A Review on Feature Extraction in Keystroke Dynamics

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Abstract. Feature extraction is an important process before an analysis of a data is carry out. Different behaviour of a user while using the keyboard is a feature that need to be identified in the Keystroke Dynamics (KD) study. Example are the difference between typing time between letters, typing speed and the force of a person pressing the keyboard. Past studies related to feature extraction for KD have been described in this paper. Various features that have been used are listed and the results of the study are compared. The results of this writing are expected to help new researchers in the process of evaluating KD.

1. Introduction

Human dependence on computers are increasing day by day. There are various systems and important information that have been stored in the computer system. Therefore, an effective and inexpensive method needs to be integrated into the systems that store this important information.

In order to help increase the safety without involving high cost, biometric studies have been conducted to make the system or application is safer. This biometric study can be divided into three categories: Morphological, Behavioural and Biological. Behavioural biometric will be discussed in detail in this paper.

As we all know, handwriting of an individual is different from the others. There are handwritings slant to the right, slant to the left and doesn’t slant in either direction. The same goes to people typing the keyboard. The difference of a person’s typing the keyboard can be determined by measuring the typing time and the pressure applied to the keyboard or the touch screen. The method of measuring the typing time and the pressure applied on the keyboard has been described in numerous previous studies. The previous study on feature extraction used by previous researchers is listed and conclusions are made.

The result of this writing can provide a comprehensive overview of KD in terms of data extraction methods. This will further help researchers continue their studies on KD in the future. This writing can be divided into two categories, the first category is a brief description on relationship of
KD and biometric. Whereas, the seconds category is related to feature extraction which is the keystroke data extraction feature used in the study.

2. Keystroke Dynamic (KD)
Authorisation using biometrics is a process of authentication and recognition based on the unique features of the person respectively. These unique features can be divided into three categories, namely physical, biological and behavioural. This writing will describe the use of KD in user identification categorized as behavioural biometric. Generally, the KD process starts with enrolment, where during this process the typing pattern of a person will be recorded. After that, the authentication or verification process will be compared against the enrolment record. Diagram flow of the enrolment, authentication and verification are shown in Figure 1.

![Figure 1. Keystroke biometric enrolment, authentication and verification flow](image-url)

3. Feature Extraction
Feature extraction is a process or method required in order to do classification on gathered data and conduct data normalization [1]. This is a crucial process for researchers to analyze raw data obtained. The purpose of feature extraction is to allow the obtained data segregated into certain classes. There are multiple data extraction method implemented by researchers to analyze obtained KD data. Method normally used for this process is by using time and pressure measurement. The result for this KD measurement will be translated into three categories; i) FAR - False Acceptance Rate, ii) FRR - False Rejection Rate, iii) EER - Equal Error Rate

3.1. Time Measurement
Time measurement method can be divided into three namely diagraph, trigraph and n-graph [2].

3.1.1. Digraph. Digraph is the time recorded when a user type and press key between pairs of letter, in other words between the first letter and the second one and the subsequent [3]. This time measurement can be divided into two parts termed as Dwell Time and Flight Time.

Dwell Time (DT)
Dwell time is the time recorded when pressing and releasing a letter or in other word termed as duration time [4, 5] or hold time [6, 7].

Flight Time (FT)
Flight time refers to time gap between to consequent letter press, whether between pressing of first letter and second, or between releasing of the first letter and the second. Flight time is also known as latency time [8, 9] or interkey time [10, 11].
Figure 2 displays an illustration to simplify the understanding of dwell time and flight time.

![Diagram](image)

**Figure 2:** Dwelling time and Flight Time [12]

### 3.1.2. Trigraph

Trigraph refers to the time recorded between press of the first letter and the third letter and then these trigraph sequence get to be analyzed and normalized [4].

### 3.1.3. N-graph

N-graph is the time recorded between press of the first letter and the last [13, 14].

A study on the use of flight time difference in KD was first implemented in 1980 by Gaines, Lisowski [15]. This study has proved that the way people typing can be differentiated. In 1989, Young and Hammon [16] had conducted a KD related study using characteristic of latency and pressure measurement. Subsequently in 1990, Joyce and Gupta [17] continued this KD study on 33 users. In their study they were using the digraph and the overall time for typing for a given sentence to the user was recorded. The FAR value obtained from this study was 16.36%.

In 1997, Obaidat, Sadoun [18] has introduced a new element of feature extraction namely hold time or is known as a dwell time. The results of the study show that misclassification error is between 0.05% to 3.25% by combining dwell time and flight time. In the same year, Lin [1] conducted a KD study using feature dwell time and flight time using neural network as a method. The study was conducted on 151 volunteers and the obtained value were FAR by 1.11% and FRR 0%. In 1997 also, De Ru and Eloff [19] conducted a KD study using only flight time as a measurement method. The results of the study on 29 volunteers using fuzzy logic method obtained accuracy up to 92.62%.

In 1998, the results of the study conducted by Robinson, Liang [20] have concluded that dwell time is more important than flight time. The average FAR results obtained from the results of the study were 9%, FRR's performance was 10%.

The study of KD was continued by Monrose and Rubin [21] on the following year against 20 volunteers by applying the use of KD in the password. Feature extraction used in this study is dwell time and flight time. The FAR and FRR results obtained were the same with 20% for each.

In 2001, Wong, Supian [22] did a research on KD by using flight time features. The typing pattern and time has been collected from 10 users based on their respective passwords. The identification rate obtained in this study was between 84.63% and 99%.

Bergadano, Gunetti [23] has introduced a new method in measuring time for KD in 2002. The time measurement method used in the study was by using trigraphs. A total of 22 users were involved in this study and the results obtained were FRR 2.3% and FAR 0%.

KD study using the free text was conducted in 2005 by Gunetti and Picardi [13] by using digraph as feature extraction. Research carry out on 205 volunteers. The result obtained was False Alarm Rate less than 5% and Imposter Pass Rate less than 0.005%. In 2006, study on KD in strengthening username and password has been carry out by Bartlow and Cukic [24]. Features extraction used in the study were dwell time and flight time. The result obtained was FAR 1% and FRR 14%. In addition, Bartlow and Cukic [24] findings were able to reduce the intrusion of username and password up to 95% - 99%.
Study to create user profile based on KD was performed by Hu, Gingrich [25] on 2008 using the k-nearest neighbor approach. The time difference between the first letter and the third letter was used as a measurement in this study. The FAR obtained was 0.045%.

Moreover, this KD study was also conducted in 2008 by Rybnik, Tabedzki [26]. The results were accomplished on 37 individuals using statistical methods. Feature extraction used in the study were dwell time and flight time. The identification rate obtained from the study was 72.97%. Subsequently in 2008, KD studies were also conducted by Leberknight, Widmeyer [27] using several different features. Among the features used besides dwell time and flight time are amplitude or peak, peak area, and peak sharpness.

In 2009, Giot, El-Abed [28] conducted a KD usability study on the systems which utilise authentication as a gateway to the system. The study was conducted at 16 individuals on three different sessions. Each session requires every person to type the word "laboratoire greyc" 5 times. Feature extraction used in this study were dwell time and flight time. The best EER result obtained from the study was 4.28% by using individual threshold.

Revett and Systems [29] has conducted a KD study to detect anomaly on a system that uses the username and password as an authentication to use the system. Results obtained for FAR was 0% and FRR 0.8% if the enrolment process had been completed multiple times by the same user.

In 2011, Epp, Lippold [2] conducted a study on KD by attempting to identify the user individually while using the keyboard. A total of 15 emotional levels have been identified in this study. Features extraction used in this study were dwell time and flight time. The accuracy results obtained ranging from 77% to 84%.

Study on classification of typing pattern based on Gender was conducted by Giot, Rosenberger [30] in 2012 by using Support Vector Machine (SVM) as a method of analysing data. Dwell time and flight time were used as feature extractions in this study. The accuracy of the results obtained were up to 91% using the GREYC91 data set.

Subsequently in 2013, Idrus et. al. [31] had conducted a KD study by classifying typing pattern in category of gender, age, handedness and one-handed or two-hands typing way. The results obtained were 86% - 100% accuracy level.

In 2016, Çeker and Upadhyaya [3] conducted a KD study using features extraction dwell time and flight time. The results of the study have improved the accuracy and recognition by 13%. Subsequently in 2018, Krishnamoorthy, Rueda [32] conducted a KD study as user authentication. A total of 155 features have been successfully extracted from raw data comprising dwell time, flight time, pressure, coordinates and touch areas. The results of 94 users obtained an accuracy of between 73% and 99%. In the same year, Wu, Ding [33] has used triboelectric nanogenerator arrays for KD studies. Among the features used in the study are dwell time, flight time and pressure-sensitive signal from the fabricated triboelectric key device. The EER result obtained from the study was 1.15% by using threshold value of 0.75.

In 2018, the study of user identification by using KD is done by Ferreira, Amorim [34]. A total of 9 volunteers were involved in the study and the results obtained were 36% for FRR and 7.2% for FAR. Feature extraction used in the study were dwell time and flight time.

Most recently in 2019, Mhenni, Cherrier [35] conducted a study in the field of KD by differentiating two different groups based on Doddington zoo theory. KD database used were from WEBGREYC and CMU database. The EER obtained for the WEBGREYC database is 2% EER's forecast for the CMU database is 1.3%. This study uses dwell time and flight time as feature extraction. Table 1 shows a few of the previous researches done by utilizing the digraph, trigraph and n-graph.
### Table 1. Previous researches utilizing digraph, trigraph, and n-graph - Time features

| Researcher | Year | Time Method | Graph | Results |
|------------|------|-------------|-------|---------|
| Gaines, Lisowski [15] | 1980 | FT | Di-Graph | - |
| Young and Hammon [16] | 1989 | Whole time | Di-Graph | - |
| Joyce and Gupta [17] | 1990 | FT | Di-Graph | FAR: 16.36% |
| Obaidat, Sadoun [18] | 1997 | FT/DT | Di-Graph | Misclassification Error: 0.05%-3.25% |
| Lin [36] | 1997 | FT/DT | Di-Graph | FAR 1.11% | FRR : 0% |
| De Ru and Eloff [19] | 1997 | FT | Di-Graph | Accuracy: 92.62% |
| Robinson, Liang [20] | 1998 | FT/DT | Di-Graph | FAR: 9% | FRR: 10% |
| Monrose and Rubin [21] | 2000 | FT/DT | Di-Graph | FAR: 20% | FRR: 20% |
| Wong, Supian [22] | 2001 | FT | Di-Graph | Accuracy: 84.63% - 99% |
| De Ru and Eloff [19] | 1997 | FT | Di-Graph | FAR: 0.05% | FRR: 1% |
| Monrose and Rubin [21] | 2000 | FT/DT | Di-Graph | FAR: 0.005% | FRR: 5% |
| Robinson, Liang [20] | 1998 | FT/DT | Di-Graph | Accuracy: 92.62% |
| Obaidat, Sadoun [18] | 1997 | FT/DT | Di-Graph | FAR: 2% | FRR: 0% |
| Lin [36] | 1997 | FT/DT | Di-Graph | FAR 1.11% | FRR : 0% |
| De Ru and Eloff [19] | 1997 | FT | Di-Graph | Accuracy: 92.62% |
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| Wong, Supian [22] | 2001 | FT | Di-Graph | Accuracy: 84.63% - 99% |
| De Ru and Eloff [19] | 1997 | FT | Di-Graph | FAR: 0.05% | FRR: 1% |
| Monrose and Rubin [21] | 2000 | FT/DT | Di-Graph | FAR: 0.005% | FRR: 5% |
| Robinson, Liang [20] | 1998 | FT/DT | Di-Graph | Accuracy: 92.62% |
| Obaidat, Sadoun [18] | 1997 | FT/DT | Di-Graph | FAR: 2% | FRR: 0% |
| Lin [36] | 1997 | FT/DT | Di-Graph | FAR 1.11% | FRR : 0% |

From Table 1, it can be concluded that most previous researchers until now use the time difference whether time press, or time release the alphanumeric keyboard as a feature in identifying someone for the KD study.

### 3.2. Pressure

The measurement in KD using pressure point exist after the touch keyboard is created which can be measured by the strength of a person touching the touch screen or using a special pressure sensor. In 2004, other than time measurement, method utilizing features of keyboard key press pressure have been introduced in a research by Nonaka and Kurihara [38]. This research concludes that accumulation of pressure when a user is pressing a key could also influence that user authentication. Later in the year of 2005, research by Loy, Lai [39] also adopt the usage of pressure features in their research to identify user. The results showed good performance when keystroke latency and keystroke pressure are combined. FAR obtained was 0.87%, while FRR was 4.4%.

Subsequently in 2009, the study conducted by Saevanee and Bhattarakosol [40] also used pressure criteria, dwell time and flight time to measure KD data. The study was conducted on 10 users.
using notebook touch pad. The accuracy of the recognition obtained is 99% when pressure criteria is used as measurement. Maiorana, Campisi [41] has also carried out a KD study based on the pressure measurement using the cellular phone keypad as input device. The study was conducted using the Nokia 6680 and the EER obtained was about 13%.

The method of typing using the touch screen is also carried out by the Trojahn and Ortmeier [42] in 2013 by studying the speed and acceleration between pressing two keys, on screen pressure, and the contact area between finger and screen. The FRR obtained was 2.03% and FAR 2.67%.

In 2014, KD study using the touch screen was done by El-Abed, Dafer [43] using the Nokia Lumia 920. The results of the study involved a total of 51 volunteers. This touch screen-based study was continued by Sulavko, Eremenko [44] by attempting to identify 20 individuals from 100 volunteers participated. The EER obtained was 0.6%.

In 2018, Lee, Hwang [45] studied various features in KD such as time interval, motion data, accelerometer, gravity, rotation, and atmospheric pressure using smartphones. The best results obtained when using motion data and the "mean" formula. The EER obtained was 7.89%.

Most recently in 2019, Lee, Hwang [46] conducted a keystroke dynamics authentication on smartphones by parameterized models’ method. The results of the study showed that there was an increase of FRR from 31.211% to 10.791%.

Research by Shen, Lin [47] determined that measurement using pressure features can be important if it is applied on ATM Machines and computers fully using touch screen. Table 2 shows a few of the previous researches that had used pressure feature in their studies.

| Researcher                      | Year | Result                      |
|---------------------------------|------|-----------------------------|
| Nonaka and Kurihara [38]        | 2004 | -                           |
| Loy, Lai [39]                   | 2005 | FAR:0.87% | FRR: 4.4 %                 |
| Saevanee and Bhattarakosol [40] | 2009 | Accuracy: 99%              |
| Maiorana, Campisi [41]         | 2011 | EER: 13%                    |
| Trojahn and Ortmeier [42]       | 2013 | FRR: 2.03% | FAR: 2.67%                |
| El-Abed, Dafer [43]             | 2014 | -                           |
| Sulavko, Eremenko [44]         | 2017 | EER: 0.6%                   |
| Krishnamoorthy, Rueda [32]      | 2018 | Accuracy: 97.40%           |
| Lee, Hwang [45]                 | 2018 | EER: 7.89%                  |
| Wu, Ding [37]                  | 2018 | EER: 1.15%                  |
| Lee, Hwang [46]                 | 2019 | FRR increase from 31.211% to 10.791%. |

4. Conclusion
The results of this study shown that there are various ways of features extraction utilised in KD research. Each feature used in KD provides different results on every study. Dwell time and flight time are feature that inexpensive (financially) to implement when compared with the methods of pressure measurement. Therefore, time measurement method (dwell time and flight time) is the best to be used by a lot of systems which utilising the username and password as the login process to the system.

From the previous studies, it can also be concluded, there is a pattern discovered from the past study that can be summarized that technology changes will produce a new feature in KD. For example, the usage of the pressure element after a touch screen technology created. This means that new researchers in the future need to be aware of the evolving technological developments in the future, for example the use of holograms or new projection keyboards in this era [48]. In addition, this writing is also expected to assist researchers in the same field to look for improvement ideas on KD.
for the future study. This writing is expected to provide significant impact on the novice researchers who are interested in keystroke dynamics.

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