# Study of Intra- and Inter-user Variance in Password Keystroke Dynamics

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**4 authors**, including:

Mahesh Banavar
Clarkson University


Daqing Hou
Clarkson University

# Study of Intra- and Inter-user Variance in Password Keystroke Dynamics

Blaine Ayotte[a], Mahesh K. Banavar[b], Daqing Hou[c], and Stephanie Schuckers[d]
*Department of Electrical and Computer Engineering, Clarkson University, 8 Clarkson Avenue, Potsdam, United States*
{*ayottebj, mbanavar, dhou, sschucke*}@*clarkson.edu*

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Abstract: Keystroke dynamics study how users input text via their keyboards. Having the ability to differentiate users, typing behaviors can unobtrusively form a component of a behavioral biometric recognition system to improve existing account security. However, because keystroke dynamics is behavioral biometric typing patterns can change over time. The temporal effects of keystroke dynamics are largely unstudied beyond empirically demonstrating that error rates will be higher for old or outdated profiles. In this paper, the effects on typing patterns over time is investigated in detail. Using a well-known fixed-text keystroke dynamics dataset, we show overall typing time for a provided password ".tie5Roanl" changes significantly over time, decreasing by almost 30%. Principal component analysis (PCA) is used to determine which monographs and digraphs tend to change throughout time. Rarely typed features, such as digraphs with a letter and number, are most likely to change over time, while commonly occurring features such as common digraphs and monographs are much more stable.

# 1 INTRODUCTION

Keystroke dynamics is a behavioral biometric that utilizes typing rhythms to determine user identity (Alsultan and Warwick, 2013; Banerjee and Woodard, 2012; Teh et al., 2013). Keystroke dynamics can be used to provide an additional layer of security to traditional single sign-on authentication systems by also requiring the typing patterns to match the profile of an individual. Furthermore, as most computers already have a keyboard, this layer of security does not require any additional hardware.

There are two main types of keystroke dynamics: fixed-text and free-text. Fixed-text analysis requires the keystrokes of the profile and test sample to be identical. The fixed-text keystrokes can constitute a password, phrase, or even a sequence of sentences. A common application of fixed-text keystroke dynamics is password hardening, where typing patterns are used to further secure a password so that users need not only the password to match but also the keystroke timings as well. Free-text keystroke dynamics puts no restrictions on the keystrokes that users can type. Common applications are continuous user authentication and it typically requires more keystrokes to achieve similar performance to fixed-text. For fixed-text systems, the keystrokes input are identical each time making investigations more straightforward.

Features commonly used in keystroke dynamics are combinations of monographs and digraphs (Gunetti and Picardi, 2005; Huang et al., 2017; Monrose and Rubin, 1997; Teh et al., 2013). Monographs are defined as the hold time of a key and digraphs are defined as the elapsed time between two consecutive keypresses, respectively. A graphical representation of sequentially pressing and releasing the "e" and "5" keys with the corresponding monographs and digraphs is shown in Figure 1.

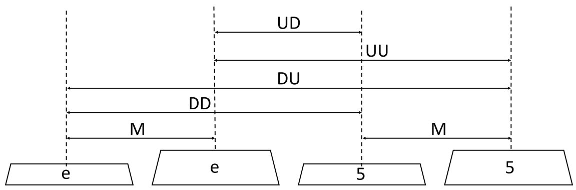


Figure 1: Graphical representation of how monograph and the four different digraph features are produced from two consecutive keystrokes. U and D correspond to key-up and key-down and are used to define the monographs and digraphs.

A survey of over 180 keystroke dynamics papers (Teh et al., 2013), found that 49% used digraphs, 41%

[a] https://orcid.org/0000-0003-1909-4951
[b] https://orcid.org/0000-0002-3916-7137
[c] https://orcid.org/0000-0001-8401-7157
[d] https://orcid.org/0000-0002-9365-9642

used monographs, 5% used pressure, and 5% used other features. The survey points out that research investigating and comparing common features used for keystroke dynamics is missing. Furthermore, there is no work that investigates which features, if any, are likely to change over time.

Keystroke dynamics systems consist of two steps, training and testing. Keystrokes from an authorized user are collected and stored in a profile. During the testing phase, keystrokes from an unknown user are compared to the previously recorded profile. If the profile and test keystrokes are similar enough the unknown user is authenticated and allowed access.

Most behavioral biometrics generally experience lower permanency compared to physiological biometrics (Teh et al., 2013). Keystroke dynamics is a behavioral biometric and is no exception. Typing patterns of users may gradually change due to some or all of the following factors: familiarity towards a password, maturing typing proficiency, adaptation to input devices, and other environmental factors. While researchers have methods to circumvent this issue by constantly updating stored keystroke profile, there is a lack of study on how keystroke patterns are affected throughout time.

In this paper, we investigate the effects of time on keystroke typing patterns. Both features that are stable and change throughout time are determined using principal component analysis (PCA). This work allows researchers to better understand and model how typing patterns change over time. This paper is organized as follows. Section 2 presents related work. In Section 3 the CMU password fixed-text dataset is described. Section 4 demonstrates how typing patterns change over time. In Section 5 principal component analysis (PCA) is performed on the keystroke data. Lastly, Section 6 concludes the paper.

## 2 Related Work

It was found by Giot, *et al.*, that the performance of keystroke dynamics systems decreased across sessions for multiple publicly available datasets (Giot et al., 2015). Using the first session as training and the subsequent sessions as testing, Giot found the equal error rate (EER) increased and area under the ROC curve (AUC) decreased. This was attributed to a change in typing patterns over the course of data collection. Keystroke dynamics is a behavioral biometric and therefore user behavior is expected to change over time, but how the typing patterns evolve over time has not been studied.

Ngugi and Kahn compared typing patterns of a four-digit PIN “1234” over three separate sessions with a week and then a month in between the sessions (Ngugi et al., 2011). The pins were solicited during a “world trivia quiz” where users answered questions by typing T/F (true or false) and entered their pins. Over time the false accept rate (FAR) did increase slightly, however, the false reject rate (FRR) increased significantly. The increase was largest after one week and after another month the increase was less severe. The only change in typing behavior observed was an overall typing speed increase over time. As users became more familiar with the PIN, their average typing speeds increased. However, further analysis was not done to see which parts of typing the PIN, if any, changed more than others.

Gunetti, *et al.*, conducted a longitudinal study of users typing behaviors across 1.5 years (Gunetti et al., 2005). The 30 native Italian speaking participants contributed free-text samples in both Italian and English. It was found that users could still be authenticated using their old profiles with FAR of 1.84% and FRR of 6.67% (in Italian). From the few studies examining profile age and performance, it is clear the that performance will be impacted especially in the FRR. Intuitively, this makes sense as imposter behavior is not likely to change to be closer to your behavior than to change farther from your behavior. However, your behavior is likely to deviate from your profile causing an increase in the FRR.

To mitigate the effects of typing patterns changing over time, Kang, *et al.*, used moving windows and growing windows for profile retraining (Kang et al., 2007). For the moving window scenario, the number of training patterns is fixed, and when a new pattern is added, the oldest is removed. Growing windows continuously add new patterns without removing the older ones. Kang, *et al.*, found that using moving and growing windows both decreased the EER, although they concluded that more work needs to be done as the typing patterns were collected over a short period of time.

While the full extent of profiling aging is unknown, many researchers have developed updating strategies, or retraining schemes, to mitigate temporal effects (Giot et al., 2011; Gunetti et al., 2005; Ngugi et al., 2011; Çeker and Upadhyaya, 2017). These template updating strategies, while effective, are useless if the only keystrokes available are old or outdated. Research is required to better understand how typing patterns evolve over time to develop robust strategies to mitigate template aging when working with outdated profiles.

In summary, keystroke dynamics is a behavioral biometric, and typing patterns can change over time.

Current research in keystroke dynamics focuses on strategies to update profiles and further improve permanence empirically. Our focus is on understanding and predicting how behavior changes so that more effective modeling can be done.

## 3 Dataset

In this work, the CMU fixed-text dataset is used (Killourhy and Maxion, 2009). This dataset was collected to study password hardening and consists of 51 users, each with 400 total password entries across 8 different sessions. Each session contains 50 password attempts and there is at least one day between each session. All users were required to type ".tie5Roanl" without any errors. The password was provided to users so they may not be initially familiar with typing the password. The dataset consists of 31 features including monographs, DD digraphs, and UD digraphs. Monographs are defined as the hold time of a key, DD digraphs are the elapsed time between the key-down of a key to the key-down of the following key, and UD digraphs are the time of a key released to the press of the following key (see Figure 1). The CMU dataset is one of the largest publicly available fixed-text datasets and is used by many different researchers. As a result, this dataset serves as a benchmark dataset for fixed-text research and is well-known in the keystroke dynamics field.

## 4 Keystroke Dynamics Over Time

It has been empirically well established that behavioral biometrics can change over time (Giot et al., 2011; Giot et al., 2015; Gunetti et al., 2005; Kang et al., 2007; Mhenni et al., 2019; Ngugi et al., 2011). These works have shown on multiple datasets that the EER increases over time without any template updating strategy. This phenomenon can be seen in Figure 2 where the average EER is shown for each of the sessions. The algorithm used for authentication is the scaled Manhattan distance, previously found to be the best performing algorithm on this dataset (Killourhy and Maxion, 2009). The EER is calculated using 31 features consisting of monographs, DD digraphs, and UD digraphs extracted from the password ".tie5Roanl", similar to the work done by Kilhourhy and Maxion (Killourhy and Maxion, 2009).

When no template updating strategy is deployed, session 1 is used as the profile and tested against the keystrokes in sessions 2-8. For our template updating strategy, we consider a simple method where the profile is updated after each session. The test keystrokes are always from the session immediately following the profile.

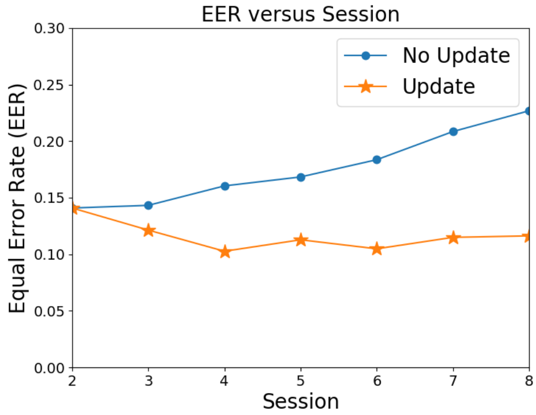


Figure 2: EER versus session averaged across user using the scaled Manhattan distance (Killourhy and Maxion, 2009). When no update strategy is used, the EER is increasing steadily as the testing keystrokes get farther away from the profile. When the profile is updated after each session, the EER does not increase.

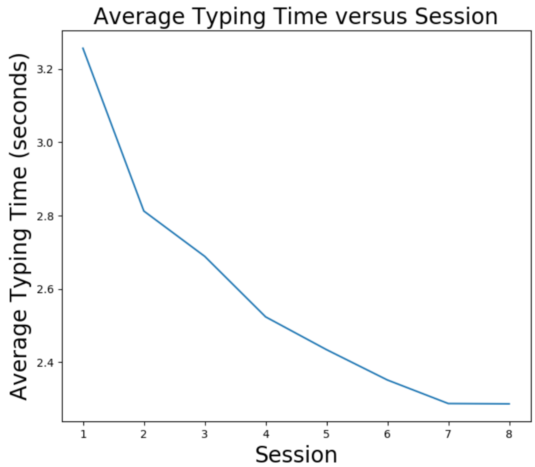


Figure 3: Total time in seconds taken to type the password ".tie5Roanl" averaged across session and users.

To investigate how typing patterns change for users typing the password ".tie5Roanl" overall typing time is examined. The password is provided to the users and therefore is unfamiliar. Prior to the first session they have had no time to practice. The password contains uncommon combinations of keystrokes (number to letter and letter to number such as "e+5" and "5+R") and as a result users may struggle at first to enter it quickly. Therefore, we expect the total time in the first session to be higher than in the sessions following. This phenomenon can be seen in Figure 3.

Figure 3 is consistent with our intuition. On average, users type the password faster than the session previously. Our findings are consistent with previous work that found the overall typing time decreased across session (Ngugi et al., 2011). From sessions 1 to 8, the average typing time drops by almost one second which is a percent decrease of 29.8%. Therefore, it is no surprise that without updating the profile after each session the EER will increase significantly.

While this difference in behavior is easy to understand, which features (the individual monographs and digraphs) are changing is unknown. To better understand the changing behavior and to determine if only certain features are changing, principal component analysis (PCA) is applied to the keystroke data.

# 5 Principal Component Analysis

Principal component analysis (PCA) is a common tool used for dimensionality reduction or noise reduction (Abdi and Williams, 2010; Duda et al., 2012). PCA works to project the data into a lower dimensional space that best represents the data in terms of variance in a least-square sense. The principal components act as linear transformations from the original data space into a new space (lower dimensionality) where the majority of the total variance in the original dataset is still explained. The components are sorted in order of the percentage of variance in the original dataset they explain.

Another common application of PCA is noise reduction. Consider a simple 2-dimensional example where the data is produced with function $f(x) = x + \varepsilon$, where $\varepsilon$ is additive white Gaussian noise with a small variance. Performing PCA on this data will return one component which explains almost all of the variance. This component corresponds to the deterministic signal $f(x) = x$. The other components explain the remainder of the variance and correspond to the noise in system. In this example, keeping only the first component will reduce noise in the system as well as reduce the dimension of the data.

For keystroke dynamics, by cleverly selecting the data to which PCA is applied, insights into how typing behavior changes over time can be obtained. We consider two scenarios for further analysis which we call, “intra-user” and “inter-user”. Intra-user applies PCA on a single user’s data to determine how each user’s behavior changes over time, while inter-user applies PCA on data from every user to determine which features distinguish between users.

## 5.1 Intra-user PCA

For intra-user PCA, PCA is performed on the typing data from all sessions for each user. As we have seen in Figure 3, the total time is changing significantly across sessions. Therefore, in this scenario, the largest source of variability within the data is from how the keystroke dynamics are changing over time for a particular user. The principal components that explain the majority of the variance in the original dataset are linear combinations of features that are causing the most change in typing patterns over time. The remaining components can be thought of as noise caused by human error, timing resolution in keystroke capturing software, time of day, the mood of the typist, and any other factors leading to different password entries.

After PCA is applied on the original 31 dimensional data consisting of monograph and digraph durations, we need to determine how many components should be kept. To keep 100% of the total variance in the original data, all 31 components will need to be kept. Usually the first few components will contain enough of the total variance and a significant number of components can be discarded. A common method of selecting the number of components to keep is referred to as a scree or elbow plot (Abdi and Williams, 2010). The idea behind a scree plot is to stop using components after their contribution to the explained variance begins to decline. In the intra-user PCA case, for the majority of users, after the third component the gain from from adding additional components decreased. This can be visualized in Figure 4, where the scree plots for four different users are shown.

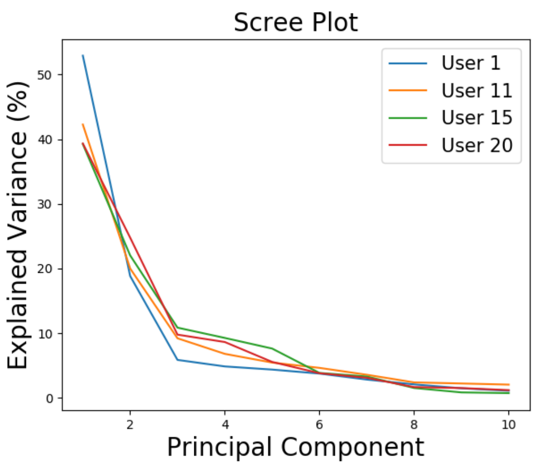


Figure 4: Scree plots for the intra-user PCA for four different users. After the third component, there is minimal gain (less than 5%) from adding additional components indicating only the first three components should be kept.

In Table 1, the explained variance for the first three components is shown for intra-user PCA. The explained variance is averaged across users and the standard deviation is also reported. To better understand which original features (monographs and digraphs) are affected by time we take in depth look at the principal components of the PCA decomposition.

It is worth noting that for every user's PCA decomposition, the explained variance and principal components obtained are different. These components are not typically compared because they can represent completely different linear combinations of original features. For example, each user may have a very different percentage of variance explained in the first component from the other users. However, because the components look similar for most users, we averaged the explained variances together in order to best demonstrate global trends.

Table 1: The average and standard deviations of the variance for the first 3 components of the intra-user PCA decompositions.

| Component | Average Explained Variance (%) |
|---|---|
| 1 | $37.7 \pm 8.4$ |
| 2 | $17.6 \pm 3.4$ |
| 3 | $11.9 \pm 2.5$ |
| Sum | $67.2 \pm 7.1$ |

The original features consist of 31 monographs and digraphs (seen in the first column of Figure 5). The principal components are linear combinations of these features. Components with a large magnitude weight for a particular feature indicates that feature is contributing strongly to explain the variance of the dataset. Therefore, that feature is considered to be strongly influenced by time. In other words, if a feature weight has a large magnitude from the principal component, then that feature is changing from session to session.

The first principal component is shown in Figure 5. On average (across users) the first component explains 37.7% of the total variance in the data. Each weight of the component is squared because we are interested in the magnitude of the weights. The principal component corresponds to a direction, and because each element of the component has been squared, the sum of every column is equal to 1.

For almost every user the DD and UD digraphs for "e+5" has the largest weight followed closely by the "5+R" UD and DD digraphs. While only 20 users are shown in Figure 5, this trend can be seen across most users. Other features that seem to contribute for most users but with much smaller weights include DD and UD digraphs of "l+Return", ".+t", and "i+e". The DD and UD digraph contributions seem to be almost identical regardless if the digraph is a strong or weak contributor. Another interesting trend is that monographs do not appear to contribute whatsoever.

The second and third components explain on average 17.6% and 11.9% of the total variance respectively. These components are not shown in order to save space, and instead we present the general trends. Unlike the first component, the second and third components have less consistent patterns across users suggesting that the important features in these components vary from user to user.

However, it is clear that some digraphs contribute more than others. The stronger DD and UD digraph contributors are shown in approximate ranked order for the top 3 components: "e+5", "5+R", "l+Return", ".+t", and "i+e". These features are the least stable features across time. No monograph feature contributes to a component within the first three components. These digraphs with a letter and number combination are not commonly typed in everyday life so users likely have little to no experience typing them. The other digraphs shown to change over time include a period and Return key (also less common in everyday life).

The digraphs that are rarely typed tend to change across sessions while the commonly typed digraphs do not. In this dataset, the password ".tie5Roanl" was provided for the participants, so users are not familiar with the key combinations. It is apparent that familiarity is a significant factor when considering typing patterns over time. The one exception to this rule appears to be the DD and UD digraphs of "i+e" as they are commonly typed digraphs yet still seem to fluctuate over time. A possible explanation is that the "i+e" digraph occurs nearby the "5" key. Nonetheless, familiarity with certain digraphs directly affects whether that digraph is likely to change over time.

Monographs contribute very little to the principal components until about the $7^{\text{th}}$ component. It is not until the $11^{\text{th}}$ component that contribution from monographs becomes common. The $7^{\text{th}}$ component, on average, explains 4.0% of the variance and the first six components explain 87.8% of the total variance in the data. This provides evidence that monographs are mostly static over time and do not change as much as digraphs. Considering only the English alphabet there are 26 different monographs but $26 \times 26$ digraphs. Therefore, each monograph may naturally get more practice due to a much smaller amount of possibilities, which reinforces that familiarity is driving the change in behavior.

Existing work by Ayotte, *et al*, (Ayotte et al., 2019; Ayotte et al., 2020) found that with small amounts of keystrokes monographs were the among

| | Feature | User 1 | User 2 | User 3 | User 4 | User 5 | User 6 | User 7 | User 8 | User 9 | User 10 | User 11 | User 12 | User 13 | User 14 | User 15 | User 16 | User 17 | User 18 | User 19 | User 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| M | . | 0.00011 | 0.00316 | 4.35E-06 | 1.43E-06 | 1.14E-08 | 0.00086 | 0.00011 | 0.00076 | 0.00026 | 4.33E-06 | 0.00016 | 3.28E-05 | 4.73E-05 | 1.27E-05 | 1.05E-06 | 5.37E-05 | 1.62E-05 | 4.54E-06 | 8.61E-06 | 1.91E-06 |
| DD | .+t | 0.00659 | 0.03038 | 0.0107 | 0.04 | 0.04671 | 0.01689 | 0.01027 | 0.00766 | 0.02659 | 0.01113 | 0.0058 | 0.01636 | 0.03485 | 0.00139 | 0.01834 | 0.01693 | 0.02629 | 0.00303 | 0.02212 | 0.00493 |
| UD | .+t | 0.005 | 0.05315 | 0.01027 | 0.03952 | 0.04675 | 0.01014 | 0.00825 | 0.0036 | 0.02159 | 0.0107 | 0.00405 | 0.01786 | 0.03746 | 0.00113 | 0.01862 | 0.01508 | 0.02761 | 0.00326 | 0.023 | 0.00512 |
| M | t | 9.89E-07 | 0.00087 | 0.00078 | 2.08E-05 | 0.00053 | 4.05E-05 | 1.66E-05 | 0.00054 | 1.91E-06 | 3.49E-05 | 5.57E-06 | 2.30E-05 | 9.04E-06 | 2.02E-05 | 3.46E-05 | 1.77E-05 | 0.00032 | 4.12E-06 | 8.03E-07 | 2.36E-08 |
| DD | t+i | 0.00021 | 0.00615 | 5.52E-05 | 0.00356 | 1.28E-06 | 0.00109 | 0.06074 | 0.00697 | 0.00086 | 5.16E-05 | 0.00078 | 0.00215 | 0.0002 | 0.00114 | 0.00529 | 0.00689 | 0.12758 | 0.00077 | 0.0025 | 5.73E-05 |
| UD | t+i | 0.00024 | 0.01166 | 0.00124 | 0.00413 | 0.00059 | 0.00071 | 0.06277 | 0.0114 | 0.00078 | 1.63E-06 | 0.00092 | 0.00262 | 0.00012 | 0.00086 | 0.00447 | 0.00621 | 0.14068 | 0.00089 | 0.00241 | 5.97E-05 |
| M | i | 4.06E-05 | 0.00103 | 0.00018 | 3.40E-07 | 3.02E-05 | 6.48E-07 | 2.68E-05 | 1.26E-05 | 2.63E-05 | 6.25E-05 | 9.19E-06 | 7.02E-06 | 3.75E-05 | 3.09E-05 | 1.31E-06 | 0.00018 | 0.00014 | 9.42E-06 | 2.29E-05 | 1.36E-06 |
| DD | i+e | 0.00284 | 0.04405 | 4.32E-05 | 0.01099 | 0.06286 | 0.00651 | 0.00789 | 0.00114 | 0.00258 | 0.00033 | 0.00084 | 0.10903 | 0.00458 | 0.00722 | 0.00785 | 0.02666 | 0.10674 | 0.00033 | 0.02479 | 0.00047 |
| UD | i+e | 0.0022 | 0.05854 | 0.0004 | 0.01111 | 0.06013 | 0.00638 | 0.00883 | 0.00091 | 0.00313 | 0.00068 | 0.00103 | 0.11079 | 0.00544 | 0.0082 | 0.00805 | 0.02247 | 0.09927 | 0.00045 | 0.02632 | 0.00053 |
| M | e | 4.16E-06 | 0.0089 | 3.68E-06 | 1.53E-05 | 5.75E-07 | 1.71E-05 | 9.18E-05 | 1.24E-05 | 0.00011 | 1.59E-07 | 2.95E-05 | 0.00022 | 2.40E-06 | 1.27E-06 | 8.65E-05 | 0.00013 | 1.57E-06 | 3.45E-06 | 2.70E-05 | 2.09E-06 |
| DD | e+5 | 0.31321 | 0.26126 | 0.44622 | 0.11766 | 0.2128 | 0.42002 | 0.23059 | 0.2705 | 0.40605 | 0.466 | 0.48373 | 0.07509 | 0.43894 | 0.32538 | 0.06621 | 0.11069 | 0.13675 | 0.30456 | 0.19383 | 0.09441 |
| UD | e+5 | 0.3155 | 0.36659 | 0.44879 | 0.12037 | 0.2135 | 0.41468 | 0.23989 | 0.26685 | 0.39273 | 0.46655 | 0.4762 | 0.08342 | 0.441 | 0.3241 | 0.06151 | 0.10332 | 0.13583 | 0.30251 | 0.19843 | 0.0953 |
| M | 5 | 0.00011 | 9.49E-07 | 0.00106 | 1.00E-05 | 7.59E-05 | 6.71E-07 | 0.00032 | 8.58E-05 | 0.00037 | 3.63E-06 | 5.28E-05 | 2.80E-06 | 2.03E-06 | 0.00016 | 0.00012 | 1.49E-06 | 5.56E-05 | 2.00E-06 | 1.53E-06 | 1.17E-06 |
| DD | 5+R | 0.12189 | 0.06805 | 0.02563 | 0.25799 | 0.07218 | 0.01493 | 0.14052 | 0.10038 | 0.03747 | 0.01808 | 0.00445 | 0.17866 | 0.01702 | 0.12227 | 0.14013 | 0.09126 | 0.03927 | 0.08274 | 0.08483 | 0.36826 |
| UD | 5+R | 0.12918 | 0.06754 | 0.03712 | 0.25478 | 0.07694 | 0.01473 | 0.1275 | 0.0946 | 0.03041 | 0.01757 | 0.00548 | 0.18008 | 0.01665 | 0.13142 | 0.13201 | 0.092 | 0.04228 | 0.08356 | 0.08412 | 0.36694 |
| M | R | 7.19E-05 | 0.00024 | 0.00094 | 0.0002 | 0.0014 | 7.35E-08 | 1.60E-05 | 0.00109 | 0.00042 | 8.42E-05 | 3.38E-06 | 9.56E-05 | 5.33E-05 | 0.00023 | 0.00018 | 7.05E-05 | 0.00045 | 1.83E-06 | 2.42E-05 | 5.26E-05 |
| DD | R+o | 0.0374 | 0.00185 | 0.00208 | 0.03551 | 0.02189 | 0.00087 | 0.00584 | 0.00074 | 0.00345 | 5.15E-05 | 0.00378 | 0.01453 | 4.33E-05 | 0.01231 | 0.00386 | 0.0413 | 0.00771 | 0.01224 | 0.00124 | 0.0243 |
| UD | R+o | 0.03419 | 0.00343 | 0.0058 | 0.04107 | 0.03434 | 0.00089 | 0.00525 | 0.00363 | 0.00627 | 4.01E-06 | 0.00355 | 0.01698 | 5.12E-07 | 0.01591 | 0.00237 | 0.03795 | 0.01191 | 0.01194 | 0.00091 | 0.02209 |
| M | o | 1.85E-05 | 0.00025 | 0.00038 | 1.46E-05 | 0.00194 | 1.32E-08 | 7.80E-05 | 0.00081 | 2.67E-05 | 2.97E-05 | 5.48E-08 | 2.68E-05 | 2.57E-05 | 8.77E-05 | 3.65E-05 | 0.00063 | 7.87E-05 | 1.38E-06 | 1.10E-05 | 5.11E-08 |
| DD | o+a | 0.00064 | 0.00047 | 0.00035 | 0.00381 | 0.00219 | 1.24E-06 | 0.00374 | 0.00032 | 0.00033 | 3.53E-06 | 0.00123 | 0.02696 | 0.00011 | 0.00911 | 0.00486 | 0.02219 | 0.00022 | 0.00314 | 0.00028 | 0.00269 |
| UD | o+a | 0.00044 | 0.0014 | 6.24E-07 | 0.00335 | 0.00826 | 9.94E-07 | 0.0049 | 0.00215 | 0.00017 | 5.37E-05 | 0.00122 | 0.02869 | 2.81E-05 | 0.01099 | 0.00574 | 0.01533 | 0.00056 | 0.00327 | 0.00018 | 0.00267 |
| M | a | 0.00016 | 0.00047 | 0.00032 | 1.12E-06 | 0.00049 | 0.00017 | 5.56E-06 | 0.00073 | 0.00053 | 0.00014 | 7.46E-05 | 4.24E-06 | 6.44E-06 | 3.84E-06 | 5.89E-06 | 0.00029 | 9.92E-06 | 6.93E-05 | 2.64E-06 | 4.43E-05 |
| DD | a+n | 0.00404 | 0.00205 | 0.00073 | 0.00852 | 0.00839 | 0.00164 | 0.00207 | 0.00434 | 0.00177 | 1.04E-05 | 0.00155 | 0.02523 | 0.00019 | 0.00597 | 0.00175 | 0.09288 | 0.01477 | 0.00164 | 6.42E-05 | 0.00187 |
| UD | a+n | 0.0026 | 0.00446 | 0.00203 | 0.00871 | 0.01295 | 0.00076 | 0.00229 | 0.00151 | 0.00422 | 0.00022 | 0.00231 | 0.02589 | 0.00027 | 0.00628 | 0.00156 | 0.08284 | 0.01402 | 0.00238 | 9.29E-05 | 0.00249 |
| M | n | 3.90E-06 | 0.00045 | 7.44E-07 | 0.00022 | 0.00079 | 0.00032 | 3.35E-05 | 0.00234 | 8.89E-05 | 1.16E-07 | 2.33E-05 | 7.39E-07 | 3.30E-05 | 3.64E-05 | 0.00012 | 5.89E-05 | 7.56E-05 | 2.89E-06 | 1.46E-06 | 6.36E-05 |
| DD | n+l | 0.00082 | 8.37E-05 | 0.00017 | 0.01044 | 0.00477 | 0.02552 | 0.00053 | 0.00241 | 0.01769 | 0.00043 | 0.00111 | 0.01116 | 0.00105 | 0.00618 | 0.00407 | 0.04096 | 0.00742 | 0.01376 | 0.00186 | 0.00172 |
| UD | n+l | 0.00071 | 0.00092 | 0.0002 | 0.01372 | 0.00944 | 0.03151 | 0.00083 | 0.0095 | 0.02029 | 0.00044 | 0.00081 | 0.01135 | 0.00146 | 0.00716 | 0.0028 | 0.03791 | 0.009 | 0.01416 | 0.00196 | 0.00244 |
| M | l | 4.05E-05 | 5.54E-05 | 4.48E-07 | 4.20E-06 | 8.92E-05 | 0.00033 | 2.26E-05 | 0.00015 | 5.74E-07 | 7.59E-06 | 6.51E-06 | 2.49E-05 | 0.00014 | 6.13E-05 | 1.04E-06 | 0.00026 | 2.76E-06 | 2.38E-07 | 5.72E-07 | 2.33E-05 |
| DD | l+Return | 0.01154 | 0.00091 | 0.00227 | 0.00695 | 0.04786 | 0.01319 | 0.03694 | 0.09854 | 0.01091 | 0.00342 | 0.00046 | 0.03047 | 0.00021 | 0.00089 | 0.2554 | 0.0635 | 0.02568 | 0.07774 | 0.16579 | 0.00152 |
| UD | l+Return | 0.01022 | 0.00142 | 0.00221 | 0.0073 | 0.05208 | 0.01767 | 0.03879 | 0.10631 | 0.01075 | 0.00374 | 0.00035 | 0.03224 | 7.06E-06 | 0.00141 | 0.25437 | 0.07192 | 0.02515 | 0.07747 | 0.16517 | 0.00192 |
| M | Return | 1.55E-06 | 0.00021 | 4.27E-06 | 1.93E-05 | 3.54E-05 | 0.00015 | 0.00086 | 1.17E-06 | 0.00013 | 0.00016 | 3.41E-06 | 1.79E-06 | 1.57E-06 | 2.33E-05 | 0.00014 | 3.56E-05 | 0.00011 | 2.99E-05 | 2.74E-07 | 2.25E-05 |

Figure 5: The first principal component of the intra-user PCA decomposition. For space, only the first 20 users components are shown. Each PCA weight is squared so the columns sum to 1. Larger values appear in red and smaller values appear in green. The DD and UD digraphs contribute roughly the same for a given letter combination and the two largest contributors are "e+5" and "5+R".

the most informative features for distinguishing between users. A password hardening scenario involves only small amounts of keystrokes so it is likely that monographs are useful for distinguishing between users. This work shows that monographs seem static across time and therefore may be a powerful feature for user authentication especially when working with an old or outdated profile.

## 5.2 Inter-user PCA

The inter-user case is designed to determine which features are useful to distinguish between users. To achieve this, the monographs and digraphs are averaged across every session for each user. If the features are not averaged, the results might depend on the particular session used. PCA is then applied on the single averaged features for each user. In this scenario the largest source of variability within the data is the different users. Therefore, the principal components that can explain the majority of the variance in the data are linear combinations of features that differentiate users. The remaining components can be thought of as noise caused by averaging across multiple sessions in addition to the sources explained in Section 5.1.

The percentage explained variance for the inter-user PCA for the top 3 components is 70.7%, 9.4%, and 5.3% for a total of 85.4%. As the first component explains a significant portion of the variance, no scree plots are needed and it is adequate to only consider the first component. Nonetheless, Figure 6 contains the first 3 principal components for the inter-user PCA. The top features primarily contributing to the first component include "5+R", "l+Return", and ".+t" followed closely by "e+5", "R+o", and "n+l". As with the intra-user PCA, the DD and UD digraphs contribute roughly the same for a given letter combination.

Many of these features are the same as for the intra-class PCA. This is consistent with empirical EERs increasing over time. If the features that explain differences between users were different from the features that changed over time, the EERs would likely not have changed over time. Therefore, digraphs such as "R+o" and "n+l", which contribute to the interclass PCA but not the intra-class PCA, may be especially more useful when working with old or outdated profiles.

Monographs start to become contributors to the principal components as early as the third component. The contributions are smaller than the digraphs. However, the monograph feature was also shown to be stable over time. This is consistent with previous work that found with small amounts of keystrokes monographs were informative features for distinguishing between users (Ayotte et al., 2019; Ayotte et al., 2020). Therefore, especially for old or outdated profiles, monographs may be a valuable feature for authentication.

| Feature | | Component | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| M | . | 2.84E-04 | 1.69E-03 | 0.01015 |
| DD | .+t | 0.07235 | 0.05786 | 0.00116 |
| UD | .+t | 0.08169 | 0.07933 | 0.00445 |
| M | t | 5.13E-07 | 8.04E-05 | 0.01119 |
| DD | t+i | 0.01101 | 0.01169 | 0.00105 |
| UD | t+i | 0.01117 | 0.00983 | 0.01909 |
| M | i | 1.41E-04 | 1.40E-04 | 0.00564 |
| DD | i+e | 0.02913 | 0.0097 | 0.01577 |
| UD | i+e | 0.03333 | 0.01216 | 0.00254 |
| M | e | 1.16E-06 | 1.59E-04 | 1.45E-02 |
| DD | e+5 | 0.0577 | 0.35568 | 0.01662 |
| UD | e+5 | 0.05719 | 0.34082 | 0.06207 |
| M | 5 | 9.24E-05 | 7.88E-05 | 5.42E-03 |
| DD | 5+R | 0.09766 | 0.01452 | 0.28728 |
| UD | 5+R | 0.10376 | 0.01246 | 0.21376 |
| M | R | 1.14E-04 | 0.00076 | 3.02E-02 |
| DD | R+o | 0.05442 | 6.30E-03 | 0.02191 |
| UD | R+o | 0.05952 | 0.01143 | 0.10357 |
| M | o | 1.59E-04 | 0.00086 | 0.01045 |
| DD | o+a | 0.0098 | 0.00064 | 2.90E-02 |
| UD | o+a | 0.01245 | 0.00298 | 0.00465 |
| M | a | 9.55E-05 | 0.00106 | 2.66E-02 |
| DD | a+n | 0.01569 | 0.00235 | 0.00407 |
| UD | a+n | 0.01334 | 0.00657 | 0.00987 |
| M | n | 2.92E-04 | 0.00074 | 8.81E-03 |
| DD | n+l | 0.04139 | 0.00261 | 0.00055 |
| UD | n+l | 0.04864 | 0.00614 | 0.01378 |
| M | l | 4.11E-04 | 0.00059 | 7.61E-03 |
| DD | l+Return | 0.0877 | 0.0215 | 0.01257 |
| UD | l+Return | 0.10012 | 0.02918 | 0.03974 |
| M | Return | 3.50E-04 | 9.38E-05 | 0.00592 |

Figure 6: The first 3 principal components of the inter-user PCA decomposition. Each PCA weight is squared. Larger values appear in red and smaller values appear in green.

## 6 Conclusion and Future Work

In this paper, we investigated the temporal effects on user typing patterns using a well-known fixed-text keystroke dynamics dataset. We showed that when provided with an unfamiliar password (".tie5Roanl"), the overall typing time decreases throughout sessions. Through intra-user PCA, we demonstrated the UD and DD digraphs rarely occurring in normal typed texts such as "e+5", "5+R", "l+Return" and ".+t" contributed significantly to the principal components that explain the majority of variance in the original data, and therefore subject to change over time. The UD and DD digraphs that were commonly typed such as "o+a" and "a+n" contributed almost nothing to the explained variance and therefore found to be invariant across time. Monographs were found to explain almost none of the variance for the intra-user PCA, which indicates they are stable over time. Monographs, in general, are typed far more frequently than digraphs due to the smaller number of total possible combinations.

This provides evidence that familiarity will greatly impact how much a feature changes over time. Features typed frequently such as monographs and common digraphs are more invariant through time than rarely typed features such as number-letter or letter number digraphs. When using old or outdated profiles, the focus should be on common features as they are less likely to have changed since the initial profile was collected.

Through inter-user PCA, features that differentiate between users were found to be the DD and UD digraphs of "5+R", "l+Return", ".+t", "e+5", "R+o", and "n+l". The majority of these features also change over time which explains the decrease in performance over time when no updating strategy is used. While digraphs were the most informative features, monographs were shown to still be useful in distinguishing between users. This is consistent with previous work by Ayotte, *et al*, (Ayotte et al., 2019; Ayotte et al., 2020) where they found with small amounts of keystrokes monographs were informative features for distinguishing between users. Since monographs are stable over time and may be able to differentiate between users, this makes them potential candidates for use with old or outdated profiles.

Future work includes investigating the effects of typing patterns on other datasets and with different fixed-text such as the datasets collected by Giot, *et al*, and Fierrez, *et al* (Giot et al., 2009; Fierrez et al., 2010). Our work will also be extended to free-text keystroke dynamics to determine if the phenomenon is generalizable beyond fixed-text. Analysis of typing patterns across multiple years could provide even more evidence of our conclusions. Lastly, we would like to extend this work to investigate other sources of variability within typing patterns such as mood, time of day, or keyboard.

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