Application of Self Organizing Maps to User Authentication Using Combination of Key Stroke Timings and Pen Calligraphy

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Abstract: - Recently, security of the computer systems becomes an important problem. Almost all computers use the password mechanism for the user authentication. But password mechanism has many issues. In this paper, we propose a kind of biometrics authentication method using the combinations of key stroke timings and pen calligraphy. For this method, selection of the phrase is important. We analyzed the key stroke timings and pen calligraphy using Self Organizing Map (SOM) and proposed the improved SOM (Pareto learning SOM) for this purpose. We examined the effectiveness of this method with the authentication experiments using the map organized by SOM..

Key-Words: - Biometrics, Authentication method, Neural network, Self Organizing Map

1 Introduction

Recently, almost all computers are connected to the networks and security of the computer systems becomes an important problem. Almost all computers use the password mechanism for the user authentication. But password mechanism has many issues. At first the password is the static plain text so it is easy to get the password from shoulder hacking, guessing from personal information or memo on which the list of the password are written not to forget the password. Secondly, some persons are using several systems recently. For the different systems, different passwords should be set, but almost users set the identical password for different systems because they can not remember many passwords. So, if a password is hacked, all system can be accessible. Thirdly, someone may feel that it is troublesome to enter password during login to the computers, especially for portable computers such that notebook computers and Personal Digital Assistant(PDA)s, because complex password phrase which includes symbols and combination of capital letters is recommended as strong password.

As the solution to the issue of password mechanism, biometric authentications are often used. The biometric authentication uses the biological characteristics, such that fingerprints, iris patters and blue pipe patterns, or the behavior characteristics, such that hand-writting patterns. The fingerprint authentication becomes the most popular recently and some computers are equipped with fingerprint readers and the readers which are connected to Universal Serial Bus (USB) are already sold. But, all of the biometric authentications using biological characteristics need additional hardware and they will cost up the price of computers. Recently, for the main stream or low end computers, the costs are the most important issue, so the makers do not want to add any additional hardware. And some persons feel bad to register their fingerprints in host systems of company. Furthermore, the fingerprint authentication can be hacked or after login, the irregular user may use the computer while the regular user is apart from the computer.

For these problems, we propose the authentication method using the integrated information of the biometrics of behavior characteristics taken from the instruments equipped with the standard computers such that keyboard, mouse and touch panel. We reported the authentication method using the pen calligraphy and pen pressure data by tracing the simple symbol displayed on the PDA touch panel[2]. And we also reported the authentication method using the keystroke timings by typing the identical phrase for all users[3]. It is well known that the pen calligraphy and keystroke timings are usable for user authentications. For our methods, the selection of the symbol and the phrase used for the authentication were important. For this purpose, we analyzed the pen calligraphies and key stroke timing data using Self Organizing Map(SOM)[1] and searched for the symbol and the phrase which were suitable to authenticate all users at login time. SOM is a kind of neural network which was proposed by Kohonen. SOM can extract the feature of multi dimensional input vectors with unsupervised learning and can visualize the relations among the input vectors on 2 dimensional plane. In [4], an authentication method based on ART maps using key stroke timings and key stroke pressures measured by pressure sensors is reported, but only some specific phrases which are usually used as the password phrases are examined Furthermore, the pressure sensors won't be generally equipped with usual PC. We reported that the authentication using pen calligraphy was depending on the characteristics of the users[2] and the authentication using pen stroke timings was depending on the skills of typing[3] , thus some users could not be authenticated using each of the method.

In this paper, we propose an authentication method using the combination of pen calligraphy and keystroke timing to improve the authentication rate. For the integration of pen calligraphy and keystroke timing, we propose an improved SOM algorithm (Pareto learning SOM) which can integrate multi-kind of vectors effectively and made the experiments of authentication using the map organized by SOM.

2 Sampling of the Keystroke Timing and Pen Calligraphy data

We used a PC which was equipped with the touch panel to sample the keystroke timings and pen calligraphy data. The specs of the PC is as follows.

Name: Sony VAIO UX50
CPU: Intel Core Solo 1.06Ghz
Memory: 512Mbyte
Screen: 5inch equipped with the touch panel of resistance film type.
Keyboard: External USB keyboard
Operating System: Windows XP home

Fig. 1 shows the photo of the system used for this experiments. The external keyboard was used because the keyboard equipped with this PC was too small to type smoothly. Fig. 2 shows a sample of key stroke timings

Fig. 1 Experiment System

```
Push A   Interval  Push B Interval   Push C      phrase
|------------|       |-------|       |------------|    ABC
   100ms   90ms  60ms 110ms   100ms     timings
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Fig. 2 Sample of the key stroke timings

For each key, the time pushing the key and the interval time between keys are sampled. The shift key is also sampled independently, so inputted phrases can be determined from the sequence of key strokes. As reported in [3], we examined some phrases of English words, combinations of alphabet and symbols and romaji words. Romaji is the ideographic writing used to input Japanese from English keyboard and the examinees were used to typing in Romaji. Among the phrases we have examined, the simple Romaji phrase "kirakira" showed the best features to authenticate the user with an identical phrase for all users. In this experiment, we selecteded the phrase "kirakira".

The pen calligraphy data were taken from touch panel. In this experiments, the pen pressure data were not measured because Windows XP did not support the detection of pen pressure from the touch panel of resistance film type. Windows XP tablet PC edition supports the detection of pen pressure only from the touch panel with electromagnetic digitizer and some of the recent TabletPC including UMPC(Ultra Mobile PC) are equipped with the touch panel of resistance film type. Thus, our method should be tested without using pen pressure data. The pen calligraphy data, which consist of x-axis and y-axis of current pen position, are sampled at every 3ms. As reported in [2], 1-dimensional pen speed was the best feature for user authentication, thus the pen calligraphies were translated to 1-dimensional pen speed data. It is also reported in [2] that the symbol composed of the oval lines, such that spiral, showed the best features for authentication, thus the spiral was used in this experiments. Fig. 3 shows the input screen of the pen calligraphy.

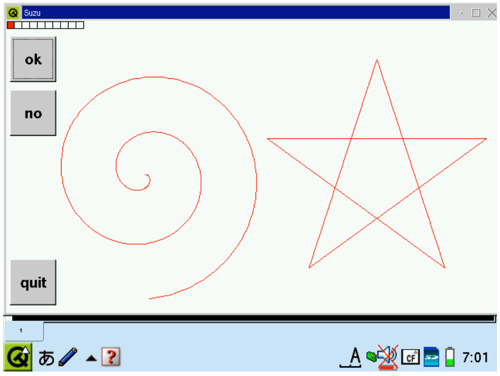

Fig. 3 Input screen of pen calligraphy

The number of the sampling was about 300-1000 for each input depending on the pen speed, thus the number of the sampling was normalized to the maximum number of samplings because of the requirement from the following SOM analysis.

3 Self Organizing Map(SOM)

3.1 Conventional Self Organizing Maps

SOM is an architecture of neural networks, which is classified as the network of feed forward type and of the unsupervised learning method. SOM can organize the feature of the input vectors on the 2-dimensional map on which the output neurons are arranged. After learning, the input vectors are mapped on the organized map, then the relations of the input vectors can be visualized on the map. Original SOM algorithm trains the map incrementally by updating the map for each presentation of input vector. The recent trend of SOM algorithm adopts Principal Component Analysis(PCA) and batch update to improve the performance. The PCA is used to reduce the dimension of input vectors and to initialize the map. The input vectors are analyzed by PCA before they are given to SOM and the vector of principal components with large contribution rates are used as the input vectors to SOM. The initial map is made as the plane of 1st and 2nd principal components. The batch update improves the effectiveness of training and the ambiguity of the resulting maps according to the order of the presentations of input vectors. In the learning phase, the inputs vectors are associated to the closest units on the map, and in the update phase, the units on the map are updated at once using the information of the associated vectors to the unit and those of the neighboring units. For this research, we used the SOM with batch update and PCA for initialization of the map. For the analysis of keystroke timings, the raw input vectors were used because the dimension of input vector was not so large. For the analysis of pen calligraphy, the input vectors were pre-processed to the vectors of 20 elements by PCA and the vectors translated by PCA analyses were used as input vectors.

3.2 Pareto Learning Self Organizing Maps

Using conventional SOM for the analysis of the combination of keystroke timing and pen calligraphy, the two different kind of the vectors must be composed in a vector $\mathbf{x}$ as follows.

$$\mathbf{x} = (\mathbf{x}_k, w\mathbf{x}_p)$$

where $\mathbf{x}_k$ is the vector of keystroke timings, $\mathbf{x}_p$ is the vector of pen calligraphy and w is the weight of pen calligraphy data relative to the key input vector. The pen calligraphy data are pre-processed by PCA to adjust the size to that of keystroke timings. Using this method, the error between the weight vector on the map and input vector is shown as follows.

$$e = \sqrt{e_k{}^2 + w^2 e_p{}^2}$$

where e_k is error of keystroke timings and e_p is error of pen calligraphy. Because the map is organized according to this error function, the resulting map is heavily depending on the weight value w. From the other side of view, this problem is a multi-objective optimization problem to minimize the errors e_p and e_k for the independent vector sets $\{\mathbf{x}_k\}$ and $\{\mathbf{x}_p\}$. For multi-objective optimization problems, the concept of Pareto optimum is important to find the optimal solution.. In this paper, we introduce the SOM which use the concept of Pareto optimum in the learning phase. The difference of this algorithm from conventional SOM is as follows. Conventional SOM searches for the closest unit to the input vector from the map and updates the unit and its neighbors. Pareto learning SOM searches for the Pareto set of the units which are closest to the input vector in Pareto meaning and updates all of the units and its neighbors which are included in the Pareto set. The Pareto learning SOM does not need the weight w and can optimize the map using the independent set of input vectors.

4 Experimental Result

4.1 Experimental settings

Next, we made the analysis of keystroke timing data and pen calligraphy data using SOM. The number of examinees was 10 and their typing skills vary from beginner to blind typist. As mentioned before, the keystroke timing of the Romaji phrase “kirakira” and the pen calligraphy data of spiral were taken alternately in 6 times from each examinee.

4.2 Analysis of the keystroke timings and pen calligraphy data using SOM

At first, we analyzed the obtained data using SOM to examine the availability of the data to identify the user. Fig. 4 shows the map organized by using the keystroke timings as input vectors.

7	8	8	8	8	9	4	9	9	3	3	3	7	7	7	7
8	8	8	8	9	9	9	9	3	3	3	3	3	7	7	7
7	8	8	8	9	9	9	9	5	3	3	3	3	7	7	7
7	7	8	8	4	4	4	5	5	5	3	3	3	3	7	7
7	7	8	8	8	9	9	5	5	3	3	6	3	7	7	7
6	6	9	9	9	9	9	5	5	4	6	6	6	4	7	6
6	6	1	1	1	1	5	5	4	4	4	6	4	4	4	6
6	1	1	1	1	1	1	5	5	5	5	5	4	4	9	8
8	1	1	1	1	1	10	5	5	5	5	5	5	9	8	8
8	1	1	1	6	10	10	10	10	5	5	5	9	9	9	8
1	1	1	6	6	6	10	10	10	10	10	10	9	9	9	8
1	1	1	6	6	10	10	10	10	10	10	10	10	6	6	6
10	1	1	1	10	10	10	10	10	10	10	2	2	6	6	6
4	1	1	1	6	10	10	2	10	2	2	2	2	2	6	10
4	4	8	6	6	6	4	2	2	2	2	2	2	2	2	4
4	8	8	8	6	4	4	4	2	2	2	2	2	2	3	7

Fig. 4 The map of user numbers organized by keystroke timings

The size of the map is 16x16 and this map is organized as cyclic map, so the upper side and the left side of the map are connected to lower side and right side respectively. The numbers shown on the map indicate the user who made the closest keystroke timing. As the result, almost of the user numbers are clustered well and a few users (e.g. 4, 6) are disjointed depending on the skills of typing.

Fig. 5 shows the map organized by using pen calligraphy data as input vectors. As the result, user numbers are not clustered well compared with the map organized by keystroke timings. Compared with the results reported in [2], this result is much worse. The reason for this result is because the pen pressure was not used in this experiment and the posture of the drawing varied for each pen input in this experiment. Indeedy, some users complained that it is hard to write identically because there is no place where they can fix their elbow. (See Fig.1)

Fig. 6 shows the map organized by conventional SOM using combination of keystroke timings and pen calligraphy data The weight w is set to 0.5. As the result, the user numbers are not clustered well because the map is heavily depending on the pen calligraphy data.

3	3	2	9	5	5	4	7	9	5	2	8	8	2	3	3
3	3	5	9	9	5	4	7	9	5	6	8	2	3	3	3
2	5	5	9	9	4	4	4	4	6	6	6	2	2	2	2
2	2	5	5	9	4	4	4	4	6	6	6	2	2	2	2
2	5	5	5	5	4	4	4	4	7	7	2	2	2	2	3
5	5	5	5	4	4	4	4	7	7	7	6	6	2	3	3
8	5	6	6	6	4	6	6	7	7	7	6	6	6	6	3
8	8	6	6	6	6	6	6	8	8	8	6	6	1	1	8
8	8	6	6	6	7	6	6	8	8	8	8	1	1	1	10
10	6	6	6	7	7	7	4	4	8	10	1	1	1	10	10
10	6	6	6	7	7	7	4	4	10	10	10	1	1	1	10
9	9	6	6	7	7	7	7	4	8	10	1	1	1	1	9
9	9	9	9	4	7	7	7	8	8	8	1	1	1	9	9
9	9	9	9	4	7	7	7	8	8	10	10	10	10	9	3
3	9	9	9	4	4	7	8	8	8	10	10	10	10	3	3
3	3	9	9	4	5	4	7	8	5	10	8	2	2	2	3

Fig.5 The map of user numbers organized by pen calligraphy data

3	3	2	2	2	5	7	7	7	8	5	10	8	8	8	3
3	3	2	9	4	4	4	7	5	5	5	2	2	8	3	3
3	3	9	9	9	4	4	4	4	5	6	2	2	2	2	3
3	5	5	9	4	4	4	4	4	6	6	6	2	2	2	3
3	5	5	5	5	4	4	4	4	6	6	6	2	2	2	3
5	5	5	5	5	4	4	4	7	7	7	6	6	2	3	3
5	5	5	6	6	4	4	4	7	7	7	6	6	6	8	8
8	5	6	6	6	6	6	6	7	7	4	1	6	6	8	8
8	6	6	6	6	6	6	6	8	8	1	1	1	1	1	8
6	6	6	7	7	7	6	6	8	8	8	1	1	1	1	1
6	6	6	7	7	7	7	7	2	8	10	1	1	1	1	1
9	6	9	9	7	7	7	7	7	10	10	10	1	1	10	10
9	9	9	9	9	7	7	7	8	10	1	1	1	10	10	10
9	9	9	9	9	7	7	4	8	8	1	1	10	10	10	3
3	9	9	4	4	5	7	4	8	8	1	10	10	10	3	3
3	9	9	9	5	5	5	7	8	8	8	10	10	2	2	3

Fig. 6 The map of user numbers organized by the combination of keystroke timings and pen calligraphy data

Fig. 7 shows the map organized by Pareto learning SOM using keystroke timings and pen calligraphy data. As the result, user numbers are clustered well for almost users. From this results good authentication results are expected for the method using keystroke timings and using the Pareto learning SOM.

2	2	8	8	8	8	4	4	4	4	3	3	3	3	3	2
8	8	8	8	8	9	9	4	4	9	3	3	3	3	7	9
8	8	8	8	9	9	9	9	9	9	5	3	7	7	7	9
8	8	8	10	9	9	9	9	5	5	5	4	7	7	7	4
8	8	10	10	10	9	9	5	5	5	5	6	7	7	7	7
8	8	5	10	10	10	5	5	5	5	6	6	6	7	7	7
8	8	8	10	10	10	10	5	5	5	5	4	7	7	7	4
4	8	5	10	10	10	10	5	5	5	5	4	4	7	4	4
4	4	10	10	10	10	10	10	5	5	4	4	6	6	5	4
4	4	10	10	10	1	10	10	10	6	6	6	6	6	6	4
4	4	1	1	1	1	1	10	10	6	6	6	6	6	5	2
2	2	1	1	1	1	1	3	3	6	6	6	5	3	2	2
2	2	1	1	1	1	3	3	3	6	6	6	3	3	2	2
2	2	2	1	1	1	1	2	2	6	6	6	3	3	3	2
2	2	2	1	1	1	2	2	2	6	6	4	3	3	2	2
2	2	2	8	8	9	2	4	4	4	3	3	3	3	2	2

Fig. 7 The map of user numbers organized by Pareto learning SOM using keystroke timings and pen calligraphy data

Table 1 Result of auhtentication experiments using keystroke timings

	Success	FRR	FAR
User1	0.633	0.367	0.0000
User2	1.000	0.000	0.0093
User3	1.000	0.000	0.0019
User4	0.400	0.600	0.0222
User5	0.633	0.366	0.0093
User6	0.100	0.900	0.0315
User7	0.733	0.267	0.0370
User8	0.700	0.300	0.0019
User9	0.767	0.233	0.0259
User10	0.933	0.067	0.0190
Average	0.690	0.310	0.0157

4.3 User authentication experiments

Next, we made user authentication experiments using the map organized by SOM. In this experiments, 4 of 6 sample data for each user are used for learning of SOM maps and the remainders are used as test data. All combinations of learning data and test data are examined, so ${}_6C_4$=15 patterns are tested.

Table 1 shows the result of the authentication experiments with keystroke timings. In these table, success, FRR and FAR means the rate of successful authentication, false reject rate and false accept rate respectively. The average rate for successful authentication is about 70% and FAR is small enough compared with successful rate. 8 users can be authenticated more than half of the inputs. Table 2 shows the results using pen calligraphy data for authentication. Average of successful authentication rate becomes much worse than that of previous one, but for some users the rate becomes better. They are considered as the user who have not good typing skill but show good characters in pen calligraphy data.

Table 2 Results of authentication experiments using pen calligraphy data

	Success	FRR	FAR
User1	0.900	0.100	0.0000
User2	0.567	0.433	0.0370
User3	0.400	0.600	0.0462
User4	0.533	0.467	0.0019
User5	0.300	0.700	0.0704
User6	0.233	0.767	0.0130
User7	0.866	0.133	0.0278
User8	0.000	1.000	0.0056
User9	0.633	0.367	0.0185
User10	0.500	0.500	0.0519
Average	0.493	0.507	0.0272

Table 3 shows the results of authentication experiments using the maps organized by conventional SOM using the combination of keystroke timings and pen calligraphy data.

Table 3 Results of authentication experiments using the combination of keystroke timings and pen calligraphy data

	Success	FRR	FAR
User1	0.933	0.067	0.0000
User2	0.633	0.367	0.0278
User3	0.267	0.733	0.0444
User4	0.633	0.367	0.0000
User5	0.366	0.633	0.0704
User6	0.200	0.800	0.0315
User7	0.833	0.167	0.0111
User8	0.033	0.967	0.0370
User9	0.633	0.367	0.0167
User10	0.633	0.367	0.0519
Average	0.517	0.483	0.0257

Compared with previous results, its much worse than that of table 1 and almost similar to that of table 2 as expected from the analyses using SOM. The authentication of the user who shows good result using keystroke timings is affected by the pen calligraphy data. Table 4 shows the results of authentication experiments using the map organized by Pareto learning SOM using the keystroke timings and pen calligraphy data. The Average rate of successful authentication becomes better than that of table 1 and almost of the users show good rate. The affection of the pen calligraphy data was decreased and it rather improves the successful authentication rate. In the practical use, the best authentication method can be selected when the keystroke timing and the pen calligraphy data are registered to the system. Table 5 shows the best successful authentication rate and method taken from table 1-4.

Table 4 Results of authentication experiments using the map organized by Pareto SOM

	Success	FRR	FAR
User1	0.967	0.033	0.0000
User2	0.967	0.033	0.0259
User3	0.900	0.100	0.0093
User4	0.533	0.467	0.0019
User5	0.833	0.167	0.0259
User6	0.067	0.933	0.0241
User7	0.967	0.033	0.0056
User8	0.333	0.667	0.0037
User9	0.767	0.233	0.0167
User10	0.767	0.233	0.0330
Average	0.710	0.290	0.0146

Table 5 Best results of the authentication experiments for all users

	Method	Success	FRR	FAR
User1	Key&Pen(P)	0.967	0.033	0.0000
User2	Key	1.000	0.000	0.0093
User3	Key	1.000	0.000	0.0019
User4	Key&Pen	0.633	0.367	0.0000
User5	Key&Pen(P)	0.833	0.167	0.0259
User6	Pen	0.233	0.767	0.0130
User7	Key&Pen(P)	0.967	0.033	0.0056
User8	Key	0.700	0.300	0.0019
User9	Key&Pen(P)	0.767	0.233	0.0167
User10	Key	0.933	0.067	0.0190
Average		0.803	0.197	0.0093

The method "Key&Pen(P)" denotes Pareto learning SOM. From 10 users, 4 users show the best rate using keystroke timings and 4 users show the best rate using the map organized by Pareto learning SOM. Only one user can not mark the rate more than 50%. Considering that all of the user typed same phrases and traced same symbols, this result is remarkable.

5 Conclusion

In this paper, we propose an authentication method using the combination of keystroke timings and pen calligraphy data of identical phrase and identical symbol for all users. For the analysis and authentication method, we propose Pareto learning SOM to organize the multi-kind of the vectors. The applicability of this authentication method and the effectiveness of Pareto learning SOM are confirmed by authentication experiments.

As the feature work, this method must be tested more broadly. And the Pareto learning SOM is considered to be applicable for other problems, thus we must study this algorithm more with other applications.

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