Identifying Emotion by Keystroke Dynamics And Text Pattern Analysis

By

A F M Nazmul Haque (084417)
Jawad Mohammad Alam (084427)

Supervised By

Hasan Mahmud
Assistant Professor
Department of Computer Science and Engineering (CSE)

Co-Supervisor

Adnan Alam Khan
Lecturer
Department of Computer Science and Engineering (CSE)

Department of Computer Science and Engineering (CSE)
Islamic University of Technology (IUT)
Organization of Islamic Cooperation (OIC)
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Certificate of Research

This is to certify that the work presented in this thesis is the outcome of analysis and investigation carried out by the candidate under the supervision of Mr. Hasan Mahmud in the department of Computer Science and Engineering (CSE), IUT, Gazipur, Bangladesh. It is also declared that neither of this thesis nor any part of this thesis has been submitted anywhere else for any degree or diploma. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

Signature of the Head of the Department

____

Prof. Dr. M.A. Mottalib
Head
Department of Computer Science and Engineering (CSE)

Signature of the Supervisor

____

Hasan Mahmud
Assistant Professor
Department of Computer Science and Engineering (CSE)

Authors

___________________	______________________
A F M Nazmul Haque	Jawad Mohammad Alam
Student ID: 084417	Student ID: 084427

Abstract

Emotion is a cognitive process and is one of the important characteristics of human being that makes them different from machines. Traditionally, interaction between human and machines like computer do not exhibit any emotional exchanges. If we could develop an intelligent system which can interact with human involving emotions, that is, it can detect user emotions and change its behavior accordingly, then using machines could be more effective and friendly. Affective computing is the field that deals with this problem of identifying user emotion through various methods. Many steps have been taken to detect user emotions. Our approach in this paper is to detect user emotions through analyzing the keystroke patterns of the user and the type of texts (words, sentences) used by them. This combined analysis gives us a promising result showing substantial number of emotional states detected from user input. Several Machine learning algorithms of Weka were used to analyze keystroke features and text pattern analysis. We have chosen keystroke before it is the cheapest medium of communication with computer. We have considered 7 emotional classes. For text pattern analysis we have used vector space model (VSM) with jaccard similarity. Our combined approach showed above 80% accuracies in identifying emotions.

Keywords

Human computer interaction, affective computing, emotion detection, keystroke dynamics, machine learning, text pattern analysis, Vector space model,

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Chapter 1

Introduction

1.1 Thesis context

Since its advent, computer systems have improved tremendously in power, performance and size. But in case of Interactions with end user's, a lot more should be done. Emotionally aware systems can be a step ahead in this regard. Systems that can detect user emotion can do a lot better than the present systems like gaming, online-teaching, text-processing, video and image processing, user authentication and so many other areas where user emotional state is crucial. For example, a gaming application that can detect and respond to end users emotion can assess the user's current emotional state and adapt accordingly (i.e. it can change the graphics quality, volume level, control sensitivity level, music selection and many more). Similarly, an emotionally intelligent online system can change its teaching style or contents, change the interface giving it a more attractive and easy-to-understand look according to a particular student's current emotional behavior.

1.2 Problem

For a computer system; detecting emotion of an user is not easy. A lot of calculations and analysis are needed. Lots of factors are needed to be considered while anticipating a particular person's emotional state. Some physiological aspects reflect emotional changes in human body. For example: temperature rise or fall, facial expression, voice intonation, heart rate change, blood pressure change, change in breathing etc. Some behavioral changes also happen like abrupt bodily movements, laughing, smiling, moving towards people/things, crying, sobbing, withdrawing from people/things etc. In computer using context, users can show particular behavioral changes while moving from one emotional state to other.

Many approaches for determining user emotion have been analyzed. They are wide in range and sometimes expensive. Procedures like voice intonation analysis, physiological sensors attached to the skin, facial expression analysis, thermal imaging of the face, gesture and pose tracking and many more[1,2] has already been done. This approaches showed good results but has some problems as well.

Almost all of them require expensive and hard-to-use hardware which may not always be available to the user and they can be intrusive [1]. We need more cheap as well as reliable methods to identify user emotion. Moreover, a very little work has been done on any combined method. Most of the works has been done on single domain.

1.3 Solution

In our approach we tried to find a way out of these problems to anticipate user emotions more easily. To solve this problem we need a more cheap and reliable means of tool of interaction between computer and human users. As it is a fact that a particular user can show certain behavioral change while moving from one emotional state to other, those behavioral changes could be used to detect user emotional state. For instance, a user types at a particular speed. It has been showed that users type slowly while they are in negative mental state and type fast while in positive mental state [2]. Standard keyboard is a very cheap and available hardware that can be used to identify user emotion. That is the main reason we have chosen keystroke features to identify user emotion. Moreover, we will use user input texts to analyze word patterns and also sentence level processing to assess user emotion. Little work has been done in such combined (Keystroke Dynamics and Text pattern analysis) approach. This combined analysis does not require any extra hardware or specialized tools described before.

1.4 Structure of the Thesis

In chapter 1, thesis context and problem definition is given with a solution proposal. Chapter 1 also contains a brief description of the technologies and softwares used to do the thesis. Chapter 2 describes related works and background studies about the thesis. It also describes some important definitions and up-to-date techniques about Emotion detection. Chapter 3 deals with the detailed problem statement and proposed mechanism. Chapter 4 describes every detail of this thesis. It gives a detailed description of every procedures followed to collect data, manipulate, transform and train them. Chapter 5 discusses results obtained from the analysis procedures.

Chapter 2

Related works

2.1 Affective Computing

According to Picard [3], Affective computing is an area that deals with or related with emotions. This is now the main field that is giving much effort for identifying user emotion. 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.

2.2 Definition of Emotion

According to [9], *"**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. "

From this definition we get an idea about human idea. Emotion detection has been a major issue in human computer interaction because it seems to carry out an important role in more effective interaction between human and computer. Affective computing is the field that concentrates on this issue and some successful steps has already been undertaken to assess emotions.

2.3 Emotion Detection

Several ways are there for describing emotions. Some use categorical approach and some use dimensional approach. Categorical approach is labeling emotions with some languages or words [5].

Dimensional approach uses two orthogonal axes called arousal and valence to describe emotions [1, 14]. 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. In [15], a computational architecture is developed to model emotions based on Markov model.

2.4 Keystroke Dynamics

There has been a noticeable amount of work done in keystroke dynamics field. Keystroke dynamics was extensively used in authentication systems previously [10, 11, 12, and 13].Some of the works was able to obtain good results in detecting emotional states. in [1], Clayton Epp, Michael Lippold, and Regan L. Mandryk's (2011) work shows classification of 15 emotional states. Their main concentration was on keystroke timing features (i.e., dwell time, flight time) and a little on content features (i.e., number of Backspaces, Delete, special characters). Both free and fixed texts were collected from users. Weka tool was used with C4.5 supervised machine learning algorithm to classify the data sets. Sasikumar, PreetiKhanna (2010) [2], showed a slightly different approach with fixed text analysis. They successfully modeled three emotional classes (positive, neutral, negative). In [1], their objective was to recognize user emotion to make appropriate decision about how to interact with the user or adapt their system response. Two main problems with current systems that use special hardwares and special sensors are-

1. They can be invasive and
2. Can require costly equipment.

A good solution to these problems may be analyzing the rhythm of typing pattern in a standard keyboard. They have used 15 emotional states each having levels. Users while giving data also marked their level of agreement with these 15 classes. Experience-sampling-methodology (ESM) is used to gather real world data rather than induced in a laboratory setting through emotion elicitation method. Data collection software was written in C# and used to scan each keystroke as it is entered by the user. It ran in background, gathering keystrokes regardless of the application currently in focus. This program prompted the user throughout the day, every 10 minutes. At each prompt, the user was presented with their keystroke text from the previous 10 minutes, then with an emotional state questionnaire. The features they have used are – dwell time (time elapsed between key press to release), flight time (time between keys), key down-to-down time. They also included a few features based on the content (Text) extracted from the free keystrokes, including separate features for the number of characters, numbers, punctuation marks, uppercase, number and percentage of special characters, number of mistakes (backspace+delete).

They used their collected data to train C4.5 supervised machine learning algorithm of WEKA and built models. Trained model was used to evaluate test data. They identified confidence, hesitance, nervousness, relaxation, sadness, tiredness with accuracies ranging from 77% to 88%. Anger and excitement showed 84% accuracies.

In [2], authors used an empirical study to know whether keyboard stroke information could compliment the emotion recognition other than audio and visual modality. Their empirical study involved 300 users (45% of Female and 55% of Male) of varying educational background, ages and levels of computer experience. The users were given a paragraph and after that they were asked how they felt (neutral, negative, positive). Each of these users was asked to fill a questionnaire relating the typing pattern and their emotional state while typing.

They have showed 6 basic actions like-

“ they need to map with six basic actions such as

1. user types normally
2. user types quickly (speed higher than the usual speed of the particular user)
3. user types slowly (speed lower than the usual speed of the particular user)
4. user uses the backspace key often
5. user hits unrelated keys on the keyboard
6. user does not use the keyboard.

The questionnaire includes the abovementioned six basic actions and the respondents need to be map their emotional states to these actions. “

The following justifications are taken from [4]. Their empirical study involved 300 users (45% of Female and 55% of Male) of varying educational background, ages and levels of computer experience

Use of backspaces

1. Most of the participants agree that when they have negative feelings, possibility of making mistakes is higher.
2. Mistakes in typing followed by many backspaces and use of unrelated keys are usually seen.
3. 28% of respondents said that they will use more backspaces and 20% agree on relatively more usage of unrelated keys when they were in negative emotional state.

4. It was observed that usage of the backspaces and unrelated keys under positive emotional state reduces drastically (from 28% to 2%).

Typing Speed

1. 88% of respondents agree that they will type normally when they are in neutral state.
2. But when they are in negative emotional state like angry, disgust, irritated, bored, and sad their typing speed will reduce as compared to their neutral state.
3. 62% of respondents said their typing speed will increase relatively when they are in positive emotional state like happy, excited etc.

Features used in [4]-

1. Typing speed
2. Mode
3. Standard deviation
4. Standard variance
5. Range

   Of # of characters in 5 second interval

6. Total time taken
7. # of backspaces used
8. Interval between typing (if any)

They used a java program to collect user data. They have used two slightly different paragraphs as fixed text. Various classification algorithms – simple logistics, SMO, Multilayer Perception, Random Tree, J48, BF Tree were used to do the analysis with the help of WEKA. Result analysis comparisons of [4] are shown in by the following table. They have compared the results of negative and positive with respect to neutral slate. This table signifies the accuracy level of identifying positive or negative emotional states by comparing with neutral state.

Table-1: Recognition rate (%) using various classification algorithms for two emotional category negative and positive with reference to its neutral states

Types of Classification Algorithms		Negative Vs Neutral	Positive Vs Neutral
Rules	Simple Logistics	71.95%	80.24%
	SMO	67.07%	62.66%
	Multilayer Perceptron	79.26%	71.6%
Trees	Random Tree	85.36%	75.30%
	J48	84.14%	88.88%
	BF Tree	89.02%	86.41%

2.5 Text pattern Analysis

Chunling Ma et al showed a chat system where textual message is analyzed to extract its affective content by an advanced keyword spotting technique. The main concept of the paper is to detect emotional state of the users of a chatting system by directly analyzing the sentences used by them and use it to express the emotion by a 2D character known as "Avatar". The approach is based on the following methods –

1. The affective content of the textual message is recognized by an advanced keyword spotting technique .
2. Syntactical sentence level processing is applied for detection of affective meaning .
3. An animated 2D full body agent performs the emotional coloring of the message using synthetic affective speech and appropriate gestures .

Emotional estimations for natural –language texts is based on a keyword spotting technique , that is the system divides the text into words and performs an emotional estimation for each of this words , as well as a sentence level processing technique (the relationship among subject ,verb ,object) . Six basic emotions were used from Ekman's research : happy , sad , anger , fear , surprise , disgust . WordNet 1.6 database was used to first find synonym sets of these 6 emotion categories and to assess their emotional weight and then compute the weight of a sentence by combining the weights of its parts .

Word spotting technique is too simple, hence two types of sentence level processing was used. First, non emotional sentences were eliminated :

(1) sentences without emotional words .

(2) sentences without 1st person pronouns.

(3) questions .

Second , detect negation in the sentences . Since negatively prefixed words such as “unhappy” are already included in the emotion database, they do not have to be considered. On the other hand, negative verb forms such as “have not”, “was not”, “did not” are detected and flip the polarity of the emotion word.

From the emotion detection process stated above, a chatting system was developed where an animated character mimicked the emotion by synthetic voice and exaggerated gestures [4].

DIANA INKPEN et al. [6] worked on Ekman’s six basic emotions plus one class for non-emotion. They used supervised machine learning algorithms for classifying text by emotions and by mood and have also generated some texts that express emotions .They proposed an approach that uses a hierarchy of possible moods in order to achieve better results rather than standard flat classification. Their work can be divided as follows:

(1) Classifying text by the expressed emotion.
(2) Classifying blogs by mood.
(3) Generation of texts with emotion.

Their annotations were made with the six basic emotions on an intensity scale of [-100,100].The task organizer employed six annotators. In classifying text by expressed emotion, they used all the 1250 headlines as one dataset. Then they report results by 10-fold cross-validation in order to be able to imply machine learning techniques. They tried several classifiers in Weka and among them SVM obtained the best result.

Again, for classifying blogs by mood they used the blog data set that Mishne collected for his research[16]. The corpus contained 815,494 blog posts from live journal, a free weblog service used by millions of people to create weblogs. They mostly used features from Mishne[16], but also added few extra features. Their feature included:

(1) Frequency counts Bag-of-Words (BoW)
(2) Length related features

(3) Sentiment Orientation for Mood Classification

(4) Special symbols called emoticons(emotional icons)

They trained a classifier into 132 mood and evaluate its performance on the Selected test set. They initially worked with feature (1) and (2), then added (3) and (4) and they called this extended feature as (BOW+SO). Among several classifiers, again SVM obtained best result.

Serious games were used for training purposes that often included exchanging messages. The player under training received messages from various game characters, in response to his/or her actions. These messages can be written manually by game developers or generated manually using Natural Language Generation (NLG) techniques. For sentence realization they used simple NLG package, which allows specifying templates in the form of JAVA code [6].

The newspaper headlines data from SemEval 2007-Task 14 was used in [6] and emotion-annotated blog corpus was used in [6, 7]. In [8], Vector Space Model (VSM) is used for emotional Classification of Text and developed a video player which detects emotions from subtitles and displays emoticons while playing video.

Chapter 3

Problem

3.1 Problem Statement

Emotion is the one of the extraordinary things of human being that made them different from machines. Machines do not have emotions or any emotion-like feelings. The most up-to-date supercomputer today does not have any emotional feeling in it. Human computer interaction is always a process without having any emotional exchanges between the user and the computer. But we can easily guess that if it is possible to incorporate emotional behavior with computers, then using computer systems would be lot more easy and effective. In our work, our primary goal is to detect user emotions. To accomplish that we need to first find out the definition of emotion. We also need to identify the basic emotional classes an user could feel. Next we have to find out a way to represent emotions of an user to be analyzed and processed by computers. This task requires various software, specialized algorithms and suitable representation of user data to computer.

In our primary attempt, we are going to use standard keyboard inputs to manipulate and analyze them to predict user emotion. From the definition of keystroke dynamics, it mainly refers to keystroke timing features where timing of each single key press is analyzed. Various timing features could be derived from timing features. Another way to detect emotion is to use user input data and analyze every word and sentence to find out their emotional meaning. This technique also works well .

In all Keystroke dynamics method so far, they concentrated on keystroke timing features only (with some additional content features like number of backspaces, number of special characters, punctuation marks, use of numbers, analyzing bigraph/digraph etc). They did not incorporate other features like Text patterns. On the other hand, The Text pattern analysis methods discussed so far, did not take into account the keystroke timing features of individuals .The problem with this approaches is that, they concentrate on a single domain of method instead of multiple methods and thus lack the chance of more accuracy. Our approach is to solve this problem and incorporate more features and combine these two methods. In our approach we are trying to assess emotion by a combined method of keystroke dynamics and text features analysis and find out a better solution with increased accuracy. We also concentrate on finding out which method gives us the best possible result.

Chapter 4

Proposed Mechanism

4.1 Proposed Mechanism

We have worked on seven basic emotional classes – ANGER, DISGUST, GUILT, FEAR, JOY, SAD, SHAME. Our main aim is to combine both keystroke dynamics and text pattern analysis and thus improve the quality of emotion detection process.

Our work is divided into 2 major parts -

a. Keystroke Analysis

b. Text Pattern Analysis

Keystroke Analysis is further divided into 2 parts –

i. Fixed Text analysis

ii. Free Text analysis

4.1.1 Keystroke Analysis

We have developed several softwares to collect data and extract features from collected data. Our data collection process is divided into two steps. First, we collected fixed text data. Free text data were collected using different software.

4.1.1.1 Fixed Text Data collection

For collecting fixed text data a number of volunteers were needed. We requested a good number of users to provide data. 25 of them responded. These users were of varying ages, educational background and computer experience. We developed software in Java to collect data for using in keystroke dynamics. This software captured all pressed key by the user and their press and release time in a log file. We supplied this software to each user and requested 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. In the software, the user was presented with two paragraphs collected from the famous children's novel "Alice's Adventures in Wonderland" [11]. According to [12], the reasons behind choosing these text excerpts are, they have relatively simple sentence structure, absence of large uncommon words and each piece of text has roughly the same length. 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 [12]. After typing these paragraphs, the user had to choose one of seven emotional states which best matched with the user's current emotional state. The interface of the software is shown below.

The emotional classes we used are: joy, fear, anger, sadness, disgust, shame, guilt. These seven emotional classes were also used with the ISEAR data set. We also incorporated two additional classes (neutral and tired) just in case the user is not in any of the seven classes. All data were collected in different log files to extract keystroke features from them. Figure 01 shows a snapshot of the software-

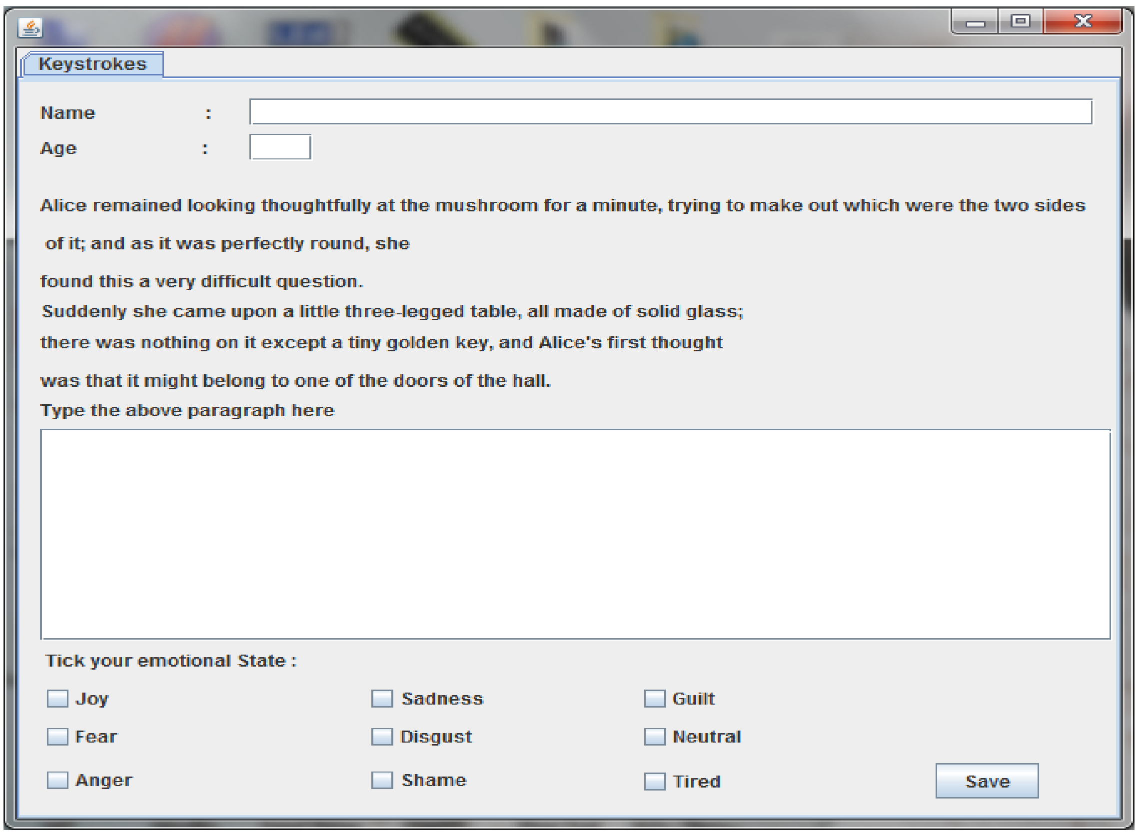

Figure 1: Interface Snapshot of fixed text data collection software

4.1.1.2 Free Text Data collection

Another software was developed (written in C#) which can run in background and collects all keys pressed by the user and their press and release time in a log file. This software collects free texts and the user is not aware of the hidden software and thus is less bothered about the data collection process. This software is functionally same as the software developed in JAVA except that it runs in background. The software prompts the user every 5 minutes to enter his/her mental state. A small window pops up with the seven 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 files by different name and different system time. An instance of the prompt window is shown in figure 02.

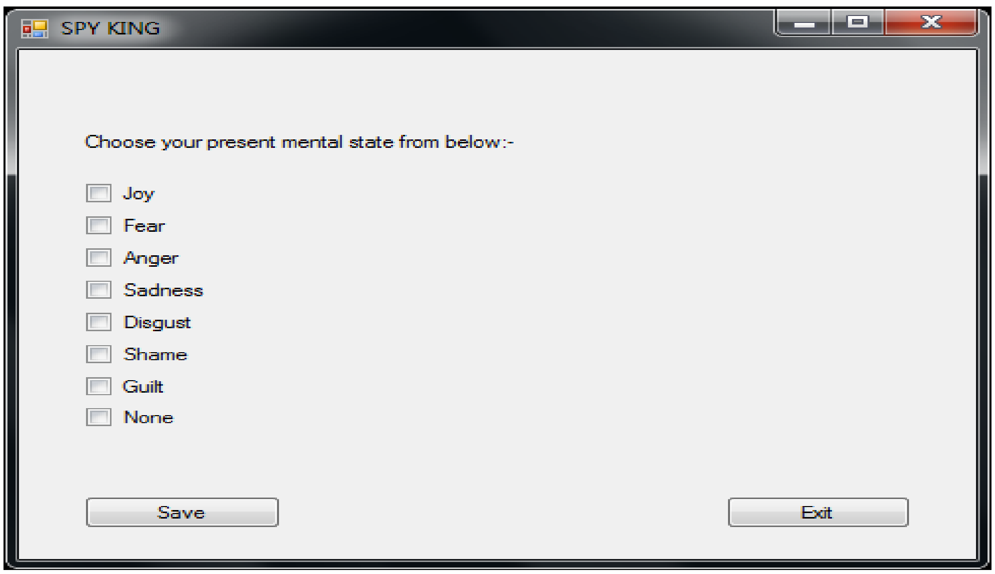

Figure 02 : Interface Snapshot of free text data collection software

4.1.1.3 Feature Extraction

After completion of collecting data from a few volunteers, another software (written in C) was used to extract keystroke features from those log files to a separate feature file. These files were later used to build models using WEKA.

4.1.1.4 Extracted Keystroke features

At first several keystroke timing features were extracted. But all of them did not show good results. We extracted a total of nineteen keystroke features extracted from the collected data. Keystroke features showed the best results -

1. Typing speed in 5 second interval
2. Mode
3. Standard Deviation
4. Standard Variance
5. Range
6. Minimum
7. Maximum

Of dwell time of each characters pressed in every 5 second.

8. Mode
9. Standard Deviation
10. Standard Variance
11. Range
12. Minimum
13. Maximum

Of flight time of each characters in 5 second interval

14. Mode
15. Standard Deviation
16. Standard Variance
17. Range
18. Minimum
19. Maximum

Of key down-to-down time of each characters in 5 second interval

These features were used to build training data set for weka. Table 1 shows all these 19 features with their meanings used in weka to train the full data set.

Table-2: Extracted Keystroke features and their meaning.

Feature	Meaning
Num_char	Number of characters pressed in every 5 sec
mode_dwell	Mode of dwell times of keys pressed in every 5 sec
stdDev_dwell	Standard deviation of dwell times of keys pressed in every 5 sec
stdVar_dwell	Standard variance of dwell times of keys pressed in every 5 sec
range_dwell	Range of dwell times of keys pressed in every 5 sec
min_dwell	Minimum of dwell times of keys pressed in every 5 sec
max_dwell	Maximum of dwell times of keys pressed in every 5 sec
mode_flight	Mode of flight times of keys pressed in every 5 sec
stdDev_flight	Standard deviation of flight times of keys pressed in every 5 sec
stdVar_flight	Standard variance of flight times of keys pressed in every 5 sec
range_flight	Range of flight times of keys pressed in every 5 sec
min_flight	Minimum of flight times of keys pressed in every 5 sec
max_flight	Maximum of flight times of keys pressed in every 5 sec
mode_d2d	Mode of down-to-down times of keys pressed in every 5 sec
stdDev_d2d	Standard deviation of down-to-down times of keys pressed in every 5 sec
stdVar_d2d	Standard variance of down-to-down times of keys pressed in every 5 sec
range_d2d	Range of down-to-down times of keys pressed in every 5 sec
min_d2d	Minimum of down-to-down times of keys pressed in every 5 sec
max_d2d	Maximum of down-to-down times of keys pressed in every 5 sec

4.1.1.5 Selected Attributes

Attribute selection involves searching through all possible combinations of attributes in the data to find which subset of attributes works best for prediction. To do this, two objects must be set up: an attribute evaluator and a search method. The evaluator determines what method is used to assign a worth to each subset of attributes. The search method determines what style of search is performed. We have selected 7 attributes from those 19 features mentioned in section 4.1.1.4. The final attributes are : Typing speed, min_dwell, min_d2d, min-flight, mode_flight, mode_dwell, mode_d2d. Finally these extracted features were used to make the models using WEKA. Weka uses the training set to build the models. The test data were evaluated against these models and the final result was obtained.

4.1.2 Text pattern analysis

To analyze text, we need a standard data set upon which we will apply our classification algorithm. For this purpose we have used ISEAR (International Survey on Emotion Antecedents and Reactions) data set for text pattern analysis [#]. Over a period of many years during the 1990s, a large group of psychologists all over the world collected data in the ISEAR project, directed by Klaus R. Scherer and Harald Wallbott. Student respondents, both psychologists and non-psychologists, were asked to report situations in which they had experienced all of 7 major emotions (joy, fear, anger, sadness, disgust, shame, and guilt). In each case, the questions covered the way they had appraised the situation and how they reacted. The final data set thus contained reports on seven emotions each by close to 3000 respondents in 37 countries on all 5 continents. The final data set contains more than 7500 entries consists of example sentences and other numeric values related to the sentences.

Table-3: Some examples from ISEAR data set

Emotion Class	Example sentence
Joy	When I got a letter offering me the Summer job that I had applied for.
Fear	When I was involved in a traffic accident.
Anger	When a car is overtaking another and I am forced to drive off the road.
Sadness	When I lost the person who meant the most to me.
Disgust	When I saw all the very drunk kids (13-14 years old) in town on Walpurgis night.
Shame	When I could not remember what to say about a presentation task at an accounts meeting.
Guilt	When my uncle and my neighbor came home under police escort.

4.1.2.1 Vector Space Model as text pattern classifier

"Vector space model or term vector model is an algebraic model for representing text documents (and any objects, in general) as vectors of identifiers, such as, for example, index terms. It is used in information filtering, information retrieval, indexing and relevancy rankings" [17]. Vector space model assigns an weight to every term of a document. There are several ways for calculating this weight. One of the best known schemes is *TF-IDF* weighting. *tf* means term frequency and *idf* is the inverse document frequency. Calculating weight of a particular word requires to first calculate the frequency of the word in a particular document. Inverse document frequency is calculated by taking the log of the division of the total number of document in the data set and the number of documents containing the particular word of which the weight is being calculated. Formally the normalized weight of a term is as follows-

$$w = \frac{tf * \log(N/d)}{\sum_1^n tf^2 * \{\log(N/d)\}^2}$$

Where ,

w = weight of the term

tf = term frequency in a particular document

N = total number of documents in the data set

d = number of documents containing this word

n = number of total unique terms.

After calculating all the term weights, all the document was converted to vectors because documents are represented as vectors to vector space model. This vectors consist of weights of terms. Each emotion class contains several vectors. To build a model of a specific demotion class, we took the mean of all these vectors. The final vector is the model for that emotion class. In this way all 7 models were built for 7 emotional classes. Finally a 7×n matrix is built which we denote as matrix *M.*

To test a query text, the query document is also converted to a vector containing all term weights. This is then converted to a n×1 matrix which we denote as *Q. Q* is multiplied with *M* row by row and 7 numeric values are obtained. The highest value of these numbers is the index of a particular emotion class in and is the indicator of that class. So the query text belongs to that emotion class.

After implementing cosine similarity, we implemented jaccard similarity to compare between these two. To implement jaccard similarity, the ISEAR data set was divided to 7 emotional classes. Each class was converted to 7 document vector as described before. To evaluate the test data, the following formula was used.

$$W=\frac{|c \cap d|}{|c \cup d|}$$

Where,

W= weight of the total test data against one particular class.

c=test vector

d= document vector of a particular class

The highest of these 7 values was the result emotion class. Jaccard similarity showed better accuracy than cosine similarity.

Chapter 5

Experimental Results

5.1 Keystroke features analysis

5.1.1 Fixed Text analysis

We used Weka's [10] several machine learning algorithms to analyze our data. Weka provides an efficient way of using its algorithms as they are implemented and train them by training data sets. We used our collected data to train several algorithms and built some models. Test data sets were evaluated against these models. The algorithms we used are: simple logistics, SMO, Multilayer Perceptron, Random Tree, J48, and BF Tree. These algorithms showed results with different levels of accuracies. Table 2 shows the results of different algorithms.

Table-4: Success rate of different algorithms in identifying different Emotional states for fixed text.

Emotion Class	Algorithm	Success Rate (%)
Anger	BF tree	88%
Disgust	Multilayer Perceptron	77%
Fear	BF tree	70%
Joy	J48	87%
Sad	J48	71%

Some output results of weka for various emotion classes are shown here for example. These results were output by weka as a final result of evaluating the test data sets against the full training data set. Some fields (algorithm name, number of instances, actual and predicted result, percentages of accuracy) were highlighted with red box for convenience.

```
=== Run information ===

Scheme:weka.classifiers.trees.BFTree -S 1 -M 2 -N 5 -C 1.0 -P POSTPRUNED
Relation:     emotion-weka.filters.AllFilter-weka.filters.AllFilter-weka.filters.AllFilter-weka.filters.AllFilter
Instances:    535
Attributes:   20
              typingSpeed
              mode_dwell
              stdDeviation_dwell
              stdVariance_dwell
              range_dwell
              min_dwell
              max_dwell
              mode_flight
              stdDeviation_flight
              stdVariance_flight
              range_flight
              min_flight
              max_flight
              mode_d2d
              stdDeviation_d2d
              stdVariance_d2d
              range_d2d
              min_d2d
              max_d2d
              class
Test mode:user supplied test set: size unknown (reading incrementally)

=== Predictions ontest split===

inst#,    actual, predicted, error, probability distribution
     1    3:anger    3:anger          0.307  0.11  *0.339  0.118  0.126  0      0
     2    3:anger    3:anger          0.307  0.11  *0.339  0.118  0.126  0      0
     3    3:anger    3:anger          0.307  0.11  *0.339  0.118  0.126  0      0
     4    3:anger    3:anger          0.307  0.11  *0.339  0.118  0.126  0      0
     5    3:anger  5:disgust     +    0.273  0.076  0.182  0.189 *0.28   0      0
     6    3:anger    3:anger          0.307  0.11  *0.339  0.118  0.126  0      0
     7    3:anger    3:anger          0.307  0.11  *0.339  0.118  0.126  0      0
     8    3:anger    3:anger          0.307  0.11  *0.339  0.118  0.126  0      0
     9    3:anger    3:anger          0.307  0.11  *0.339  0.118  0.126  0      0

=== Evaluation on test set ===
=== Summary ===

Correctly Classified Instances           8               88.8889 %
Incorrectly Classified Instances         1               11.1111 %
Kappa statistic                          0
Mean absolute error                      0.194
Root mean squared error                  0.2942
Relative absolute error                 84.7762 %
Root relative squared error             87.0337 %
Total Number of Instances                9

=== Confusion Matrix ===

 a b c d e f g   <-- classified as
 0 0 0 0 0 0 0 | a = joy
 0 0 0 0 0 0 0 | b = fear
 0 0 8 0 1 0 0 | c = anger
 0 0 0 0 0 0 0 | d = sadness
 0 0 0 0 0 0 0 | e = disgust
 0 0 0 0 0 0 0 | f = shame
 0 0 0 0 0 0 0 | g = guilt
```

Figure 03: Result showing accuracy of classifier bf tree for emotion class ‘Anger’ in WEKA

Here are some example snapshots for another 2 emotion classes:

```
=== Predictions ontest split===

inst#,     actual, predicted, error, probability distribution
     1     1:joy  4:sadness      +   0.025  0.075  0.1   *0.75   0.05    0      0
     2     1:joy      1:joy         *1      0      0      0      0       0      0
     3     1:joy      1:joy         *0.625  0      0.125  0.125  0.125   0      0
     4     1:joy      1:joy         *0.625  0      0.125  0.125  0.125   0      0
     5     1:joy      1:joy         *1      0      0      0      0       0      0
     6     1:joy      1:joy         *0.667  0      0.333  0      0       0      0
     7     1:joy      1:joy         *1      0      0      0      0       0      0
     8     1:joy      1:joy         *1      0      0      0      0       0      0
     9     1:joy      1:joy         *1      0      0      0      0       0      0
    10     1:joy      1:joy         *1      0      0      0      0       0      0
    11     1:joy      1:joy         *0.333  0.333  0.333  0      0       0      0
    12     1:joy      1:joy         *1      0      0      0      0       0      0
    13     1:joy      1:joy         *1      0      0      0      0       0      0
    14     1:joy      1:joy         *0.625  0      0.125  0.125  0.125   0      0
    15     1:joy      1:joy         *0.6    0      0      0      0.4     0      0
    16     1:joy      1:joy         *1      0      0      0      0       0      0
    17     1:joy      1:joy         *0.667  0      0.333  0      0       0      0
    18     1:joy      1:joy         *1      0      0      0      0       0      0
    19     1:joy      1:joy         *1      0      0      0      0       0      0
    20     1:joy      1:joy         *0.8    0.2    0      0      0       0      0
    21     1:joy  5:disgust      +   0.333  0      0      0     *0.667   0      0
    22     1:joy      1:joy         *0.625  0      0.125  0.125  0.125   0      0
    23     1:joy      1:joy         *1      0      0      0      0       0      0
    24     1:joy      1:joy         *0.667  0      0.333  0      0       0      0
    25     1:joy    3:anger      +   0.4    0     *0.6    0      0       0      0
    26     1:joy      1:joy         *0.6    0      0      0      0.4     0      0
    27     1:joy      1:joy         *1      0      0      0      0       0      0
    28     1:joy      1:joy         *0.75   0      0      0.25   0       0      0
    29     1:joy      1:joy         *0.8    0.2    0      0      0       0      0
    30     1:joy      1:joy         *0.667  0      0      0      0.333   0      0
    31     1:joy    3:anger      +   0.333  0     *0.667  0      0       0      0
    32     1:joy      1:joy         *0.667  0      0.333  0      0       0      0
    33     1:joy      1:joy         *0.667  0      0.333  0      0       0      0

=== Evaluation on test set ===
=== Summary ===

Correctly Classified Instances          29               87.8788 %
Incorrectly Classified Instances         4               12.1212 %
Kappa statistic                          0
Mean absolute error                      0.0738
Root mean squared error                  0.1826
Relative absolute error                 32.2619 %
Root relative squared error             54.02    %
Total Number of Instances               33

=== Confusion Matrix ===

  a  b  c  d  e  f  g   <-- classified as
 29  0  2  1  1  0  0 |  a = joy
  0  0  0  0  0  0  0 |  b = fear
  0  0  0  0  0  0  0 |  c = anger
  0  0  0  0  0  0  0 |  d = sadness
  0  0  0  0  0  0  0 |  e = disgust
  0  0  0  0  0  0  0 |  f = shame
  0  0  0  0  0  0  0 |  g = guilt
```

Figure 04: Result showing accuracy of classifier J48 Tree for emotion class ‘Joy’ in WEKA

5.1.2 Free Text features analysis

Same techniques were used to extract 19 features of free text data. These features are same as the features used for fixed text data.

Table 3 shows the results of different algorithms for free text data analysis.

Table-5: Success rate of different algorithms in identifying different Emotional states for free text.

Emotion Class	Algorithm	Success Rate (%)
Anger	**Random tree**	**82%**
Disgust	**Multilayer Perceptron**	**69%**
Fear	**SMO**	**66%**
Guilt	**SMO**	**60%**
Joy	**BF tree**	**64%**
Sad	**J48**	**78%**
Shame	**Multilayer Perceptron**	**69%**

```
=== Predictions ontest split===

inst#,    actual, predicted, error, probability distribution
     1    3:Anger    3:Anger          0     0    *1     0     0     0     0
     2    3:Anger    3:Anger          0     0    *1     0     0     0     0
     3    3:Anger    3:Anger          0     0    *1     0     0     0     0
     4    3:Anger    3:Anger          0     0    *1     0     0     0     0
     5    3:Anger    3:Anger          0     0    *1     0     0     0     0
     6    3:Anger    3:Anger          0     0    *1     0     0     0     0
     7    3:Anger    3:Anger          0     0    *1     0     0     0     0
     8    3:Anger    3:Anger          0     0    *1     0     0     0     0
     9    3:Anger    3:Anger          0     0    *1     0     0     0     0
    10    3:Anger    3:Anger          0     0    *1     0     0     0     0
    11    3:Anger    3:Anger          0     0    *1     0     0     0     0
    12    3:Anger    3:Anger          0     0    *1     0     0     0     0
    13    3:Anger    3:Anger          0     0    *1     0     0     0     0
    14    3:Anger    3:Anger          0     0    *1     0     0     0     0
    15    3:Anger    3:Anger          0     0    *1     0     0     0     0
    16    3:Anger    3:Anger          0     0    *1     0     0     0     0
    17    3:Anger    3:Anger          0     0    *1     0     0     0     0
    18    3:Anger    3:Anger          0     0    *1     0     0     0     0
    19    3:Anger    3:Anger          0     0    *1     0     0     0     0
    20    3:Anger      1:Joy     +   *1     0     0     0     0     0     0
    21    3:Anger      1:Joy     +   *1     0     0     0     0     0     0
    22    3:Anger      1:Joy     +   *1     0     0     0     0     0     0
    23    3:Anger      1:Joy     +   *1     0     0     0     0     0     0

=== Evaluation on test set ===
=== Summary ===

Correctly Classified Instances          19               82.6087 %
Incorrectly Classified Instances         4               17.3913 %
Kappa statistic                          0
Mean absolute error                      0.0497
Root mean squared error                  0.2229
Relative absolute error                 20.9233 %
```

Figure 05: Result showing accuracy of classifier J48 Tree for emotion class 'Joy' in WEKA for free text

```
=== Predictions ontest split===

inst#,    actual, predicted, error, probability distribution
     1 4:Sadness  4:Sadness          0       0.125  0      *0.875  0       0       0
     2 4:Sadness  4:Sadness          0       0      0.333 *0.667  0       0       0
     3 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
     4 4:Sadness      1:Joy      +  *0.667  0      0       0.333  0       0       0
     5 4:Sadness  4:Sadness          0.111  0      0      *0.889  0       0       0
     6 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
     7 4:Sadness  4:Sadness          0       0      0      *0.8    0       0.2     0
     8 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
     9 4:Sadness      1:Joy      +  *0.6    0      0.1     0.3    0       0       0
    10 4:Sadness  4:Sadness          0.2    0      0      *0.8    0       0       0
    11 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    12 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    13 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    14 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    15 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    16 4:Sadness      1:Joy      +  *0.667  0      0       0.333  0       0       0
    17 4:Sadness    3:Anger      +   0.043  0     *0.87    0.087  0       0       0
    18 4:Sadness  4:Sadness          0.111  0      0      *0.889  0       0       0
    19 4:Sadness  4:Sadness          0.333  0      0      *0.667  0       0       0
    20 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    21 4:Sadness      1:Joy      +  *0.765  0      0       0.235  0       0       0
    22 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    23 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    24 4:Sadness  4:Sadness          0.2    0      0      *0.8    0       0       0
    25 4:Sadness  4:Sadness          0.333  0      0      *0.667  0       0       0
    26 4:Sadness  4:Sadness          0       0.125  0      *0.875  0       0       0
    27 4:Sadness    3:Anger      +   0       0     *0.857  0.071  0       0       0.071
    28 4:Sadness  4:Sadness          0.2    0      0      *0.8    0       0       0
    29 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    30 4:Sadness  4:Sadness          0.333  0      0      *0.667  0       0       0
    31 4:Sadness  4:Sadness          0       0      0      *1      0       0       0
    32 4:Sadness  4:Sadness          0.2    0      0      *0.8    0       0       0
    33 4:Sadness     2:Fear      +   0     *0.929  0       0.071  0       0       0

=== Evaluation on test set ===
=== Summary ===

Correctly Classified Instances          26               78.7879 %
Incorrectly Classified Instances         7               21.2121 %
Kappa statistic                          0
Mean absolute error                      0.0725
Root mean squared error                  0.2094
Relative absolute error                 29.4556 %
Root relative squared error             59.5065 %
Total Number of Instances               33
```

Figure 06 : Result showing accuracy of classifier J48 Tree for emotion class ‘Sad’ in WEKA for free text

Chapter 6

Conclusion

6.1 Conclusion

In this paper we have shown the method of determining user emotion by combining two methods: keystroke dynamics and text pattern analysis. For keystroke dynamics method, timing features of fixed texts has been analyzed because fixed text showed better results in indication of specific emotions. After analyzing keystroke timing features we analyzed text patterns. Two levels of analysis were done: word level processing, sentence level processing. Word level processing includes finding out each word's emotional weight. WordNet was used to accomplish this task by finding out each emotional word's synonyms. For sentence level processing, we trained and built some models using ISEAR data set. Each input sentence was evaluated against this model to find its emotion class. Non-emotional words and sentences were identified and removed from consideration. A final result was then output according to both keystroke and Text pattern analysis. Our work showed remarkable results for anger, neutral and tired category and also showed good opportunities for other categories to work on.

6.2 Future Work

In the future we will build a chatting software that will assess user emotions from conversational data. This software will implement both keystroke dynamics for free and fixed text and text pattern analysis of our present work. We will also improve accuracy by incorporating more features (keystroke and text pattern). In our present work some inefficiency remained due to various unexpected and inevitable reasons like improper participation of users to data collection process, lack of variations in age and computer using experience. Also, users are normally unwilling to provide data when they are in negative emotional states like anger, disgust or sad. This also hampers normal data collection and attempt to persuade users for data collection can alter their emotions. In our future work we will also try to mitigate these effects.

Chapter 7

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