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Non Invasive Human Stress Detection Using Key Stroke Dynamics and Pattern Variations

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***Abstract*— Stress is considered as a very harmful health problem in the modern world. A large proportion of sick leave in the industrial world is believed to be related to stress. While some level of stress can act as a positive factor, extensive exposure to high levels of stress can have detrimental effects on one's health. Depression, panic attacks, high blood pressure, diabetes, heart problems are few of such diseases that can be initiated or worsened by stress. With the increasing people centricity in contemporary developments of computer science, Affective Computing has become a popular research area. According to the existing research, affective computing has shown positive results in detecting human stress. Stress detection has been tackled in various approaches including heart rate variability (HRV), skin conductance (SC), pupil diameter (PD) based detection, Finger Temperature (FT) and etc. Our focus in this study is to utilize a readily available yet underutilized resource in Affective Computing, key stroke dynamics (KSD). Recent developments in KSD based affective computing and Biometrics research proves that key stroke variations is a very powerful source of input that provides a valuable insight about an individual's psychological and emotional states. Our methodology suggests a personalised approach in detecting stress levels through key stroke variations. An application specific Individual key stroke pattern profile is created for an individual based on his normal typing patterns. This profile consists of trained average values for a set of typing features. Real time stress specific deviations of these features are analysed in order to arrive at the individual stress level.**

The remainder of the paper is structured as follows. First we introduce the research problem that this study is attempting to address. Then the significance of our approach is brought to the attention. The related work section tries to analyse and evaluate the existing related literature revolving around this research area. After that we present the details of our approach through the methodology section. The experiment section describes about the experiment conducted to gather the keystroke data that are to be analysed as stress and non-stress data samples. A brief overview of the results of the experiment is provided towards the end of the paper.

***Key words*— Stress detection, key stroke dynamics, non-invasive, keystroke patterns**

I. INTRODUCTION

Mental stress causes when individuals feel that they are unable to meet high levels of demands placed upon them [19]. Stress and related illnesses have become one of the largest and most costly health problems in the industrialized world. Continuous high levels of stress put a lot of strain on person's psychology and may lead to reduced productivity. Studies have found that long term exposure to high stress levels can give rise to a lot of other illnesses such as depression, high blood pressure and even diabetes [13].

A simple technique which would measure stress levels may significantly help to avoid long-term stress and promote healthy life style. Although it is difficult to measure stress level directly, it is quite possible to annotate stressful events and relate them to physiological signal changes (Ex; Heart Rate variability, Skin Conductance) [8], [12], [18], [7] that can be easily measured. Most of the existing stress measuring techniques use physiological signal changes to measure stress level. But these techniques are not very suitable for real time stress monitoring specially in an office environment. Most of them use body worn sensors or monitoring equipment that needs to be attached to the user's body. This can be very disturbing in user's daily routines and normal working patterns. There can be social challenges about wearing a stress monitoring device in a normal working environment also.

This research attempts to propose a non-invasive mechanism which does not demand any additional commitment from the user but still provides an accurate stress level measurement to the user. Many of the muscles that are affected by stress tension are in the area around the shoulders, neck and arms these are the same muscles that are used in working with a computer [1]. Therefore key stroke patterns can be affected by tension in these muscles .Recent developments in the keystroke based Biometrics [9] holds evidence to the fact that an individual has a unique pattern in his keystroke dynamics. The emotional status identification research conducted using variations in keystroke dynamics [4] proves that emotional and psychological states of an individual are reflected in changes in their key stroke dynamics. Our study attempts to investigate the viability of human stress detection through the variations in keystroke dynamics.

An increasing number of people use computers in their daily work, responding to emails, accounting, writing reports, programming and etc. Most of the human computer interactions involve a key board based input making keystroke data a readily available, yet underutilized input source. Our approach of utilizing a simple and already available natural input source such as keystroke dynamics makes this approach very strong with regards to its non-invasiveness.

II. RELATED WORK

The problem of stress detection has been tackled with different approaches. However, the existing literature can be divided in to three major groups depending on the use of physiological signals, other behavioural characteristics, or psychological

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aspects such as questionnaires as illustrated in Fig. 1 which is proposed by authors. Most of the physiological signal based approaches to stress detection are invasive due to the use of body worn sensors to acquire the biological signals.

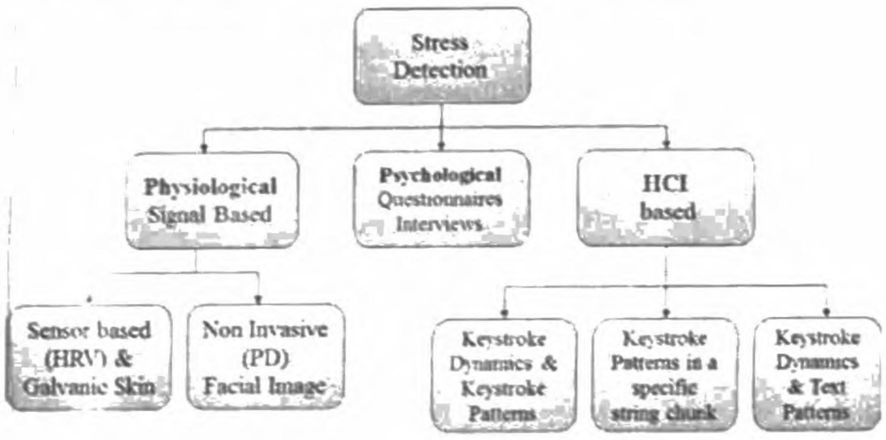

Fig. 1 Overview of existing solutions for stress detection

A. *Physiological Signal Based Stress Detection*

Most of the existing stress detection approaches use physiological changes to trigger the human stress. Some of the physiological changes that occur in human body with stress are,

- Variations in heart rate [8]
- Differences in skin conductance [12]
- Dilations in pupil [18]
- Changes in facial appearance [7]

Variations in heart rate

Heart Rate Variability is the variations in between heart beats, occurring consecutively [3]. This is one of the commonly used approaches in identifying and measuring human stress. There are several successful researches which were conducted in order to prove the relationship between the heart rate variability and human stress. Most of these researches use the relationship between heart rate variability and the autonomic nervous system in mapping stress with the heart rate variability.

Comparison of Heart Rate Variability Measures for Mental Stress Detection

This research has been conducted in order to prove the ability of using heart rate variability (HRV) measures in identifying the mental state of a human. This research consists of three steps as: pre-processing, HRV measure calculation and HRV measure evaluation. In this research authors have used different kinds of heart rate variability measures like: mean of heart rates, mean of RR intervals, low frequency and high frequency ranges etc. They have gathered heart rate variability data at two different mental states like stressed and normal. For this they have used 6 subjects and for each subject there were 60 time segments where each segment has 50 seconds. In order to get reliable HRV measure values, researchers have done ultra-short term analysis within time segments. In analysing collected RR interval results they have used time data and the frequency data. In transforming time data in to frequency data they have used Fourier transformation [3]. In calculating and evaluating HRV measures the research group has used different mathematical and statistical models. Through these activities it is proved that several measurements they used can be used in measuring stress within an average accuracy level range of 68% - 80% [3].

Another approach in monitoring heart rate variability is, using clinical ECG devices [8]. For this the user will have to consult doctor at a hospital.

Nowadays, there are mobile applications developed for monitoring human stress through heart rate variability. Stress Check by Azumio Inc [10], Instant Heart Rate by Azumio Inc, SweetBeat by SweetWater Health [2] are some of the examples for mobile applications which are used in identifying stress through heart rate variability.

Skin Conductance (GSR) Based Research

This is also another successful research area which has successfully tackled the problem of stress detection to an acceptable level of accuracy. Galvanic Skin Response (GSR) is also known as electrodermal response, psychogalvanic reflex, or skin conductance. This is a method of capturing the autonomic nerve response as a parameter of the sweat gland function (i.e., measuring the electrical resistance of the skin). As stress levels increase, changes in the electrical resistance of the skin are detected by GSR sensors.

A Stress Sensor Based on Galvanic Skin Response (GSR) Controlled by ZigBee

The study conducted by Villarejo M,V; et al; in 2012 in order to prove that Galvanic Skin Response can be used in detecting stress at a success rate of 90.97% [12]. In order to gather the skin conductance related data as inputs to their system they have used two wearable electrodes placed on two fingers of the user. These electrodes work as two terminals in a one resistance in order to track skin conductance.

This solution consists of two parts as the hardware part and the software part [12]. In this the hardware part is responsible for gathering skin conductance data and transmitting those to relevant places within the system while the software mainly focusing on analysing, evaluating and generating the results accordingly. The hardware component of this solution consists of three major parts as two electrodes (sensors), controller and a computer. In addition to these things they have used two ZigBee (this is a specification for a suite of high level communication protocols used in personal area networks [17]) boards for the purpose of transmitting data within the system. Fig.2 depicts how data flow happens between system components. In this research the group has considered about situations like, user is making an effort, the user is stressed and the user is relaxed. Proposed solution finally distinguishes these situations using defined threshold values for each situation type [12].

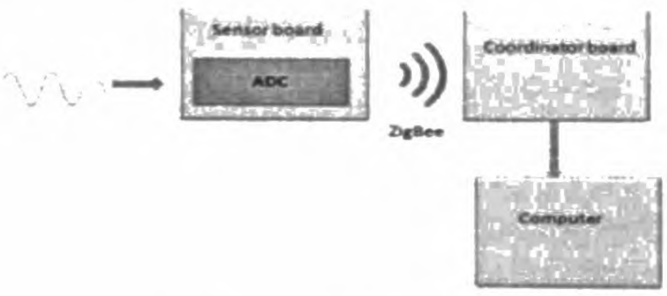

Fig. 2: Acquisition diagram [12]

Stress Identification Using Pupil Dilations

Pupil is a hole located in the centre of the iris of the eye that allows light to enter the retina. Using pupil dilations is also a widely used non-invasive approach to detect the stress of a human [11]. The pupil diameter (PD) has been found to respond to cognitive and emotional processes. It is evident that this approach does not interrupt the user's other activities mainly because the user does not require wearing any kind of equipment in order to provide inputs to the stress measuring system. However this may need additional devices to measure the diameter of the pupil and that might make this approach bit expensive in personal usage.

As other areas this area also has several studies that were conducted by different groups in order to prove the applicability of pupil diameter measurements in identifying human stress. Following are some of those kinds of researches.

Convenient Evaluation of Mental Stress with Pupil Diameter

This is one of the researches which have been conducted in order to prove the relationship between autonomous nervous activities and changes of pupil diameter with the intention of proving relationship between stress and the pupil diameter. In this first they have proved that there is a relationship between autonomous nervous activities and changes in pupil diameter. For this they have used electrocardiograms to measure autonomic nervous activities. The tool they have used for getting the electrocardiogram is a multi-telemeter system [18]. Outputs were taken with a sample frequency of 100Hz and transferred them to a digital recorder [18]. Also they have measured pupil diameter using an eye mark recorder at the same time with a sample frequency of 60Hz [18]. All these data have been gathered with imposing time pressure on each user. In recording these outputs they have used a personal computer with maintaining the features at a same level for each user. Through the data gathered from above ways, the research has proved there are changes in pupil diameter with respect to the changes in autonomous nervous activities using graphs and with using time pressure deviations as a link [18].

Image based stress detection

This is another approach which has not taken much of attention by research groups who are searching methods for stress detection. This approach uses dynamic facial image sequences to identify the stress. deformations of different parts of the subject's face with respect to surface shape, position and orientation in movements is used to detect stress. However there are several successful researches which prove the applicability of image processing in identifying stress of human.

Image-Based Stress Recognition Using a Model-Based Dynamic Face Tracking System

This is one of the researches conducted focusing on usage of image processing for stress identification. In this the authors have used dynamic facial image sequences to identify the stress. They induce stress of the subject with using several psychological tests. In this they are focusing only on high and low stress states.

In the research a model-based tracking system is used in order to track deformations of different parts of the subject's face. In that they focus on deformations of different parts of the face, like: eyebrows, lips and mouth etc. Also those are tracked in a parameterized form with using the tracking system. With using these parameters they train a Hidden Markov Model system for stressed and unstressed situations. After that they use this system in order to identify high and low stress situations [7].

In this, the tracking system uses a face model which deforms with respect to the movements of the face of each subject. In that, the models surface shape, position and orientation gets changed accordingly. When tracking deformations, first they take measurements from image and then use low-level computer vision algorithm to generate 2D displacements on selected points of the model. Then the difference between current positions according to the deformable model and measurements taken from the image are taken. Those are called "image forces". After that, these image forces are generalized [7].

In detecting stress situations, the research group has focused on two stages. First is recognizing possible individual displays of stress response and the second is deciding whether the response can be classified as a stress response according to the frequency of the occurrence. Finally through these activities the research group has shown that, this approach can distinguish high and low stress situations with a proportionate of 12 out of 13 subjects [7].

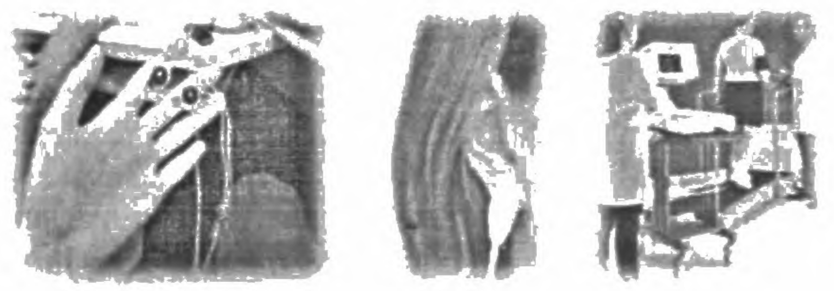

Fig. 3 Existing Invasive Stress Detection Methods

Following section attempts to critically evaluate the other existing alternative stress detection approaches.

When considering heart rate variability for stress detection, rich existing research literature with high success rates suggests that this is a promising approach [3]. One of the obvious positives inherent to this approach is it's robustness of the measurement of cardiac activity. Its instantaneous detection allows integration with real time systems. It is also an inexpensive reliable quantitative marker. On its' negative side, although there is a relationship, determining the specific emotion being elicited can be difficult. Also its' Invasiveness due to the requirement of sophisticated expensive equipment becomes a prominent negative factor when real-time monitoring is considered.

Galvanic skin response based method presented in [12] has long been considered as a measure of physiological and mental stress. This approach is known for its reliability and continuous data collection. Unlike HRV, GSR is a relative indicator of stress. (Higher GSR levels recorded during certain tasks suggest higher levels of stress.) However, many emotions may produce similar GSR responses and there are no absolute levels of GSR indicative of high workload or stress. Again, Requirement of expensive specialized equipment to capture the GSR signals may render this approach less suitable for real time monitoring.

Image based stress detection [7] is strongly built on the argument that facial features can have a connection with emotional states. It is also non-invasive in its approach. Ability of real time and continuous measurement combined with non-invasiveness makes it a strong candidate for real time stress monitoring. On the negative aspects, requirement of high quality expensive cameras can be seen as a prominent factor. Apart from that, stress may not be the only reason for facial deformations. Every face may not be equally expressive of its emotional state and such expressions cannot also be generalized over the entire population. On the other hand when real time monitoring is concerned user may not always be focused to the camera as expected by the system. A number of cameras may need to be employed to avoid this issue.

The other approach to stress detection discussed in the paper is pupil diameter based stress detection [18]. The pupil diameter (PD) has been found to respond to cognitive and emotional processes. Ability of real time monitoring and continuous measurement adds to its positives. It can be non-invasive if it can be developed to a level where the diameter can be measured through a computer web cam. On the negative side, it requires very special cameras placed close to the user's eyes. This may act as a condition that limits the usefulness of the device. Also, stress may not be the only factor that affects the size of the pupil, especially in front of a computer monitor.

Most of these mechanisms that detects stress using above physiological changes provides an acceptable level of accuracy in stress detection and can also be used for real time stress monitoring. However, all of these approaches require some external body worn devices to be attached to the user's body in order to acquire the real time changes in above signals. This makes these approaches invasive and not suitable for regular and continuous stress monitoring.

Key Stroke Dynamics Based Detection

Another promising research area that has successfully tackled identification of different emotional states of humans is key stroke dynamics. [4]

Keystroke dynamics is detailed timing information that describes the keys that were pressed and their timing durations when a person was typing on a keyboard. There is a pattern or rhythm in typing on a keyboard or a keypad. Through the keystroke dynamics a unique pattern for each user can be identified [9]. These rhythms or keystroke dynamic patterns are used to develop unique biometric templates of each user which can be used for authentication purposes. Keystrokes that needed to analyse is captured through keystroke logging [25]. Normally the keystrokes are recorded and monitored without interrupting the user as a backend process. Software based key loggers are commonly used.

Common characteristics of a person in keystroke dynamics are typing speed, the time of depressing a key (Seek time), time for holding a key (Hold time), timing gaps between bigrams and trigrams (Rapid-fire sequence), common errors such as substitutions, reversals, dropouts, double strikes, hold length errors and even language errors [16]

Clayton Epp et al in their research "Emotional Status identifying through keystrokes dynamics" have categorized 15 emotional statuses such as alert, excited, elated, happy, contented, serene, relaxed, calm, bored, depressed, sad, upset, stressed, nervous, and tense. [15] This study was mainly focused on keystroke timing features such as dwell timing (the time a key pressed) and flight time (the time between "key up" and the next "key down"). Apart from keystroke dynamics authors has also focused on content features (i.e., number of backspaces, deletes and special characters). The data collection has been done through providing both free and fixed texts to capture the inputs of the user. Users were also asked to provide their emotional states according to the 15 emotional statuses while they were providing data. Experienced sampling methodology (ESM) is used in the data gathering stage. The collected data was used to train and build models. Trained models were used for evaluation. At the end of the evaluation they claim an accuracy level of 77% to 88% for few emotional status including confidence, hesitance, nervousness, relaxation, sadness and tiredness. There was 84% of accuracy level for anger and excitement.

Another similar research [6] conducted by Sasikumar and Preeti Khanna "Recognizing Emotions from Keyboard Stroke Patterns" Their focus was mainly about three emotional states Positive, neutral and negative states of emotions mainly. There were 300 users for the study with 45% of female and 55% of male. Users were given a paragraph in data gathering process and feedback was taken from them through a questionnaire regarding the emotional state while the data gathering process. Typing features considered for this study included Typing speed of the user, Total time taken for typing, Backspace key pattern (Total number of backspaces used), Idle time taken and Mode, Standard Deviations, Standard Variance and Range of number of characters typed in five second interval. Research results claims accuracy in emotional state classification that ranges from 62% to 89%.

Another Research by Nazmul Haque et al, [5] has focused on identifying emotional states using an approach which combines both key stroke dynamics and text patterns. The study attempts to differentiate between seven emotional states Anger, Disgust, Guilt, Fear, Joy, Sad and Shame. Both free text and fixed text data has been gathered during the experiment and free text data has been used to analyse text pattern variations. Key stroke timing features analysed were similar to the features in the above studies.

III. METHODOLOGY

There are three major phases within the methodology.

1. Selecting and designing a viable non Invasive stress detection mechanism.
2. Experimentally proving that the selected mechanism can effectively identify human stress.
3. Suggesting a personalised approach to stress detection based on the outcomes of the experiment.

Our Objective of this study is to propose a practical, cost effective and non-invasive mechanism to detect and continuously monitor stress of an individual without demanding any additional attention from the user or without major alterations to the normal user environment so, that a user can regularly monitor their stress level while they are working in their personal computers.

In order to identify the most non-invasive and least demanding stress detection approach we critically evaluated the existing approaches that were suggested in the literature and ran an elimination process to arrive at most viable and practical way to detect stress which was through keystroke data analysis. After analysing the existing research in literature a pool of keystroke features were identified that are suitable to be evaluated. Identified feature set included,

1. Durations between key pressers of selected digraphs (Selected Digraphs : th, he, in, er, an)

   Several instances are considered between key presses of digraphs.

- The duration between 1st and 2nd down keys of the digraphs
- The duration of the 1st key of the digraph
- Duration between 1st key up and the next key down of the digraph
- The duration of the 2nd key of the digraph
- The duration of digraph 1st key down to last key up

2. Durations between key pressers of selected trigraphs (Selected Trigraphs : the, and, ing)
3. Error rate of backspace and delete.

After the experiment the most responsive feature set that indicates considerable deviations in stress and non-stress situations will be identified. These feature sets are identified by analysing the stress and non-stress data collected in the experiment.

Our approach is to create a personal profile where an individual's stress and non-stress averages are separately maintained for each of the above identified features. These averages will be created through an iterative stress and non-stress data gathering. These suggested individual typing pattern profiles should ideally be application specific and we are considering only the Microsoft Word based scenario in this study.

Real time keystroke data will be acquired as and when the user is using the keyboard. The suggested process will classify the stressed nature of the individual by comparatively assessing the acquired keystroke data stream against the previously trained individual profile. We conducted a pilot study to experience the process beforehand and to understand how successful the process is. Learning and changes identified in the pilot study was used to better design the final experiment.

Overview of the Future Plan

Within this phase the main focus is on creating and training individual profiles. For this purpose individual stress and non-stress data gathered from subjects are used. For each individual, two profile states are trained as stress and non-stress. As this is a classification problem in which stress non-stressed data are classified in to two categories, currently we have identified several possible alternative approaches which can be used in conducting the classification task. Neural Networks, Bayesian Classification Networks, Decision Trees and Case Based Reasoning are those approaches.

Mainly the training process has three major steps: pre-processing, training through iterations, identifying stress. Basically pre-processing contains arranging individual keystroke data and normalizing data (if necessary). The training phase contains creating individual profiles and training as stress and non-stress using stress and non-stress data gathered. The third phase focuses on acquiring new data sets from participants, classifying against trained profiles, getting the error and fine-tuning.

Within the testing phase, basically three steps are followed as capture classify and confirm. Capturing step will focus on capturing new keystroke data from participants. At the second step classification is done against trained profiles of relevant individual. Within the third step, confirmation of results is done using parallel verification mechanisms (Questionnaire and stress monitoring device (measures human stress based on heart rate variability)).

Important considerations

Throughout our experiment we have identified few very important considerations that require attention to be drawn in devising a stress detection solution through keystroke dynamics. There are different typing speeds and patterns for different individuals. Due to this reason keystroke pattern variation identification mechanisms should respect individual averages. That is why an individuals' real-time key stroke data should be compared against his own individual typing pattern profile which contains his own typing feature averages. In order to incorporate different behaviour patterns of individuals within different applications, the solution needs to maintain separate keystroke data averages for separate applications. Another Important aspect that has drawn our attention is the fact that people's typing pattern and the speed could change over time. Continuous learning concept can be used to incorporate this complexity. Our approach here is that average values for keystroke features in personal profile should be continuously trained and updated with latest keystroke data.

IV. EXPERIMENT

In this we used 20 students from University of Colombo School of Computing (UCSC) as the sample. The experiment was based on a hypothesis that "students are stressed during the period in which they get ready for their semester end examinations". We gathered data with this assumption, in two different situations: when students were free (not with exam pressure) and when students were getting ready for the exam. However, we also used a mental arithmetic test to induce the stressed nature of the participants during stress data collection. Data gathered during non-exam situation were considered as non-stress data while the data gathered during exam situation were considered as stressed data. Stressed nature of the participants was also verified through other two verification mechanisms stress monitor (HRV based) and the questionnaire.

In stressed and non-stressed situations the subjects were given a task in which they have to type several textual excerpts. An additional stressor (Mental Arithmetic Test) was used prior to the task in order to make sure that the subject was stressed during the task given in "stressed key stroke data collection". In order to remove the familiarity effects, we conducted two stages in each typing task as pre-seen and unseen. A detailed description about the experiment is given bellow. Here is the detail description about the non stress data collection procedure while not with exam pressure.

Step 1: In this step the subjects were given two sets of three excerpts. The subjects were asked to read these excerpts until they get familiar with them. These excerpts are used in pre-seen situations.

Step 2: After reading the textual excerpts, the subjects were given a questionnaire which contains questions to confirm the stress level of the subject before the task.

Step 3: After completing the questionnaire the subject was given one set of pre-seen textual excerpts to type. During this typing task key stroke data were gathered using a key logger (Inputlog).

Step 4: Then a set of unseen textual excerpts was given to the subject and asked to type. During this task also the keystroke data were gathered.

Step 5: As the final step of the whole task, the subject was asked to fill a questionnaire which includes questions to confirm the stress level of the subject during the task.

When considering the stress data collection phase apart from the above steps there was an additional step between step 2 and step 3 in the above procedure. As the additional step the subject was exposed to a stressor (Mathematical Arithmetic Test)

Figure 04 illustrates the high-level design of the experiment in two different situations. The upper part of the figure shows the steps of non stress situation and the lower part shows the steps of non stress situation. During the experiment Inputlog and Stress monitor were continuously used in both the non-stress and stress phases in order to collect keystroke data and to monitor the stress level variations provided through stress monitor.

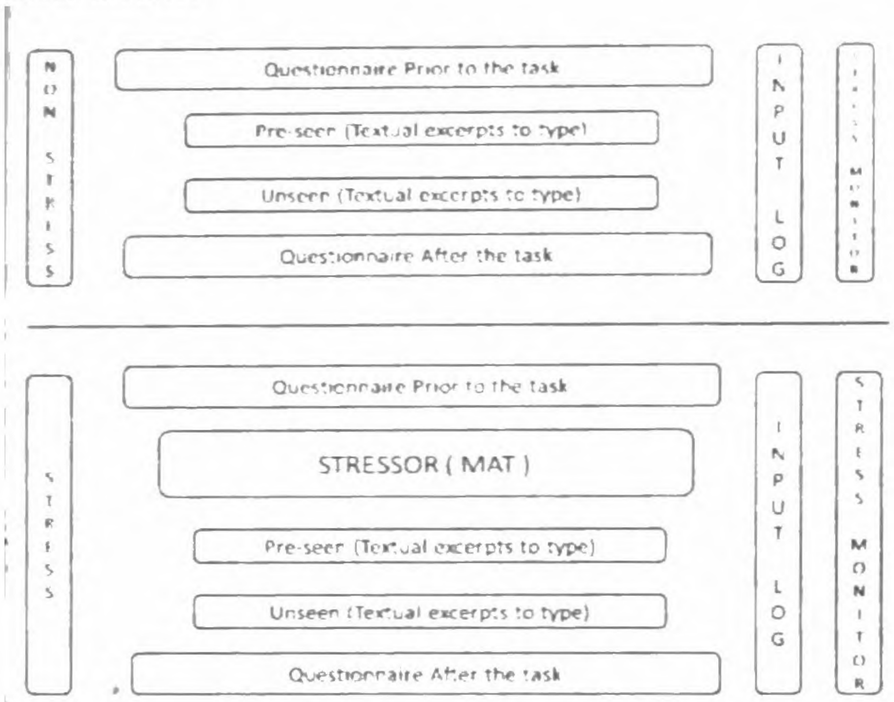

Fig. 4 Overview of the two phases of experiment (Non-stress and Stress Situations)

During the experiment we used two parallel verification mechanisms representing other two major approaches, physiological and psychological to stress detection to confirm the stress level of the participants.

Questionnaire: This was a self-developed questionnaire to record the current level of stress of a participant at any given time, which was developed with the expertise of a subject matter expert. This is developed based on standard questionnaires used in assessing the stress level of an individual. This was a 3 point Likert scale questionnaire that contains 10 closed ended questions. Participants also had to rate their assumed stress level in a three point Likert scale. Questionnaire was used in both stress and non-stress data collection. The responses to the questionnaires clearly verified the difference in stress levels.

Stress monitor: The device used for parallel verification is the "stress monitor" by "Biocom Technologies". This device uses a pulse wave sensor (Which can be attached to the ear-lobe or finger tips) to capture the heart rate variability. Stress monitor uses a proprietary algorithm to identify Heart rate variability patterns and measure stress level through them. (http://www.heartwizard.com/Content/Sections/StressManagement/StressMonitor) This was the other parallel verification mechanism to verify whether the subject was at a certain stress level throughout the task. Biocom Technologies is a global leader in the development, and manufacture of Heart Rate Variability products. Specifically, biomedical software and hardware products designed to monitor physiology for research and educational purposes. Their researches are majorly around heart rate variability.

Stressor: A Mental Arithmetic Test (MAT) was used as the stimuli which aroused stress in an individual. According to the literature MAT can be used as an effective artificial stressor [20]. This was a task in which the subject had to engage in mathematical calculations without any support of calculators or papers. A countdown timer was also used to add the time pressure. Our assumption during stressed data collection was that students were stressed very close to the exam. The use of MAT ensured that even the exceptions to the first assumption were also under some level of stress. (MAT - (http://www.quizfactor.com/quiz/mentalarithmetic/80?url=quiz/mentalarithmetic/80/play&gameid=80&quizid=192&method=post&target=quiz-ajax)

V. RESULTS OF THE EXPERIMENT

Within the phase two our objective was to establish that keystroke dynamics can be used to capture the stress of an individual. In order to prove that, we analysed the collected data using statistical analysis techniques. Our null hypothesis was that stress and non-stress keystroke data does not have a significant difference. We used a non-parametric test because our sample size was relatively small at 20 participants. We opted for Wilcoxon Signed Rank Test since we had paired data as stress and non-stress. This was used to assess the significance of the difference between stress and non-stress data samples. Below are the set of keystroke features that showed positive results.

TABLE I
SIGNIFICANCE LEVELS OF THE PS BIAGRAPHS

biagraphs	PS significance levels		
	A	B	C
an	0.044	0.063	0.008
er	0.121	0.004	0.326
he	0.006	0.004	0.098
in	0.036	0.007	0.056
th	0.002	0.007	0.034

TABLE II
SIGNIFICANCE LEVELS OF THE PS TRIGRAPHS

triagraph	PS significance levels			
	A	B	D	E
and	0.008	0.063	0.023	0.1
ing	0.004	0.026	0.278	0.163
the	0.02	0.11	0.07	0.134

TABLE III
SIGNIFICANCE LEVELS OF THE US BIGRAPHS

biagraphs	US significance levels		
	A	B	C
an	0.017	0.005	0.079
er	0.063	0.088	0.408
he	0.002	0.002	0.039
in	0.001	0.001	0.196
th	0.044	0.003	0.07

TABLE IV
SIGNIFICANCE LEVELS OF THE US TRIGRAPHS

triagraph	US significance levels

	A	B	D	E
and	0.027	0.017	0.001	0.004
ing	0.001	0.006	0.015	0.047
the	0.061	0.004	0.134	0.044

A. Duration of the 1st key
B. Duration of the 2nd key
C. Duration of 1st key down to last key up
D. Duration of the 3rd key
E. Duration between 1st key up to 3rd key down

Most of the above significance levels are less than 0.10 rejecting the null hypothesis that "There are no significant differences in stress and non-stress data of the same feature" and proving the alternative hypothesis at 90% confidence level.

But few other features also showed some negative results with higher than 0.1 significance level. Those features were majorly measuring very close time gaps between key presses such as 'first key up to next key down'. Most users of our sample were fast typing people. So there were a relatively higher number of negative times recorded for such features in collected keystroke data. This occurred because second key was pressed without releasing the earlier key due to the speedy typing and usage of both hands in typing. Key logger recorded these time gaps between two keys as a negative number in such incidents. These negative numbers has caused balancing off effects in calculating the average value for a particular feature and has caused deviated answer in statistical significance calculations also.

VI. DISCUSSION

One of the major issues we faced in the experiment was finding an exact situation where we can say that the samples are stressed. As a solution for that we considered a pre-exam situation, but we only had few exams during the time period we conducted the experiment. In addition to that the time taken by each individual in the experiments was unexpectedly lengthy. Due to above reasons the sample size was limited to 20.

In this experiment we used two typing scenarios as pre-seen and unseen, with the assumption that there can be a difference in keystroke patterns between situations where a person typing an already seen fixed text chunk and typing an unseen fixed text chunk. We have continued the research with considering both of these scenarios separately.

In capturing keystrokes we considered about time durations between different key presses and releases. In this approach we came up with an unexpected issue with the keystroke features in which we captured time durations between first key up and next key down. According to the results we received for bigraphs and trigraphs the above feature generally did not show a significance level which is below 0.1(p value). Eventually we identified that, this happens due to a practical issues which can occur with a person who is typing fast. The actual issue was the trend of not releasing previously pressed key before pressing next key.

VII. CONCLUTION

Stress has become a major issue throughout the world which can lead to reduced productivity, intricate personal interaction problems and complicated health issues. It seems to be difficult for many people to understand whether they are in a harmful level of stress. When they understand the harmfulness of stress they might have already reached the critical stage. It may be quite costly in both time and money wise to recover the person to a normal healthy position when they have reached a critical stage. Although there are solutions provided by different researchers using various approaches almost all those solutions are invasive as those require body worn sensors to detect stress. In this study we suggest a solution which does not require any additional sensors or equipment to detect human stress. The solution provided through this study mainly focuses on using keystroke dynamics (KSD) in detecting stress while a person is using the keyboard. KSD is a very powerful, readily available yet underutilized resource that provides a valuable insight about an individual's psychological state. In suggesting the solution existing literature were critically evaluated and gathered information were used in designing the experiment. In order to refine the experiment in proper manner a pilot study was used and the results of the experiment are published in this paper.

The usefulness of this research is not limiting to the importance of revealing an individuals' stress level. Suggested methodology is equally implementable to recognize other emotional state changes of users as well. In that case it can help Identification and incorporation of user emotional status to make much more sensible and relevant decisions in intelligent environments and artificial intelligence related appliances.

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