Arousal mode

VII. Conclusions And Future work

This research work was ours contribution to human computer interaction. Since touch screen is going to be a part of every future device for human computer interaction, accessing emotional state from touch gestures will enhance overall interface and application development. We conclude that it is possible to efficiently analyze emotional state using touch gestures and it is the less costly way. Our future work will be to test ours result on a much broader scale. The following research will dedicated to additional data collection for producing detection algorithm, learning process and applications.

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