

Some Remarks on Keystroke Dynamics*

Global Surveillance, Retrieving Information and Simple Countermeasures

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Abstract: In this paper we discuss some security issues related to keystroke dynamics. Up to now these methods have been used mainly for supporting authentication protocols. We point out that they can be also used against privacy and potentially lead to some other malicious behavior like for example impersonation. We also present some simple fairly realistic and usable countermeasures. We discuss fundamental issues about efficient and accurate representation of user's profile in keystroke dynamic methods. More precisely, we discuss statistics of so-called timings used for building user's profile. We give some observations about distributions of timings that substantially differ from assumptions used in numerous papers. Some of our theories are supported by experimental results.

1 INTRODUCTION

Keystroke dynamics is one of the methods used mainly for behavioral biometric authentication. Being behavioral, thus more variable and less dependable, biometric keystroke dynamics it is commonly used as a secondary security mechanism typically with password authentication. This method requires no additional infrastructure and authentication is possible remotely. In our paper we discuss this behavioristics methods from a different perspective – we point out some possible threats as well as some related issues including representation of individuals' profiles.

Our Contribution and Organization of the Paper.

In the rest of this section we recall some related results. Section 2 is devoted to description of possible risks brought by keystroke methods. In Section 3 we describe a number of issues related to representation of user's profiles - in particular we analyze statistical properties of so-called timings of n -graphs used commonly as characteristic of individuals. We support some our conjectures with experimental results. In Section 4 we outline several simple protocols for protecting privacy and preventing impersonation-type attacks. We conclude in Section 5.

Related Work. There is a long list of papers as well as implementations based on keystroke dynamics. To the best of our knowledge in (Gaines et al., 1980) authors presented their study about typing patterns for the first time. However, these observations were not used in the context of behavioristics until the seminal paper (Joyce and Gupta, 1990), when authors presented their algorithm to measure latencies of pressing keys during typing and comparing it with previously stored information. In (Cho and Hwang, 2006) authors suggest using artificial rhythm of typing and long pauses between some characters to enhance security and in (Revett et al., 2007) authors use neural networks to improve classification accuracy. In (Bergadano et al., 2002), followed by (Zhang et al., 2006) a method of continuous identification is proposed, where user's activity is constantly monitored and thus their typing latencies have to be predicted. In (Stefan et al., 2012) authors make first attempt to implement software protecting from a bot attacker. Many further references can be found in (Chudá and Durfina, 2009; Revett, 2009). Practical use of keystroke data has been implemented in BioPassword (BioPassword Inc., 2007) an authentication system that employs most of current knowledge.

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2 GLOBAL RISK

In this section we point out some risks related to methods of keystroke dynamics. Two main risks we have in mind are

- Privacy threat - the individual can be recognized against their will.
- Impersonation - someone can collect the biometric data and pretend to be a particular individual.

To the best of our knowledge those problems were not addressed in literature except the paper (Stefan et al., 2012), wherein authors study the threat of impersonating user by a bot. Note that the privacy threat **is not** limited to biometric authentication systems. Indeed, collected data in one system can be used to recognize the user in other systems. Generally, such attacks seem to be applicable to all biometric systems, however there are some peculiarities that increase the risk that one can be recognized by characteristic keystroke dynamics. Among most notable risks are the following:

- data about keystroking of individuals can be collected over long period of time leaving user unaware of such process;
- keyboards are still a very important and most common computer interface device; most population in many countries use systems with a keyboard to perform many operations including communication, entertainment or various e-service;
- the users may unwittingly be susceptible to data collection by various kinds of keyloggers while performing their regular tasks;
- simple and compact data representation, results in ease of collecting and storing the information about keystroke patterns (i.e. profiles of users) for huge number of individuals for a long time;
- collecting as well as storing information does not require any significant resources.
- to some extent, historical data can be used for a long time. More precisely, to launch an attack the adversary may use data much older than the security mechanism that they try to by-pass.

Another fact that has to be underlined is that identification using keystroke dynamics can be at least in some cases carried out in a remote manner. When using SSH1 protocol an eavesdropper can easily derive *inter-key times* as every key-press generates data package (see e.g. (Song et al., 2001)). Such attack cannot be carried out easily using much more common nowadays SSH2. Nevertheless one cannot exclude that similar attacks exist and can be exploited while using other protocols.

Aforementioned facts make building user profile quite realistic. Moreover users are potentially exposed to profiling attacks on different systems. Then his profile can be transferred and even if these destination systems employ some privacy protection means his identity could be recovered. Let us stress that we do not claim that such attacks can be realistic in all cases. We do claim however that there are some potential risks that should be investigated more carefully.

3 REPRESENTATION OF USER'S PROFILE

In this section we discuss issues related to representation of a user's profile in widely-understood keystroke dynamic methods. User's typing behavior is reflected in several values. The most general values are so-called *timings*, or *delays* that occur when pressing various keys. In the literature of the subject one can encounter *dwelt time* – the time between events of key down and key up, *flight time* – the time between pressing two consecutive keys. Two consecutive keys are called *digraph*. By *trigraphs* we mean three consecutive keys and consequently we use term *n-graphs* to describe *n* keys in a row.

One can easily see that timings for each digraph for the same individual can differ - it is a random variable. Collection of such random variables is a natural representation of an individual. Below we give some observations and experimental results about their distribution.

3.1 On Normality of Digraphs

In several papers there has been explicitly stated that the flight time for each single digraph could be assumed Gaussian (i.e., (Monrose and Rubin, 1997; Sheng et al., 2005; Zhang and Wang, 2009)). Such approach seems to be essentially unjustified. In fact, to the best of our knowledge, there is no reason why flight times could have normal distribution. In particular it is hard to use Central Limit Theorem in this case. It should be stressed that in the paper (Sim and Janakiraman, 2007) one can find a suggestion that the distribution of flight times for digraphs is (in general) not Gaussian. In this section we present some results of statistical tests that say that digraph timings' distribution is **not** normally distributed.

Experimental Results. Let us start with methodological remarks. We have collected over 60 000 individual samples of digraphs with *flight time* in range

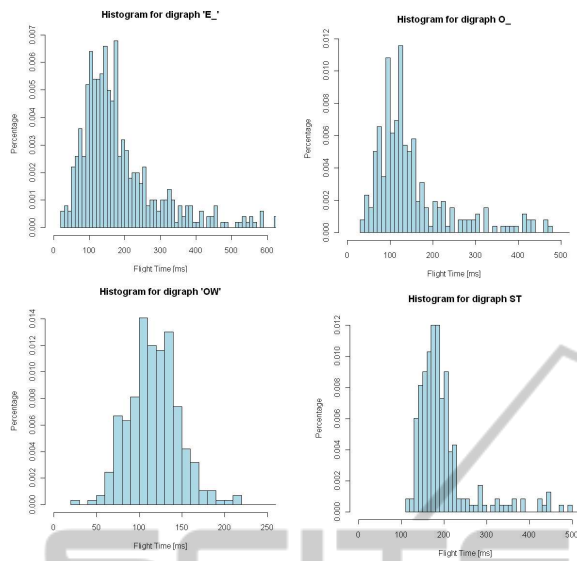


Figure 1: Distribution of flight time timing for digraphs "OW", "E_", "ST", "O_".

from 21 up to 800 ms. We rejected samples which include flight time greater than 800 ms treating them as breaks in typing. Entire dataset was collected in a controlled environment from trained typists, typing in Polish as a native language². The results are obtained from form so-called *free text* – i.e., the data was collected using special key-logger during regular work of the typist. We believe that such approach reflects real settings of keystroke dynamics.

Our first goal was to examine whether the distribution of the digraphs is normal. For tests we chose digraphs with largest amounts of collected data to obtain reliable results.

Table 1: Occurrence of ten the most common digraphs.

Digraph	IE	E_	A_	NI	_P
Occurrence[%]	2.12	1.96	1.71	1.67	1.30
Digraph	OW	”	ZE	_O	PO
Occurrence[%]	1.11	1.07	1.06	1.01	1.00

Below we present histograms for some of investigated digraphs.

Even perfunctory analysis of histograms suggests that the distribution of timings of digraphs is not normal. Indeed, in the case of some histograms one can see that they are bi-modal (e.g., Figure 2). To provide more reliable evidence we performed normality tests for ten most numerous digraphs. We used two

²We believe that language does not affect the type of distribution and only parameters can be changed, provided that this is a native-language of the typist (compare (Bergadano et al., 2002)).

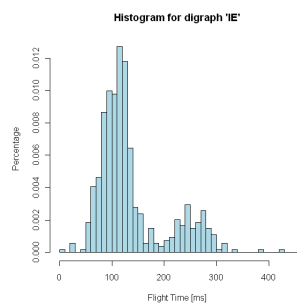


Figure 2: Distribution of flight time timing for digraph "IE".

tests: *Lilliefors test* (Lilliefors, 1967) and *Shapiro - Wilk* (Shapiro and Wilk, 1965) The level of significance is set to $\alpha = 0.05$ (statistically significant). The null hypothesis H_0 - flight time timings are normally distributed is tested.

Table 2: Normality tests for some digraphs.

Graph	Amount of probes	Test (p-val) Shapiro-Wilk	Test (p-val) Lilliefors	Rejection H_0
ie	542	< 2.2e-16	< 2.2e-16	YES
e_	501	< 2.2e-16	< 2.2e-16	YES
a_	438	< 2.2e-16	< 2.2e-16	YES
ni	426	< 2.2e-16	< 2.2e-16	YES
_p	332	< 2.2e-16	< 2.2e-16	YES
ow	284	< 2.2e-16	< 2.2e-16	YES
”	273	< 2.2e-16	< 2.2e-16	YES
ze	271	< 2.2e-16	< 2.2e-16	YES
o_	259	< 2.2e-16	< 2.2e-16	YES
po	256	< 2.2e-16	< 2.2e-16	YES
wa	170	< 2.2e-16	< 2.2e-16	YES
do	152	< 2.2e-16	< 2.2e-16	YES
ad	100	5.612e-15	< 2.2e-16	YES
io	64	8.741e-11	1.262e-14	YES
el	50	1.097e-08	3.228e-11	YES

Results presented in Table 2 allow us to safely reject the hypothesis about normality of digraphs timings.

3.2 n-Graphs Approach

In the paper (Sim and Janakiraman, 2007) one can find a very important observation – the distribution of digraph flight times depends on their contexts (key pressed before and after the digraph) and the longer context is the more the shape of the histogram resembles Gaussian distribution. In other words, this means that *n*-graphs for $n \geq 3$ should have distribution closer to Gaussian.

In Fig. 3 a histogram for *ie* digraph is disunited in histograms of contributing trigraphs.

Let us investigate Fig. 3. We can observe two peaks: first over 100ms and the second around 250ms.

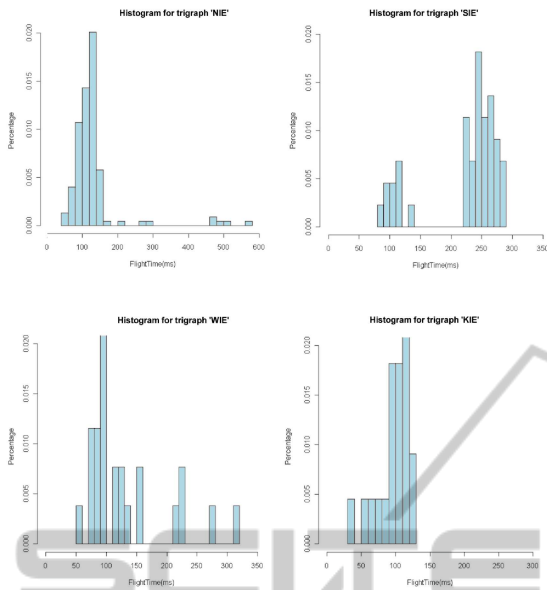


Figure 3: Distribution of flight time timing for trigraphs included in the digraph "IE".

One can conjecture that in general the distribution of timings of a digraph xy would be a combination³ of some other, basic unimodal distributions defined as follows:

$$X_{xy} = \sum_{pre,post} Y_{pre||xy||post} \mathbf{1}[\text{Prefix} = pre, \text{Postfix} = post]$$

Where Y_a are from the same family of distribution, however with different parameters depending on individual user and particular string a . Note that $\mathbf{1}[W]$ denotes an indicator function, i.e., it is equal 1 if assertion W is true, otherwise it is 0. Such approach would be coherent with observation from (Sim and Janakiraman, 2007) and seems to be, at least to some extent, justified. Indeed, typing a digraph for a fixed context can be treated as an experiment that is repeated under the same conditions. In such model close approximation of X can take into account only prefixes of length 1 - i.e., trigraphs.

It is not clear, however, if Y_a for different a 's are Gaussian, at least for short context. One can observe that histograms of trigraphs have high skewness that suggests that normal distribution is very unlikely. Initial analysis suggests that this may be Lognormal, Beta or Burr distribution, though due the small size of dataset these experiments could not be very reliable. We performed some tests and obtained following results given in Table 3.

Presented results are ambiguous – we cannot definitely reject any hypothesis about real distribution of

³This is **not** a mixture of distribution.

Table 3: Normality tests for some trigraphs.

Graph	Amount of probes	Test (p-val) Shapiro-Wilk	Test (p-val) Lilliefors	Rejection H_0
nie	137	< 2.2e-16	< 2.2e-16	YES
wie	26	1.059e-06	0.0001074	YES
sie	44	2.354e-09	1.440e-09	YES
pre	51	0.06108	0.02186	NO
cji	42	0.9153	0.9535	NO

Table 4: Occurrence of all trigraphs forming the space of "?IE".

Trigraph	EIE	BIE	ZIE	PIE	KIE
Occurrence[%]	0.89	2.37	4.45	5.64	6.53
Trigraph	MIE	WIE	CIE	SIE	NIE
Occurrence[%]	6.53	7.72	11.57	13.06	40.65

trigraphs since collected dataset is too small. Investigating this problem as well as testing the conjecture about the distribution remains future work.

Beyond n-Graphs. We believe that there is many other data that can be used for recognizing particular typist. One example is frequency of some characteristic mistakes. Another rich source of information is the usage of SHIFT key with digraphs containing a key of double meaning (e.g. : / ; or " / ').

Due to space limitation we do not present experimental results.

4 EFFECTIVE COUNTERMEASURES

In this section we present methods that can, to some extent, protect users from threats pointed out in Section 2. The algorithms we present below relay on interception of pressed keys and obfuscating real timings by injecting artificial delays. The defense methods should be planted on a level when modification is possible before the attacker can intercept the data, though basically they acts similar to keyloggers. We can think about a hardware device installed on a keyboard's plug or a special software controlling messages sent later thorough the network. One may argue that in many distributed systems some delays occur as side effects of realizing basic functionalities (e.g., SSH2). Nevertheless usually one cannot have any control when we aim at providing mechanisms that guarantee provable security.

The most challenging aim in designing security mechanisms of that kind is to provide high level of security without affecting significantly the usability of the system. One can easily notice that idea behind

our protocols leads to lags in communication, that can significantly lower responsiveness of the system and be unacceptable for users. This pertains in particular to users working in an interactive mode.

All methods described below use a kind of buffer and require access to precise time. Pressed keys are stored in the buffer and are released with some precisely assigned delay, thus every key in the buffer needs to have a special auxiliary data (a timestamp) when the key was put into the buffer. Of course size of the buffer should be possibly small. Nevertheless limiting the size of the buffer is much less important than limiting the delay.

4.1 Threshold-constant Time Delays Method

The most obvious defense strategy is to withhold sending keys so that all flight times would be perceived as constant that is equal the longest observable flight time over all digraphs. Such an approach cannot be implemented directly, since in some cases Flight Times can be extremely long (e.g., pause in typing). In Algorithm 1 we obfuscate all timings up to a given threshold. That is, Δ is the threshold value beyond which obfuscating ends.

Main Features. The proposed solution is very simple in implementation and does not require knowledge of distribution of flight times. Moreover changing the parameter Δ regulates obfuscation/delay threshold. Heuristic approach providing high level of security would be setting $\Delta = 800$ ms. According to some data revealed in (Monrose and Rubin, 1997) one may expect that bulk of all digraphs fall to “obfuscated interval”. On the other hand, flight time of most common in our data digraph ‘IE’ is slightly larger than 100ms, and other common digraphs have flight time around 200ms. Thus the time of inserting the message can be over 4 times longer. Moreover basic observations of queuing theory suggests that one can expect the required size of the buffer up to size equal to the length of the input text. On the other hand, this method provides very strong level of security - indeed - most timings are totally obfuscated and the picture seen by the adversary is oblivious. In effect, the adversary gets no knowledge about the typist.

Algorithm 1 works best for consistent typists and in a scenario where the user types short texts and interaction is needed. It can be also considered for systems with texts of moderate size where delay is accepted.

Algorithm 1: Threshold-constant strategy.

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Read Key1; Release Key1

Read Key2; Release Key2

if  $FlightTime(Key_1, Key_2) < \Delta$  then
     $FlightTime \leftarrow \Delta$ 
else
     $FlightTime \leftarrow FlightTime(Key_1, Key_2)$ 
end if

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4.2 Pool Buffer Method

For protecting user privacy in typing longer text one may apply another strategy. Algorithm described in this section follows two simple rules: gather and flush. We ensure a large buffer of size n and in first stage of algorithm, when the user types, algorithm withholds the pressed keys until $\frac{n}{2}$ slots are filled. Starting at that point second stage begins and buffer outputs stored data in short and constant time intervals (e.g. 5 ms), simultaneously receiving new input and storing it in the second half of the buffer. Note that this approach is similar to some kinds of MIX protocol used for protecting anonymity in communication (Serjantov and Newman, 2003).

Problem with short texts can be solved by fixing a time parameter T depicting time period after which we consider typing as completed. One solution is as follows – when time since last key press is longer than T , buffer, starting from current position up to $\frac{n}{2}$, is filled with neutral symbol (i.e., NULL) and the procedure continues until all positions from 0 to $\frac{n}{2}$ contain only neutral symbols. Of course choice of protocol parameters n and T depends on particular scenario.

Main Features. One can easily see that security offered by the protocol depends on parameter n . Instead of timings $T_1, T_2, \dots, T_{n/2}$ the adversary obtains only their sum i.e., $S = T_1 + \dots + T_{n/2}$ that provides significantly less information. Generally security guarantees offered by this algorithm are lower than those offered by algorithm described in 4.1, especially for small buffer size n . However, this protocol clearly has some unquestionable merits - size of the buffer as well as delay are strictly controllable and limited. Moreover some extremely long flight times are to some extent hidden. This can be important since very long timings can provide significant information about distinctive behavior of individuals.

4.3 Masquerade Method

Another approach is to replace the real flight time for particular digraph XY by a random δ_{XY} chosen randomly from some distribution defined for XY . Such approach not only hides real timings of the user but also can pretend other individual. Similarly, this approach can be extended to n -graphs. The method offers moderate delay and requires relatively long size of the buffer. The main disadvantage is the need of keeping distribution of the digraphs, which is quite difficult as shown in Section 3.

5 CONCLUSIONS

In this paper we discussed several issues related to keystroking biometric techniques. We pointed out some potential risks with particular focus on privacy threat as well as some simple countermeasures. We believe that issues related to this area are generally underestimated. In effect many fundamental questions – theoretical as well as practical are left unanswered. In particular there is no convincing and possibly exact statistical model of timings of n -graphs. It is also not clear which other information (e.g., mistakes in typing) can be used for recognizing individuals.

We also see the need of providing much more experimental results about statistics that appear in our paper. The volume of data we used allows us to test only a few simple hypothesis e.g., about normality of distribution of digraphs. With this respect, this paper is a preliminary work revealing only a fraction of problems in the area of profiling based on keystroke dynamics.

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