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# Web Based Keystroke Dynamics Application for Identifying Emotional State

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**Abstract**—Emotion is one of the important features of human being that makes them different from machines. Traditionally, today's computer system do not incorporate any emotional exchange in the decision making process. If we could develop an emotional aware system which can interact with human involving emotions then using machines could be more effective and friendly. Conventional emotional identification methods (facial expressional analysis, voice intonation analysis, thermal imaging of the face) use intrusive, lab-based, and expensive tools which are unsuitable for real-world situations. A possible solution for emotion identification without these drawbacks is to determine user emotion by analyzing the rhythm of their typing pattern on a keyboard. This paper presents techniques to recognize the emotional state of the user through analyzing the keystroke patterns of the user.

**Keywords**— Affective Computing, keystroke dynamics, biometric, emotion detection

## I. INTRODUCTION

There are two categories of Biometric: physiological (fingerprints) and behavioural (handwriting). Keystroke dynamics falls within the category of behavioural biometrics. The idea behind keystroke dynamics is that people have different typing styles and by analysing the timings of keystrokes, a person can be identified. A benefit of this metric is that measuring keystrokes can be done through a keyboard, thus negating the cost of typical physiological biometric systems which require expensive hardware to measure physical attributes.

"Keystroke dynamics is the study of unique timing patterns in the individual's typing and it includes extracting keystroke timing features such as the duration of key press and the time elapsed between key presses"

Traditionally, Machines like computer do not adapt according to user's emotional states. If the computer system were capable of extracting the emotional state that the user is going through in a particular period of time they would have many benefits for intelligent computers. A form of emotional intelligent would provide a richer context from which computer could change its behavior accordingly.

There have been various methods for evaluating emotional states like facial expression analysis, voice intonation analysis, change in breathing and physiological sensors attached to the skin etc. that have varying rates of success, but they still exhibit one or both of two main problems preventing wide scale use: they can be intrusive to the user, and can require specialized equipment that is expensive and not found in typical home or office environments.

This technique is relatively straightforward to apply and is one of the least expensive biometrics. No additional devices need to be purchased, installed, or integrated.

We proposed a web application that can recognize the user's emotional state by analyzing the keystroke patterns of the user.

## II. RELATED WORK

Previously before 1980's telegraph operators observed distinct patterns of keying message over telegraph lines. Today, the telegraph keys have been replaced by keyboard. The first research work in this domain was realized in 1980 with the report of the *Rand Corporation* [1]. The RAND report used a digraph representation for the keystrokes and conducted experiments on a small population of users. The majority of studies in keystroke dynamics are for authentication and verification purposes.

### A. Affective Computing

Our feelings affect the way we interact with the computer. According to Picard [2], Affective computing focuses on giving computer systems the ability to recognize an individual's emotions and to respond intelligently to the user's emotions. Having the capability to recognize users' emotions would especially benefit for online tutoring systems that interact with humans and mimic human reactions. Keystroke dynamics and other approaches are related with affective computing. We are interested in identifying a user's emotional state, so we must first consider how emotions are described, and what other approaches have been used to classify emotion.

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**B. Emotion**

According to [5], *"two generally agreed-upon aspects of emotion are:*

*(a) Emotion is a reaction to events deemed relevant to the needs, goals, or concerns of an individual and*

*(b) Emotion encompasses physiological, affective, behavioral, and cognitive components.*
*Fear, for example, is a reaction to a situation that threatens (or seems to threaten) an individual's physical well-being, resulting in a strong negative affective state, as well as physiological and cognitive preparation for action. Joy, on the other hand, is a reaction to goals being fulfilled and gives rise to a more positive, approach-oriented state. "*

Emotional state is an attribute of certain states. e.g. – "His voice was tinged with emotion".

**C. Emotion Detection**

There have been two main approaches for describing emotions: categorical and dimensional. The categorical approach applies labels to emotions with some languages or words (e.g. sadness, fear, joy) [3]. Dimensional approach uses two orthogonal axes called arousal and valence to describe emotions [4].Arousal is related to the energy of the feeling and is typically described in terms of low (i.e., sleepiness) to high (e.g. excitement) arousal. Valence describes the pleasure and displeasure of a feeling.

**D. Keystroke Dynamics**

Keystroke dynamics is the process of analyzing the way a user types on a keyboard and identify him based on his habitual typing rhythm. Keystroke dynamics is not what you type, but how you type.

Much of the previous research in keystroke dynamics has been for authentication and verification purposes. Since Gaines et al. [1] first proposed an approach using keystroke dynamics to verify users' identity; typing patterns have been studied extensively for security applications, to enhance the authentication process by comparing the current typing pattern with a previously constructed typing pattern.

Monorose and Rubin [6] made an automated classifier that used keystroke features including keystroke timing and key latency to detect unsuitability in users' typing patterns to enhance the authentication process. The typing features were extracted from both predefined text (fixed text) and spontaneously generated text (free text). Their proposed method yielded a 48.9% accuracy-recognition rate for a population of 31 users.

Monorose et al. [7], in another study, suggested that individuals' typing patterns are not stable, and change according to their environment, stress level, and cognitive function.

Classification algorithms for the analysis of keystroke dynamics include neural network [8], distance measures [7, 9], decision tree [10], and other statistical methods [7].

Affective Computing and Keystroke Dynamics

Recent work by Vizer, et al. [11] diagnosed individuals' cognitive and physical functions using keystroke dynamics. Their approach utilized the users' everyday interactions to detect changes in their cognitive and physical functions. The experiment consisted of control (no stress) condition, cognitive stress condition, and physical stress condition where the participants were asked to provide a text sample under each condition. The extracted features included timing, keystroke and linguistic features. The collected data was analyzed using several machine learning techniques: decision trees, support vector machine, k-nearest neighbor, artificial neural network They achieved correct classification of 62.5% physical stress and 75% for cognitive stress. They also tested their experiment with varying physical and cognitive abilities and with varying typing habits and keyboard.

Zimmermann et al. [12] described a method which uses keyboard and mouse interactions to detect users' emotions. This study used the categorical approach that uses emotional valence and arousal dimensions. Participants' emotions were assessed using physiological sensors that measured their respiration rate, pulse rate, and skin conductance. They were also asked to self-report their emotional states by using the Self-Assessment-Manikin (SAM) [2], which consisted of graphical manikin that each represents score in the valance and arousal dimension. Zimmermann et al's classiffer was able to distinguish between neutral and other emotional states, but was not able to distinguish between the other four induced states.

## III. METHOD FOR IDENTIFIYNG EMOTIONS

To build emotional classifier, typically researchers have to collect users' behavioral or physiological patterns which are then mapped to emotional categories. To accomplish these goals, there would be two method: They either induce participants' emotions in a laboratory setting using one of the Mood Induction Procedures (MIPs) e.g., video or story, or in a real-world setting in which participants use their personal computers in their daily lives [14]. Both approaches have advantages and disadvantages: a laboratory-based study using mood induction procedures will yield more cleanly labelled data. However, the induced emotions do not necessarily represent the emotions that users experience in the real world.

On the other hand, using a real-world approach generates a greater amount of data compared to a time-limited laboratory-based approach, but with more noise and more in-complete data points. In this study, we chose to gather spontaneously generated interaction data without using

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any Mood Induction Procedures (MIPs), using same laboratory setting, computer application, and computer settings.

We are working on six basic emotional classes – confidence, sadness, nervousness, happiness, tiredness, hesitation. Our aim is to develop a web application to recognize human emotional states.

A. **The Data Collection Process:** It consists of gathering and labeling users' keystroke and mouse data. This process runs in the background, gathering keystrokes regardless of the application that is currently in focus. The only visible sign that the application is running has an icon in the desktop system tray. The data collection server is allowed us to preserve participant anonymity and supported remote users.

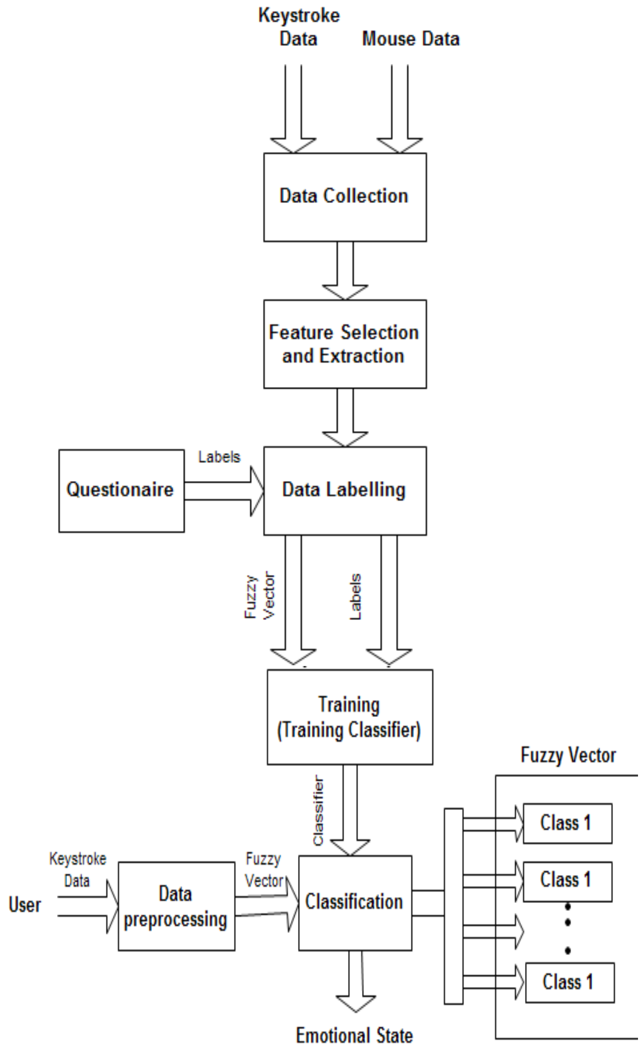


Fig. 1. Flow Chart for Emotional Classification

**Fixed Text Data collection**

This data collection method asked the user to type some fixed piece of text from the famous novel *"Alice's Adventures in Wonderland"* [15]. The user was unable to copying and pasting the fixed text. The user could close the data collection window if they were too busy.

We will develop a Java application to collect users' keystroke data for using in keystroke dynamics. This application will record all pressed key by the user and their press and release time. We asked the user to enter data at least once in a day. This ensured data collection under different emotional states of the same user. This took about 4 weeks to collect all the data. There are several reasons behind choosing fixed text over free text. It is very likely that while normal computer use, the user may use mouse more than keyboard. Using fixed text ensures a minimum number of keystrokes per sample and produces good results in building models. After typing these paragraphs, the user had to choose one of seven emotional states which best matched with the user's current emotional state.

**Free Text Data collection**

We will use a java application which can run in background to collect keystroke timings (key press time and key release time). The user is not aware of the hidden software and thus is less bothered about the data collection process. The software prompts the user every 15 minutes to enter his/her mental state. A small window pops up with the six emotional states stated in the previous section and prompts the user to tick one of them according to their present emotional state. All collected data are stored in different tables of the database by different name.

**B. Feature Extraction:** Due to the large number of raw data we perform attribute selection which reduces the number of attribute to facilitate the classification process. We could select the necessary features like keystroke latency, duration of key hold, typing rate etc. These biometric features are converted into fuzzy vector which are further used for classification.There are several keystroke features, but we have extracted following essential features

*1) Session time* is the total time spent by the user on the system. Session time is calculated by computing the difference between the starting time and user response times.

$$\textit{Session time} = \textit{Starting time} - \textit{User response time.}$$

*2) Keystroke latency* is the time interval between the key release of the first keystroke and the key press of the second keystroke. However, the latency of longer n-graphs ( n > 2) is defined as the time interval between the down key events of the first and last keystrokes that make up the n-graph.

*Keystroke Latency*

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$$= \frac{\sum Releasing\ times\ of\ Key1 - \sum Depressing\ time\ of\ Key2}{Character\ per\ sentence}$$

*3) Held Time (or Dwell Time)* is the time (in milliseconds) between a key press and a key release of the same key.

*4) Sequence* is a list of consecutive keystrokes. For example 'REVIEW' is a Sequence. A Sequence can be of any length (minimum two). In this example, the Sequence is a valid English word, but this need not be the case. Thus, 'REV', 'IEW' are also valid Sequences from the same keystroke stream.

- A length-2 Sequence is called a digraph
- Length-3 Sequence is a trigraph; etc
- A general Sequence is therefore an n-graph.

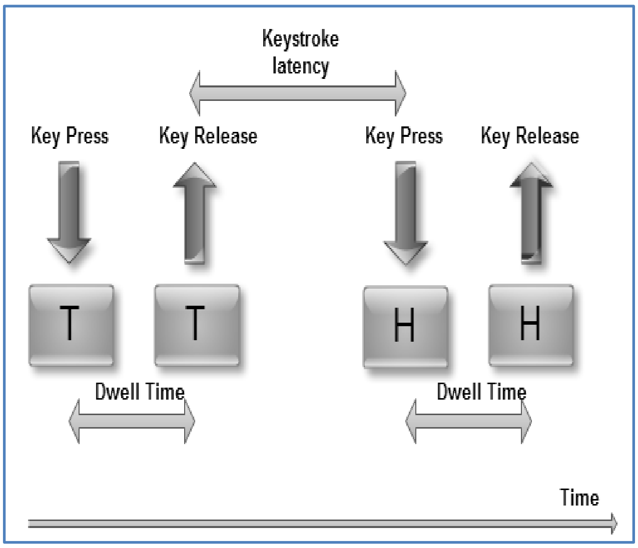


Fig. 2. Relationship between key hold-time and key latency for the digraph "th".

5) *Typing speed* is the total number of keystrokes or words per minute. The typing speed could be an indicator of different emotions.

6) *Frequency of error* is the use of backspace key and delete key. This rate may provide evidence of a state of confusion, as individuals who tend to delete are more likely to be confused.

$$Frequency\ of Error = \frac{\sum Use\ of\ backspace\ key}{Characters\ per\ Sentence}$$

7) *Pause Rate* is the time the user spends responding to a question, in other words the time difference between the question time and the response time. Spending more time answering a question could indicate confusion or boredom, whereas spending less time could indicate delight or neutral feelings.

$$Pause\ Rate = System\ response\ time - User\ response\ time$$

**8)** *Capitalization Rate* is the rate of using the Shift + letter or caps locks key.

$$Capitalization\ Rate = \frac{\sum \text{Use of Shift and Letter} + \text{Use of Caps locks}}{Characters\ per\ sentence}$$

### C. Data Labeling:

There are two main approaches to emotion labeling. One of the method is to label emotions by a human, the second approach is automatic labeling. There are different types of labels (like excitement, boredom, joy, surprise etc.) where people are able to choose from a predefined list of word labels during questionnaire . The questionnaires may use scales such as the Likert scale presenting a range of responses to each question [16] or Self-Assessment-Manikin (SAM) technique, which is a graphical way of expressing valence, arousal and dominance [17].

We are going to labels the data provided by the human while questioning for the best accuracy of the trained system as shown in figure 1.

### D. Classification:

Several classification methods (Discriminate Analysis, Bayesian Analysis, k-Nearest Neighbor, Artificial neural network and Decision Trees) were used in the previous studies. It was difficult to evaluate which classification methods produced the best model due to the variability in experimental conditions.

Rule based systems for classification have the disadvantage that they involve sharp cutoffs for continuous attribute so used fuzzy logic as a solution to recognize users' emotional state. Fuzzy logic systems provide graphical tools to assist users in converting attribute values to fuzzy truth values (low, medium, high).

## IV. CONCLUSION

In this work we have focused on the problem of human emotion recognition in the case of naturalistic, rather than acted and extreme, expressions. Keystroke dynamics has become an interesting research topic in the area of behavioral biometrics due to its non-intrusiveness and convenience. The current methods for detecting user emotions are voice intonation analysis, facial expression analysis, and physiological sensors attached to the skin etc. But these techniques use expensive, specialized, and invasive technologies not found in typical home or office.

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Our solution is to identify user's emotional state through their typing rhythms or keystroke dynamics. The main benefit of using keystroke dynamics is that the required equipment, any standard keyboard which is in expensive and already widely used in most computer systems.

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