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Evaluating Tonic and Phasic Variations for User Perception by Moisture Detection on Fingerprint

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Abstract

Users often experience wetness cursed by stimuli using their hands, and little is known of how this sensitivity in the fingers to moisture is released and the mechanisms underlying this sensory function. This paper, therefore, is aimed to quantify the minimum moisture content required to detect wetness in the user's first two fingers on the touchpad, the moisture detection threshold and assessment are modulated by the body temperature. The participants were asked to rate the wetness and the sensations based on subjective reports to identify areas of tonic and phasic changes in their physiological response based on a visual analog scaling. The MoistureC detection threshold at a temperature similar to $((3.5) \times 10oC)$, and this temperature reduces at $((2.5) \times 10oC)$ and increases at $((3.7) \times 10oC)$ for warmer conditions similar to stress and relaxed mood of the participants. At neutral settings over the contact area, the hotness in moisture content is similar to the maximum normal body temperature $((3.6) \times 10oC)$. The differences in threshold (*baseline*) are reflected by the magnitude estimation data that were used for analysis.

Keywords: Skin conductance response, Skin temperature, Moisture content, Baseline, Touchpad, User Perception

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1 Introduction

User perception of task performance that results in wetness or moisture content in the skin is a fundamental sensory experience that defines many aspects of user activity of life, from complex task performance to enjoyable user experiences. Previous research ((Filingeri and Havenith, 2015; Merrick et al., 2021)) has highlighted the major importance of sensations felt during task performance and reaction such as human wetness perception, sensing system remains a

topic to be established. This paper presents a custom method of moisture detection methodology that uses a touchpad with electrodes that senses the moisture content and response that has been quantified based on intelligent analytics that can analyse and detect response parameters. The major contribution is its high sensitivity to the users' first two fingers to contain wetness and its modulation by the moisture temperature of the body, and this allows for constant moisture modulation. The process is quantified using a second-order differential equation.

2 Literature Review

Recent work ((Filingeri and Havenith, 2015; Merrick et al., 2021; Greenstein and Arnaut, 1988; Vu et al., 2013; Hinckley and Sinclair, 1999; Rosenberg and Perlin, 2009; Kubitza et al., 2013; Bhalla and Bhalla, 2010; Savage et al., 2012)) has improved the application of touchpad and measurement circuitry for enabling input to a computer and other devices that are electronically connected. The systems include an X electrode and a Y electrode, a common sensing electrode, and a liquid detector electrode with four separate electrodes implemented in different physical configurations to obtain the desired effects, the moisture content can be identified and compensated for interference with the input of data matrix made by fingerprint image captured ((Sousedik and Busch, 2014; Ravikanth et al., 2017; Tang et al., 2016; Oh et al., 2014; Rocamora et al., 2020; Liu et al., 2022; Rath et al., 2023; Chhabra et al., 2023; Zhao et al., 2024; Dutton et al., 2013; Avola et al., 2022)) the system is also noise rejection enabled and can be achieved by using a tie aperture filtration procedure that can improve scanning technique which is focussed around the identified image input object. The adaptive motion filter responds to the speed and the acceleration of the moisture detected on the surface of the skin that is being tracked and the measurement circuitry has an increased dynamic range enabling the touchpad to operate with a great tolerance ((Nassar, 2017; Rao et al., 2020; Gao et al., 2021; Yin et al., 2021; Yan et al., 2021; Jang et al., 2020; Isiaka and Adamu, 2023)).

Today, almost all user interfaces are based on touch, the range of applications is countless and most of them are mobile phones, tablets, and laptop computers. They are embedded sensors for touchscreen applications((Xu et al., 2012; Walker, 2012; Lim et al., 2015; Nam et al., 2021; Salkanovic and Ljubic, 2021; Wang et al., 2019)). The applications can also be adapted to read moisture content on fingertips and measure the continuous reaction to the stimuli-induced interface. The sensors from the touchpad detect touch or proximity without relying on physical contact, in most cases, the tactile sensor is sensitive to touch, force, and pressure (Figure 2). When there is a slight contact with the surface of the touch sensor the circuit is closed inside the sensor and there is a flow of current, the contact is realised the circuit is then open, and no flow. During the connection of the fingertips to the surface of the sensor pad, the current reads in the contact using a well-defined module that links the port sensor to the analytical application and reads in input data from the surface of the pad. The capacitance is a simple form of capacitor that is made to read signals based on:

$$C = \epsilon_0 \times \epsilon_1 \times \frac{A}{d} \quad (1)$$

ϵ_0 is the permittivity of free space, ϵ_1 is the relative permittivity or dielectric constant, A is the area of the plates and d is the distance between them. The capacitance is directly proportional to the area and inversely proportional to the distance. In the touch sensor, the electrode represents one of the plates of the capacitor. The sensor electrode is connected to the measurement circuit and this is measured periodically with time.

The wetness or moisture perception is experienced by humans daily, such as in subjective assessment and interacting with a visual interface most especially when the person is very sensitive to mood swings. There exists a behavioural and learning element, such as being able to sense and react to environmental conditions that include damp weather, and hot atmosphere during a subjective perception, this can be quantified when a touch sensor is applied and reads into the user's mood and integrates the visual environment.

Though there is clear importance to the role given to moisture perception in humans, there is not enough evidence to conclude that the model integrates a range of senses that underpins this concept. However current research has indicated that thermal stimuli have a significant role in moisture perception in a person. Using the fingertips to interact with the visual environment is a primary way of exploring action and forms of the foundation of a lot of sensorial and learning experiences for most adults and children alike. This paper aims to use the concept of touchpad sensors to read user emotions and visual perception of visual image color display and analyse its content using the physiological analytical tool for data interpretation and predictions. The proceeding sections discuss the methods and results obtained from the experimental study.

3 Method

Twenty participants were recruited to participate in and test the analytical process. Ten females and Ten males without age restrictions and approved consent, these participants were asked to sit in front of a PC embedded with visual display stimuli with different colors, the task was simply to observe the display and changes in the color of the image in front of them while their physiological readings are taken, by asking them to place their first two fingertips on the touch-sensor pad (Figure 2). This reads in the emotional response and mood changes as they interact with the visual stimuli, the response readings are connected to the designed module that visualises the displacement of response or reactions sensed from the contact to the touchpad cursed by the changes in the electrical field and capacitance on the sensor, this reaction is proportional and equal to the basic human emotion and can be quantified.

The moisture content is first detected as X, and the continuous time-variant expression equivalent to SCR is given as:

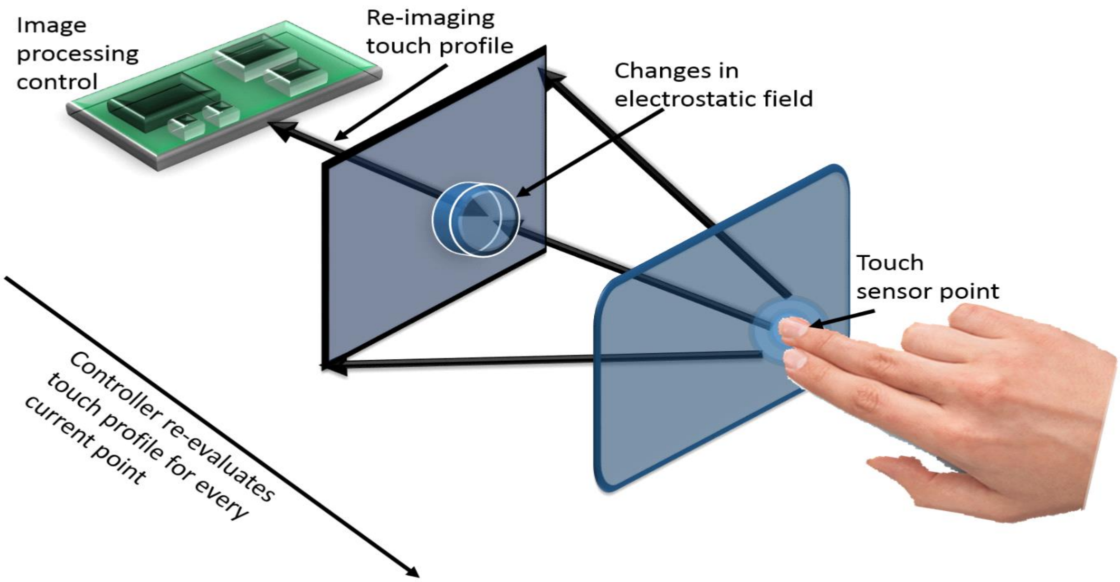

Figure 1: The model architecture of the sensor touch signal from the touchpoint

Figure 2: An Example scene of Participant interaction with visual stimuli on the interface while their first two middle fingers are placed on the wireless touchpad.

$$\begin{aligned}\frac{d^3X}{dy^3} &= \frac{d^2X}{dy^2} + \frac{dX}{dy} + aX + C \\ X &= \int_{i=1}^{n} \left(c + 6\frac{dX}{dy} \right) \times \frac{1}{2} \forall i \epsilon X\end{aligned} \tag{2}$$

Where a and c are constants due to environmental constraints. The hotness measure from the continuous reading is given as the ST of the person and is approximately equal to the normal human temperature of $((3.6) \times 10oC)$. The aim is to differentiate the normal reaction while it increases and decreases with time in reaction to the visual stimuli.

4 Result

To detect tonic and phasic changes that correlate to user perception in response to the readings, the baseline (skin conductance level) is first detected using a moving average that defines the clear peaks, the local minima are the absolute negative reaction to the SCR and this too is measured periodically. Figure 3 shows the index page with the physiological response from the experimental setup, each user attribute is recorded from the image input of the touchpad through the fingertips. The noisy signal is applied to a moving average filter and produces a smooth signal output (Figure 4) which contains the SCR, $MoistureC$, and ST. The baseline is a measure based on local minima and helps to differentiate the tonic changes from the phasic response. The aim is to observe the reaction to basic video stimuli and register the response correlation.

Figure 4 shows the detected response signal based on a moving average filter, the baseline is used to determine the tonic and phasic level of the response signal, and the point of high moisture content detection is located and correlates to the normal body SCR and ST. The inference engine is based on the standard control motor dynamics that help to detect moisture content and SCR of the participants, one of the aims is to see the performance of the model used for prediction. Electrodermal activity is a process used to determine the physiological response of a person based on what they look at; this is a simple way of understanding the user. The MoistureC detection

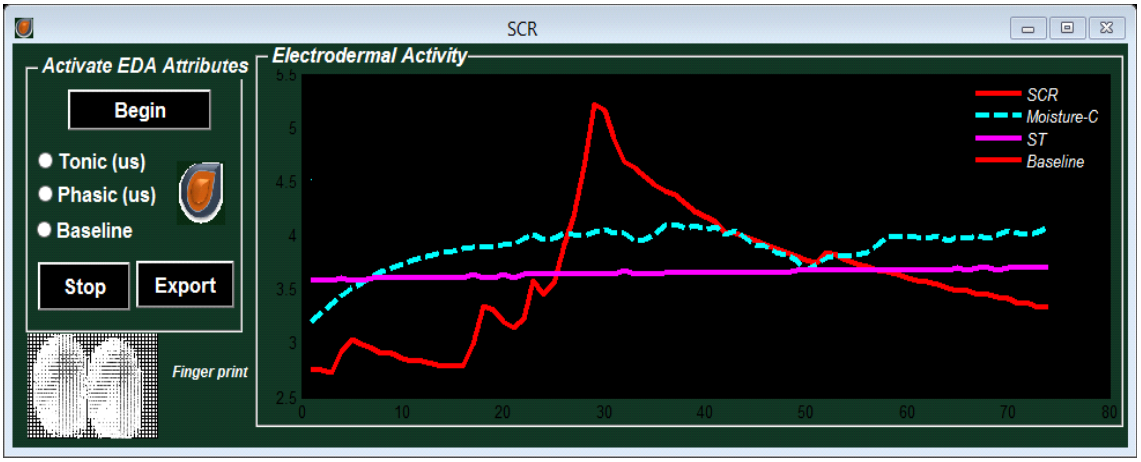

Figure 3: Index page for Physiological readings from fingertip contact to touch-sensor pad.

threshold at a temperature similar to $((3.5) \times 10oC)$, and this temperature reduces at $((2.5) \times 10oC)$ and increases at $((3.7) \times 10oC)$ for warmer conditions similar to stress and relaxed mood of the participants. At neutral settings over the contact area, the hotness in moisture content is similar to the maximum normal body temperature $((3.6) \times 10oC)$. The differences in threshold (baseline) are reflected by the magnitude estimation data which were used for analysis based on a linear regression model that shows both SCR and Moisture content can predict the cognitive response similar to user perception of task concentration.

The initial parameters A, B, C, and D are the input matrices and are used to measure the user attributes to the model performance; the resultant response signal is the $MoistureC$ used to determine the performance of the model, Figure 5 shows the performance in system report of the processes quantified data using a sample time of 0.08 seconds, input data matrices is first set as an identified state-space model with the free parameters. The prediction focus is the absolute-70% on all data input, with the moisture content having a 0.004% error rate in performance and contribution to detecting correlates to user perception. The entire result is based on the participant aggregate data which is just a summary of the entire experimental study.

5 Conclusion

This paper investigates moisture detection and correlates to user perception through motion recognition on the first two fingertips sensor touch, the participants recruited, were asked to rate the wetness and the sensations based on subjective reports to identify areas of tonic and phasic changes in their physiological response based on a visual analogue scaling. The MoistureC detection threshold at a temperature similar to $((3.5) \times 10oC)$, and this temperature reduces at $((2.5) \times 10oC)$ and increases at $((3.7) \times 10oC)$ for warmer conditions similar to stress and relaxed mood of the participants. At neutral settings over the contact area, the hotness in moisture content is similar to the maximum normal body temperature $((3.6) \times 10oC)$. The differences in threshold (baseline) are reflected by the magnitude estimation data which were used for analysis based on a linear regression model that shows both SCR and Moisture content and is used to predict the cognitive response of the users to task concentration. However, this is simply based on a pilot investigation; future perception will be to integrate other physiological responses such as heart rate and interpret the results is based on multimodal physiological measure procedures.

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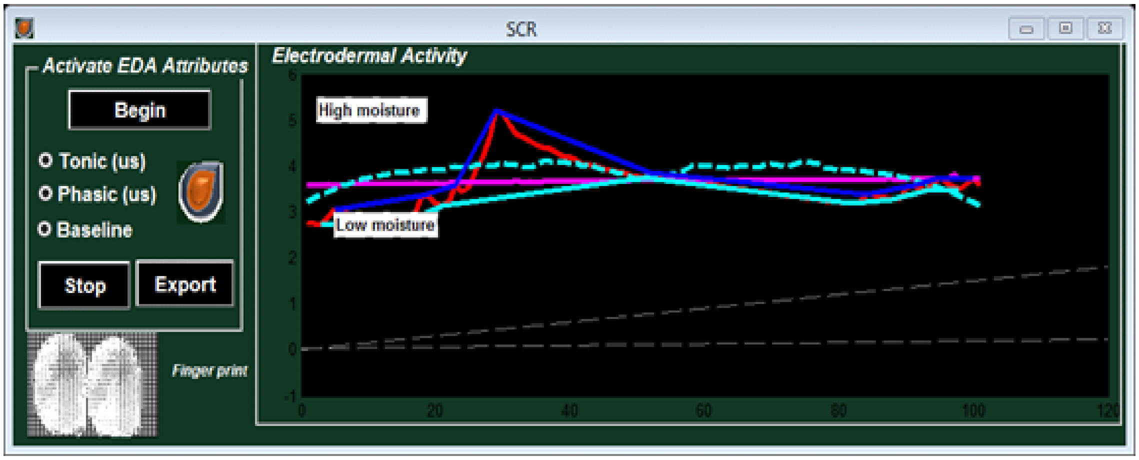

Figure 4: Application of moving average filter on the index page for baseline estimates and response correlate detection.

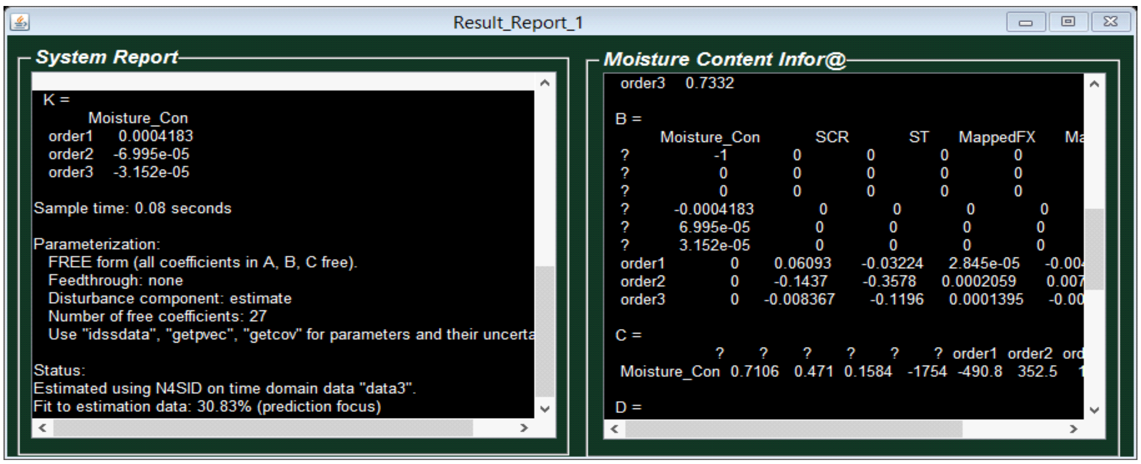

Figure 5: Window interface shows the performance of user attributes and contribution to model performance.

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