Comparison of the Adaptive Authentication Systems for Behavior Biometrics using the Variations of Self Organizing Maps

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***Abstract*— The biometrics authentication systems take attentions to cover the weakness of password authentication system. In this paper, we focus attention on the multi modal-biometrics of behavior characteristics. For the integration of multi modal biometrics, some variations of Self Organizing maps and its incremental learning method for implementing adaptive authentication system are implemented and their performances are examined for the time varying inputs and the noised inputs.

I. Introduction

%Recently, many security issues are reported concerning the information systems. The entrance to the information system is the authentication of the user. The password is still mainly used for authenticating the users. But, password authentication involves some issues. At first, password is the simple text, so it may be peeked while typing password on keyboard, guessed from the personal informations(e.g. birthday, family's name, telephone number) and taken from memos in which the passwords are written down. Secondly, as the strong password, the complex combination of alphabets, digits and symbols are recommended, but it is difficult to memorize such password phrase, so the user may forget it. Recently many users have some accounts for different systems and the password should be different for each system. Such users can not memorize so many different password phrases, the passwords are set as identical one or the user might write down the password on memo. Once the password is obtained by illegal users, they can easily spoof the legal user.

As the solution of this problem, the biometric authentication is used. Biometric authentication uses biometric characteristics to identify the user. Biometric characteristics are classified in two types, the biological characteristics and behavior characteristics. As the biological characteristics, the fingerprint, iris pattern and blue pipe patterns are often used for authentication[1]. Recently, the fingerprint reader becomes more popular for personal computers, but it is possible to pass the authentication using the imitation of the fingers or more simply using the photographic copy of fingerprints. This weak point of authentication method using biological characteristics originates from the static information of biological characteristics. Additionally, someone finds to register the fingerprint pattern in authentication system offensive. As the behavior characteristics, handwritten signatures, keystroke timings and mouse moving patterns can be used for authentication. Behavior characteristics are the dynamic information, so each user can be identified independently even if all users act in same manner, e.g. typing identical phrase or drawing same symbol. And it is considered to be difficult to imitate even if the authentication process is observed by hackers. Additionally, the behavior characteristics can be measured from the standard devices equipped to the computers.

It is well known that the key stroke timings and hand written signatures are available for biometric authentications[2][3][4]. We have also reported some types of authentication systems which use behavior characteristics, e.g. handwritten symbols on touch panel[5] and keystroke timings[6].In these papers, we have proposed the authentication methods using a identical phrase or identical symbols for all users specified by the authentication system, so the users do not need to memorize the password phrase or signature registered to the system. But, behavior characteristics includes more variance for each input compared with biological characteristics, so the accuracy of the authentication becomes worse compared with that of biological characteristics. For this problem, the authentication method using the integrated information of multi-modal biometrics is reported[7]. We have also reported that multi-modal behavior characteristics, e.g. combination of keystroke timings and handwritten symbols[8][9] or combination of keystroke timings and key typing sounds[10], can improve the accuracy of the authentication compared with the isolated use of each biometrics. In [11], the authentication method using key stroke timings and pressure sensors for key stroke power is proposed, but this method is not practical because pressure sensor needs large amounts of additional equipments (pressure sensors, AD converters and IO-interfaces) for implementation.

For the integration of multi-modal behavior characteristics, we used Self Organizing Map (SOM)[12]. Self Organizing map has variety of applications such that classification, unsupervised clustering, control etc[13]. Self Organizing Map can integrate multiple vectors by using the combination of the weighted vector for each characteristics. SOM can use to visualize the relations among the input vectors, so the separation of the characteristics among the user can be confirmed visually using the map. Furthermore, SOM can be used as the authentication system by labeling the output units with user id. But, the accuracy of the authentication system is heavily depending on the weight for each characteristics because the resulting map changes according to the weight values. For, this problem, we proposed Pareto Learnig SOM (P-SOM)[14]. The concept of Pareto Optimal is introduced to SOM for organizing the set of vectors as to

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minimize the quantization error of each vector. Furthermore, we proposed Supervised Pareto Learning SOM (SP-SOM) which improved the accuracy of authentication by adding the supervised learning ability to P-SOM. We reported the effectiveness of SP-SOM for authentication system using the combination of keystroke timings and handwritten symbols and the combination of keystroke timings and key typing sounds[9].

Considering the feature of behavior characteristics, the robustness to the variation of the input vectors and adaptation to the temporal changes are required for the authentication system. Compared with biological characteristics, the behavior characteristics varies in each trial of authentication depending on the behavior of user. In this paper, we show the robustness of SOM and SP-SOM to the variation of input vectors affected by noises. On the other hand, the behavior characteristics may vary by time. For example, keystroke timing will become faster with accustoming oneself to the computer. In this paper, we show the adaptation ability of SOM and SP-SOM to the temporal changes of input vectors by adding the relearning or incremental learning scheme to SOM and SP-SOM. The robustness and adaptation ability are confirmed by the computer simulation using the artificially modified data of keystroke timings and key typing sounds.

II. Self Organizing Maps and Pareto Self Organzing Maps

%

A. 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 features 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 between 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 learning algorithm of conventional of SOM is as follows.

Learning algorithm of Conventional SOM

1) Initialization of the map
   Initialize the map using random vectors.
2) Searching for the winner unit
   Select an input vector $\mathbf{x}$ randomly from learning set. Search for the unit U_w which is associated to the closest vector $\mathbf{m_w}$ to $\mathbf{x}$ which minimize the quantization error $|\mathbf{x} - \mathbf{m}|$.
3) Updating the winner unit and its neighboring units
   For the winner units U_w and its neighbor U'_w, update the vectors associated to the units using the following equation.

$$\mathbf{m_w} = \mathbf{m_w} + \mathbf{fn(d)} * \eta * (\mathbf{x} - \mathbf{m_w}) \qquad (1)$$

   where fn(d) is neighborhood function which is the decreasing function of distance d between U_w and U'_w and η is the learning rate.

   Repeat Step 2, Step 3 with decreasing neighborhood function fn(d) and learning rate η until the quantization error converges enough or during the pre-defined iterations.

The recent trend of SOM algorithm adopts Principal Component Analysis(PCA) and batch update to improve the performance. In this paper, we use the simple SOM algorithm because the dimension of vector is small enough.

To apply SOM to classification problem such as authentication problem, recalling algorithm is needed. The recalling algorithm of SOM is as follows.

Recalling algorithm of SOM

1) Labeling of the units
   After learning map of SOM, the each unit is labeled with the identifier of the class which is associated to the input vector closest to the vector associated to the unit.
2) Recalling of the class of test vector
   For each test vector, find the winner unit using the Step.2 of learning algorithm and classify the test vector as the label of the winner unit.

Using this algorithm, the accuracy of the classification can not be tuned because there is no tunable parameters in this algorithm. Using this algorithm, it tends to be fail safe side which puts specificity above sensibility. For this problem, we introduce Multi-Winner SOM (MW-SOM). The learning algorithm of MW-SOM is same as that of conventional SOM. For the MW-SOM, the test vector is examined whether it belongs to the specified class or not using the following recalling algorithm.

Recalling algorithm of MW-SOM

1) Labeling of the units
   After learning map of SOM, the each unit is labeled with the identifier of the class which is associated to the input vector closest to the vector associated to the unit.
2) Recalling of the class of test vector
   For each test vector, find the 1st to n-th winner units using the Step.2 of learning algorithm. If more than k units in n winner units are labeled as the specified class, the input vector is identified as belonging to the class, otherwise not belonging to the class, where k is the pre-defined threshold.

By setting the threshold k, the accuracy of the classification can be tuned from specificity dependent to sensibility dependent.

Re-learning and incremental learning of SOM and MW-SOM

As mentioned before, authentication system should be made to adapt to changes of keystroke timings by the skill etc. For this purpose, re-learning method and LVQ incremental learning method are used for SOM and MW-SOM. SOM re-learning method re-organize the map at each time using the combination of new input data and past input data with discarding the oldest input data one by one. The map is initialized at every time, so information in the map made previous time is not succeed to the next map for forgetting the old data effectively.

LVQ learning method update the map after the authentication using new input data incrementally. The map is updated in every 3 times of authentications because too much updates make bad effect to the map. From LVQ1, LVQ2 and LVQ3, which are well known LVQ methods, LVQ1 is used from the results of several experiments. The following equations are used for LVQ incremental learning method.

$$\mathbf{m'}_{\mathbf{ij}} = \mathbf{m'}_{\mathbf{ij}} + \eta'(\mathbf{x'} - \mathbf{m'}_{\mathbf{ij}}) \tag{2}$$

when authentication is succeeded,

$$\mathbf{m'}_{\mathbf{ij}} = \mathbf{m'}_{\mathbf{ij}} - \eta'(\mathbf{x'} - \mathbf{m'}_{\mathbf{ij}}) \tag{3}$$

when authentication is failed, where η is learning rate of LVQ1,$\mathbf{x'}$ is input vector and $\mathbf{m'}_{\mathbf{ij}}$ is the vector associated to winner units (for MW-SOM, multiple winners).

B. Pareto Learning Self Organizing Map(P-SOM)

%Using conventional SOM for the analysis of the multi-modal vectors, the different types of the vectors $\mathbf{x_1}, \mathbf{x_2}, \dots, \mathbf{x_n}$ must be composed in a vector $\mathbf{x}$ as follows.

$$\mathbf{x} = (w_1\mathbf{x_1}, w_2\mathbf{x_2}, \dots, w_n\mathbf{x_n}) \tag{4}$$

where w_i is the weight value for vector x_i. Using this method, the error between the vector $\mathbf{m} = (\mathbf{m_1}, \mathbf{m_2}, \dots, \mathbf{m_n})$ assigned to the i-th unit on the map and input vector is shown as follows.

$$e = \sqrt{\sum_{j=1}^{n} {w_j}^2 {e_j}^2} \tag{5}$$

$$e_j = |\mathbf{x_j} - \mathbf{m_j}| \tag{6}$$

where e_j is error between the $\mathbf{x_j}$ and $\mathbf{m_j}$. Because the map is organized according to this error function, the resulting map is heavily depending on the weight values w_i. From the other side of view, this problem is a multi-objective optimization problem to minimize the errors e_i for the independent vector sets $\mathbf{x_i}$. 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(P-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 P-SOM can organize the multi-modal vector according to the concept of Pareto optimal, thus it does not need to convert the error of each vector into a scalar value using the weight values w_i and P-SOM can optimize the map for the independent set of input vectors. The learning algorithm of P-SOM is as follows.

P-SOM Algorithm

1) PCA analysis
   Calculate the Principal Components(PC) of input vectors $\{\mathbf{x^i}\}$ where $\mathbf{x^i} = (\mathbf{x^i_1}, \mathbf{x^i_2}, \dots, \mathbf{x^i_n})$ is the i-th training data which consists of n multi-modal vectors $\mathbf{x^i_j}, 1 \le j \le n$.
2) Initialization of the map
   Initialize the vector $\mathbf{m^{ij}}$ which are assigned to unit U^{ij} on the map using the 1st and 2nd principal components as base vectors of 2-dimensional map.
3) Batch learning phase
   (1) Clear all learning buffer of units U^{ij}.
   (2) For each vector x^i, search for the pareto optimal set of the units $P = \{U^{ab}_p\}$. U^{ab}_p is an element of pareto optimal set P, if for all units $U_{kl} \in P - U^{ab}_p$, existing h such that $e^{ab}_h \le e^{kl}_h$ where $e^{kl}_h = \left|\mathbf{x^i_h} - \mathbf{m^{kl}_h}\right|$.
   (3) Add x^i to the learning buffer of all units $U^{ab}_p \in P$.
4) Batch update phase
   For each unit U^{ij} update the associated vector $\mathbf{m}^{ij}$ using the weighted average of the vectors recorded in the buffer of U^{ij} and its neighboring units as follows.
   (1)For all vectors x recorded in the buffer of U^{ij} and its neighboring units in distance $d \le Sn$, calculate weighted sum $\mathbf{S}$ of the updates and the sum of weight values W.

$$\mathbf{S} = \mathbf{S} + \eta fn(d)(\mathbf{x} - \mathbf{m^{i'j'}} \tag{7}$$

$$W = W + fn(d) \tag{8}$$

   where $U^{i'j'}$s are neighbors of U^{ij} including U^{ij} itself, η is learning rate, $fn(d)$ is the neighborhood function which becomes 1 for d=0 and decrease with increment of d.
   (2) Set the vector $\mathbf{m^{ij}} = \mathbf{m^{ij}} + \mathbf{S}/W$.

Repeat 3. and 4. with decreasing the size of neighbors Sn for pre-defined iterations.

For P-SOM, PCA analysis is important for organizing the pareto set of units in the initial stages of the learning because the pareto set of units for a input vector will be fragmentized for randomly initialized map.

Because the learning algorithm of P-SOM is not supervised, each unit on the map is labeled as categories by inverse pareto mapping from the unit to the training vectors for the application of classification problem. For classifying test vectors, the pareto optimal set of the units for the vector is searched and the category is determined by majority rule in the categories labeled to the units.

C. Supervised Pareto learning Self Organizing Map(SP-SOM)

%To improve the accuracy for classification, the Supervised learning of the categories is introduced to P-SOM.

Because P-SOM can organize any multi-modal vectors in a map, the supervised learning can be introduced by joining a vector which represent the category to the input vector. The new input vector for Supervised Pareto Learning SOM(SP-SOM) is

$$\acute{\mathbf{x}}^i = (\mathbf{x^i}, \mathbf{c^i}) \tag{9}$$

$$c^i_j = \begin{cases} 1 & \mathbf{x^i} \in C_j \\ 0 & otherwise \end{cases} \tag{10}$$

where C_j is j-th category. Learning algorithm of SP-SOM is same as that of P-SOM mentioned in the previous sub-section, but the labeling of the units is not necessary because information of the categories are already learned inside the vector associated to the units. The recalling algorithm for a test vector is as follows.

SP-SOM - recalling algorithm

1) Searching for the pareto set of units
   For given test vector $\mathbf{x^t}$, search for the pareto optimal set of the units $P = \{U^{ab}_p\}$.
2) Determination of the category
   Calculate

$$c^t_k = \sum^{m}_{U^{ij} \in P} c^{ij}_k \tag{11}$$

   where $m^{ij} = (\mathbf{x}^{ij}, \mathbf{c}^{ij})$. The category of $\mathbf{x^t}$ is C_l for $l = argmax_k(c^t_k)$.

As shown in this algorithm, category for a test vector is determined by the sum of the classification vectors for pareto set of units.

D. Incremental learning of SP-SOM

%For the adaptation to the input vectors, incremental learning using the test vectors is introduced. Two types of incremental learning mode, supervised learning and unsupervised learning are considered depending on the condition of test data. For supervised learning, the vector for incremental learning is composed with the category vector described in the previous sub-section. For unsupervised learning, only the test vector is used for learning. The equation of the incremental learning is as follows.

$$\mathbf{m'_{ij}} = \mathbf{m'_{ij}} + \eta'(\mathbf{x'} - \mathbf{m'_{ij}}) \tag{12}$$

where $\mathbf{m'_{ij}}$ is the vector associated to $U_{ij} \in P$, P is the pareto optimal set for test vector $\mathbf{x}$, $\mathbf{x'} = (\mathbf{x}, \mathbf{c})$ for supervised learning, $\mathbf{x'} = \mathbf{x}$ for unsupervised learning, $\mathbf{c}$ is category vector of $\mathbf{x}$ and η' is learning rate for incremental learning. This equation is equivalent to the equation for updating the winner unit in SOM except the targets are the units in pareto set. From the other side of view, this equation is almost identical to LVQ updating equation(2) except that the supervised signal is embedded in the category vector.

III. Experimental Setting of Authentication using Keystroke Timings and Key Typing Sound

%vspace-4pt In this paper, we use the keystroke timings and key typing sounds as multi-modal behavior characteristics. We used a notebook PC and microphone fixed aside the keyboard for sampling the keystroke timings and key typing sounds(Fig.1). Fig.2 shows the sample of keystroke timings and key typing sounds. We used the phrase ”kirakira” for this experiment because this phrase was found as the suitable phrase to identify the japanese university student users using identical phrases for all users. For each key, the time pushing the key, the interval time between keys and the typing sounds are sampled. The intervals of keystroke timings are used as the feature vector for keystroke timings, thus the length of vector for keystroke timings is (2N-1)=15, where N is the

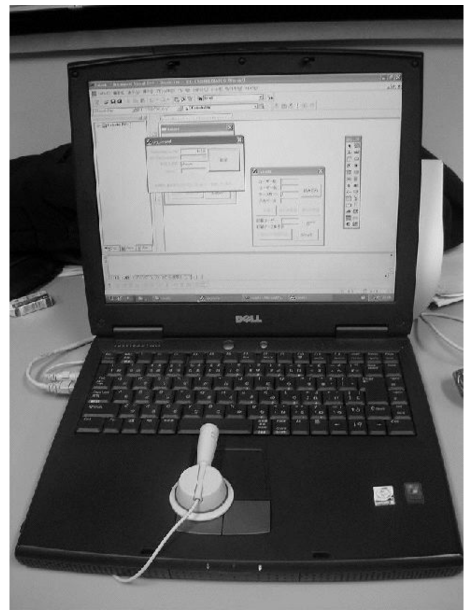

Fig. 1. Keystroke timings and key typing sounds

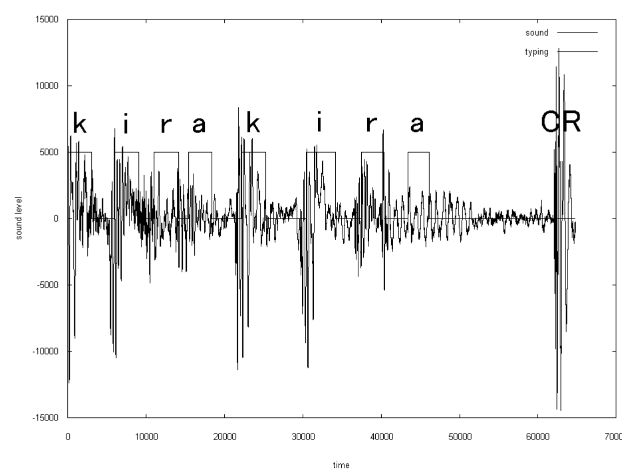

Fig. 2. Keystroke timings and key typing sounds

length of phrase. The key typing sounds are pre-processed to the maximum level of the sound for each key, thus the length of vector for key typing sounds is N=8.

In this experiment, we took ten samples of keystroke timings and key typing sounds from each of 10 users. In the authentication experiment, 5 of the samples for each user are used for learning the map, which means the registration of the biological characteristics to authentication system, and 5 remainders are used as the test data for authentication. All of the combinations of the learning data and test data are examined, so ${}_{10}C_5$ experiments are made. For the evaluation, we used the indexes FRR and FAR. FRR and FAR means the False Reject Rate and False Accept Rate respectively and the smaller values are more ideal for both indexes. FRR is the rate for the rejection of legal user and 1.0-FRR becomes the rate for successful authentication. FAR is the rate for acceptance of illegal user who should not be authenticated as the user.

IV. Authentication Experiments using SOM and MW-SOM

In this section, the experimental results for authentication using SOM and MW-SOM are mentioned. As mentioned before, the authentic method using SOM authenticate the user as the registered user labeled to the unit whose distance to the input data is the shortest to unit on map. But Multi-Winner method authenticate the user if the number of the units registered to the user from 1st to n-th high ranks according to the distance to input data is more than the pre-defined threshold k. At first, the map organized by SOM, which is used in both SOM and MW-SOM in authentication is shown in Fig.3 It can be visually confirmed that each user

08 08 01 01 01 01 01 01 01 06 06 06 06 08 08 08 04 04 04 04
08 08 01 01 01 01 01 01 01 06 06 06 06 08 08 08 04 04 04 04
08 08 08 07 07 07 01 01 01 06 06 06 06 06 08 08 04 05 05 05
08 08 08 07 07 07 07 07 01 06 06 06 06 06 08 08 00 05 05 05
09 09 07 07 07 07 07 07 07 06 06 06 06 06 02 02 05 05 05 00
09 09 07 07 07 07 07 07 07 10 10 06 06 02 02 02 02 05 05 05
09 09 07 04 07 07 07 07 10 10 10 03 03 03 02 02 02 05 05 05
09 09 09 04 07 07 07 10 10 10 10 03 03 03 03 02 02 05 05 05
09 09 09 07 07 10 10 10 10 10 03 03 03 03 02 02 02 02 02 05
09 09 09 09 07 10 10 10 10 10 03 03 03 03 02 02 02 02 02 01

Fig. 3. The map labeled with user-id organize by SOM

is organized in cluster on the map. Next, the authentication result is shown in Fig.4. In Fig.4, the Multi-Winner method denotes the MW-SOM. FRR and FAR are False Reject Rate and False Accept Rate respectively. For MW-SOM, the parameters are set as number of winners n=10 and threshold of authentication k=3 from the following result. In the practical use of authentication system, the noise or variation of the authentication input should be taken account. To emulate the noises, the random noises whose amplitudes are maximum 50% of original signal are mixed to the half number of the elements of each vectors and the authentication experiments are made with changing the threshold. Fig.5 shows the result. The crossing point of FRR and FAR, which is usually

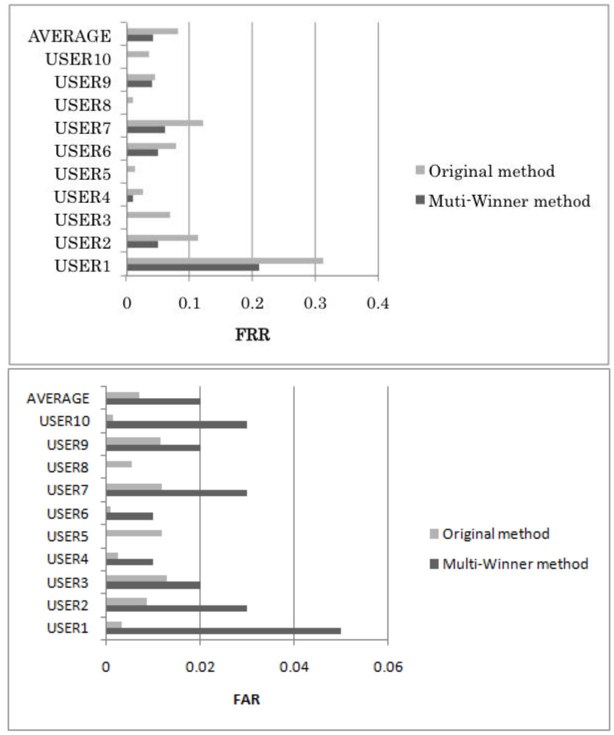

Fig. 4. Results of authentication experiments using SOM and MW-SOM

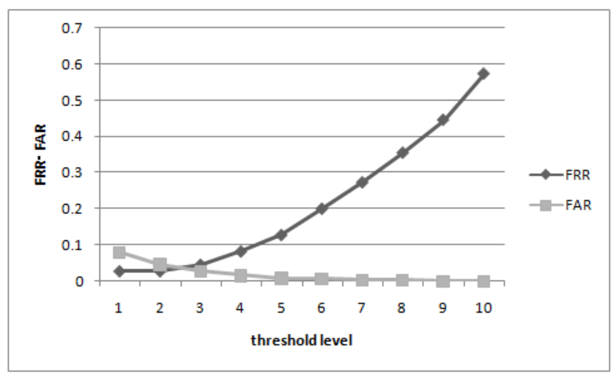

Fig. 5. FRR and FAR with changing threshold parameter for authentication

used as the parameter for authentication system, is found between 2 and 3. Therefore, k=3 is chosen in this experiment. This parameter is used in all experiments for MW-SOM. Comparing the original SOM and MW-SOM, the FRR is better for MW-SOM. On the other hand, FAR is better for original SOM. From the viewpoint of authentication systems, MW-SOM is more balanced with setting the parameter k, but original SOM, which does not have tunable parameters, slants to fail safe side which reject too much legal users.

Next, the adaptation to the temporal changes of the input vectors is examined. It will take too long time(some weeks or some months) to wait for the temporal changes of keystroke timings and key typing sound of real user. So, we made the artificially modified data for this experiments. In the following experiment, 4 out of 15 keystroke timings and 2 out of 8 key typing sounds in the input vector are selected randomly, multiplied by 0.9 and replaced with the value at each authentication test. Fig.6 and Fig.7 shows the results for original SOM and MW-SOM. Without re-learning, both

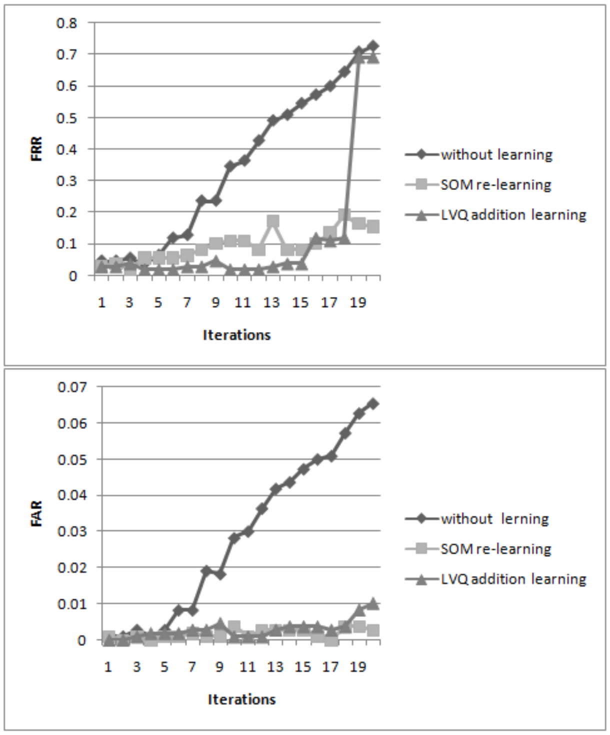

Fig. 6. FRR and FAR with temporal changes of input vectors using SOM

FRR and FAR become worse with iterations of authentications because input data is changing temporally. On the other hand, SOM re-learning method and LVQ addition learning method can keep FRR and FAR until 15 iterations. FRR for LVQ learning method is better in the first half of iterations, but it becomes worse suddenly in the last half. With checking the updated map, poorly characterized users are vanished by LVQ addition learnings and they can not be authenticated. Comparing the result of SOM and MW-SOM, MW-SOM, MW-SOM is more robust to the temporal changes even for the case of without-learning and FRR is kept small as specified by parameters for the case of re-learning method.

Next, the robustness to the variations of input vectors and noises are examined. The re-learning and LVQ learning contribute to adapt the temporal change of input vectors, but it may weaken the robustness because the input vectors with variations or noises are learned on the map. As is the case with previous experiments, we made artificially modified data. In the following experiments, 8 out of 15 keystroke timings and 4 out of 8 key typing sounds in the input vector are selected randomly and 50% random noises are added at each authentication test to the temporal changing input vector used in the previous experiments. Fig. 8 and Fig.9 show results. Using SOM、FRR becomes worse with iterations for the case of without learning and with LVQ learning. With re-learning, FRR becomes gradually worse, but it much better

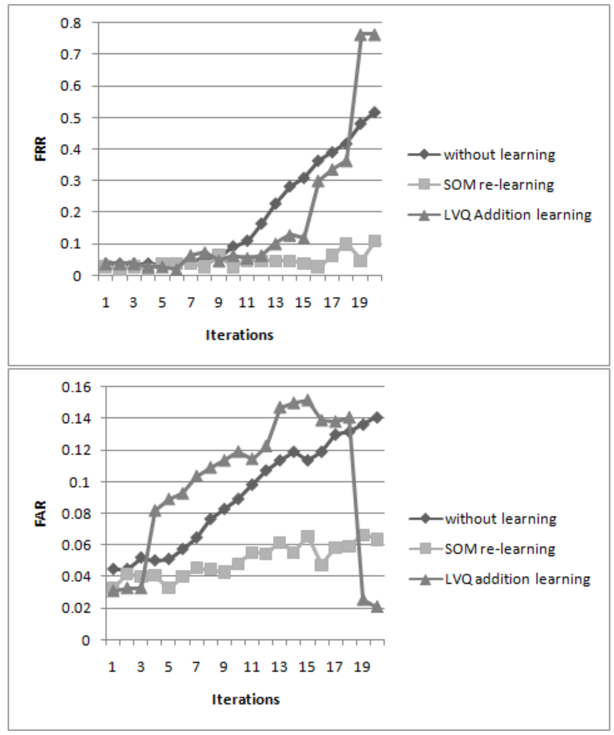

Fig. 7. FRR and FAR with temporal changes of input vectors using MW-SOM

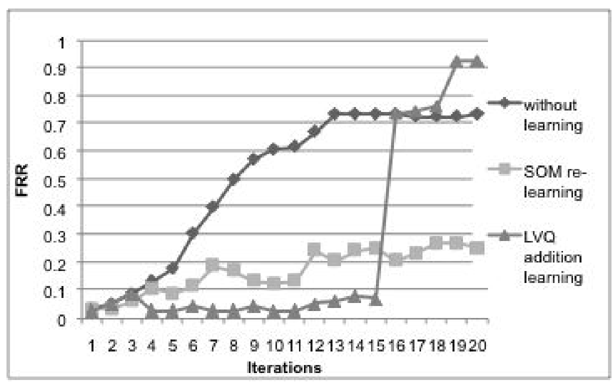

Fig. 8. FRR for temporal changing input vectors with noises using SOM

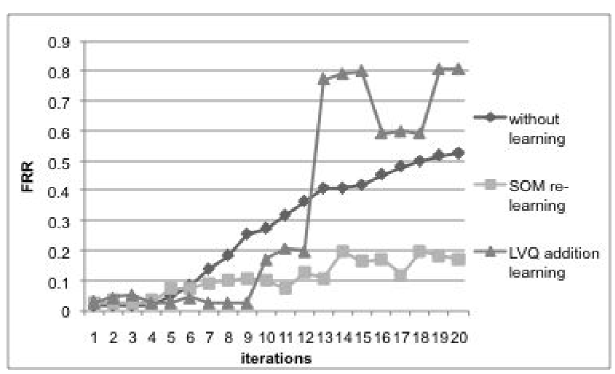

Fig. 9. FRR for temporal changing input vectors with noises using MW-SOM

than those of others. Using MW-SOM, FRR also becomes worse with iteration for case without learning and with LVQ learning. With re-learnig, FRR becomes worse slowly, and it is better than that using SOM. In this experiment, MW-SOM is more robust to the noises compared with SOM.

V. Authentication Experiments using SP-SOM

Next, we made experiments using SP-SOM At first. the map organized by using SP-SOM is shown in Fig.10. The

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

Fig. 10. Map labeled with user id organized by SP-SOM

size of the map is 16x16 and the iteration of the learning is 50 batch cycles for all input vectors. The resulting map is labeled by the user id which is associated to the largest category vector. The map is organized as the torus map, so the upper side and the left side of the map are connected to lower side and right side respectively. Fig.10 shows that each user id is clustered well on the map.

Next, we will show the result of authentication experiment. For the sake of comparison, the results of keystroke timing, those of key typing sounds and those of integration of the keystroke timings and key typing sounds are shown. For almost all users, the integrated method marks the best results. Averages among the user are 0.213, 0.386 and 0.108 for FRR of keystroke timings, key typing sounds and integration of both of them respectively and 0.213, 0.0363 and 0.0097 for FAR. In average, both of FRR and FAR are largely improved by integration.

Next, the effectiveness of the incremental learning is examined. At first, we introduced incremental learning during the authentication process in previous experiments. That is, for each authentication, the test data is learned on the map. Fig.12 shows the result. With incremental leaning, FRR of 8 users and FAR of all users are improved, but the average of FRR(=0.00895) is not so much improved. The reason why it was not so much improved is that the each test data is used only once for authentication. Thus, if the incremental learning is effective, the results will be improved by repeating the authentications and incremental learnings. Fig. 13 shows the average of FRR and FAR in 5 iterations. It is confirmed that incremental learning can improve FRR and FAR.

Next, the adaptation to the temporal changes of the input vectors is examined. In the following experiment, 4 out of 15 keystroke timings and 2 out of 8 key typing sounds in the input vector are selected randomly, multiplied by

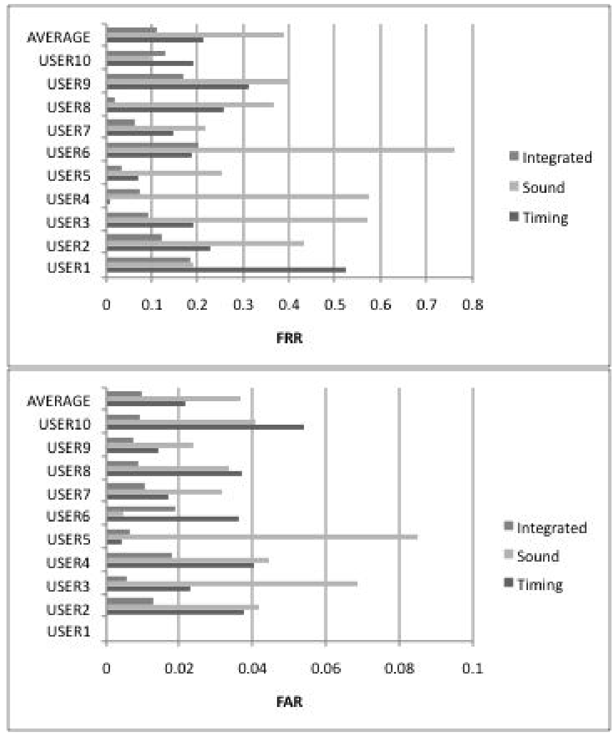

Fig. 11. FRR and FAR for keystroke timings, key typing sounds and integration of both of them using SP-SOM

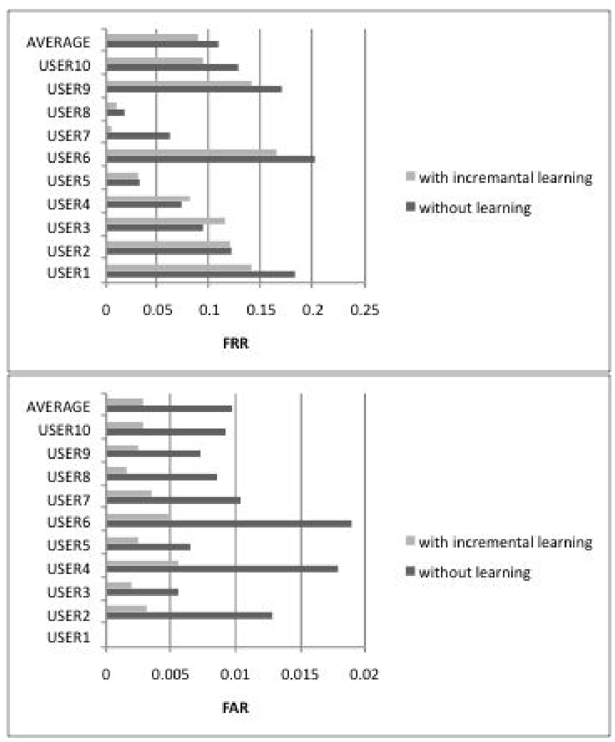

Fig. 12. Comparison of FRR and FAR concerning incremental learning using SP-SOM

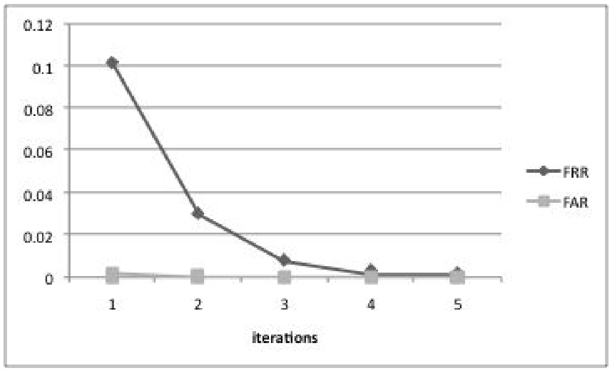

Fig. 13. Changes of FRR and FAR with incremental learning using SP-SOM

0.9 and replaced with the value before each authentication test. At the beginning of authentication tests all of the input vectors are learned by SP-SOM and the case that test vectors are not learned, the case test vector are learned by unsupervised learning and the case that test vectors are learned by supervised learning are compared. The tests are repeated 20 times. Fig.14 shows the result. Without

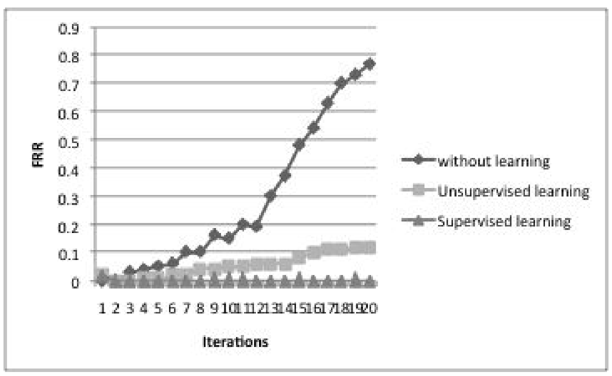

Fig. 14. Changes of FRR with temporal changes of input vectors using SP-SOM

incremental learning, FRR becomes worse with iterations. With unsupervised learning, FRR becomes slightly worse and with supervised learning FRR is kept almost 0 even if the input vectors are modified continuously. Considering the authentication system, the legal user for the input is known, so the supervised learning is available, so the authentication system can keep the high accuracy of authentication using incremental learning.

Next, the robustness to the variations of input vectors and noises are examined. In the following experiments, 8 out of 15 keystroke timings and 4 out of 8 key typing sounds in the input vector are selected randomly and 50% random noises are added at each authentication test. Fig.15 shows the result. The FRR is kept about 0.05 for the case without learning and with supervised learning. But, FRR becomes gradually worse for the case with unsupervised learning because unsupervised learning is affected by noises. As mentioned before, supervised learning is available for

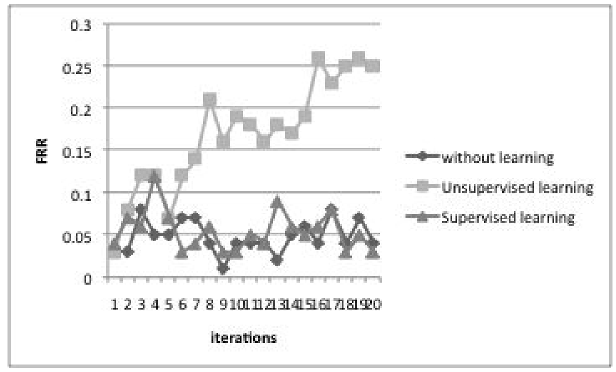

Fig. 15. Changes of FRR with the input vector with noise using SP-SOM

authentication system, so considering the noises or variation of input vectors, the incremental supervised learning should be used.

Next, both of the temporal change and noises are added to the input vector as shown in the Fig 8 and Fig 9 for SOM and MW-SOM. Fig.16 shows the result. For the case

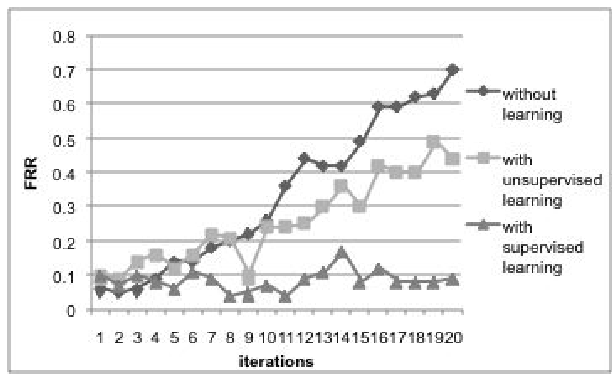

Fig. 16. Changes of FRR with temporal changing input vector with noise using SP-SOM

of without learning and with unsupervised learning, FRR becomes worse with iterations. On the other hand, FRR is kept about 10% for the case with supervised learning.

VI. Discussions

We made authentication experiments in same conditions using SOM, MW-SOM and SP-SOM. SOM shows good results for any conditions of temporal changes of inputs and input vectors with noises combined with re-learning method, but shows poor result combined with LVQ re-learning method. For the comparison with SP-SOM (SP-SOM is not affected small amplitude of temporal changes and noises), the large amplitudes of temporal changes and noises are added to the input vectors in this paper, we have already confirmed that SOM with LVQ learning method showed better result than that of re-learning method for smaller amplitudes of temporal changes and noises. Using MW-SOM, the authentication rates FRR and FAR can be tuned and the results of authentication experiments are better compared with SOM. But, FAR of MW-SOM is worse than that of SOM with selecting the threshold at cross point of FRR and FAR. As for the robustness, FRR is better for the case of without learning using MW-SOM, so MW-SOM itself is more robust for the noises than SOM. But, it should be mentioned that MW-SOM sometimes becomes unstable with re-learnings or with LVQ learnings. In some cases, the results of MW-SOM becomes much worse than those of SOM with re-learning and with LVQ learning. We must improve the re-learning and LVQ learning method for MW-SOM. As for SP-SOM, FRR and FAR without temporal changes and noises is almost same for those of SOM. Fig.17 shows the comparison of SOM, MW-SOM and SP-SOM using the input vector with temporal changes and with noises. FRR becomes better

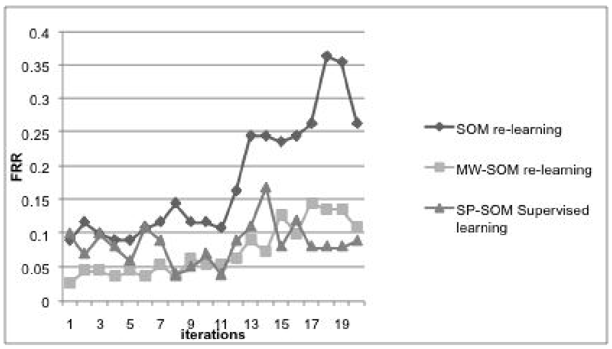

Fig. 17. Comparison of SOM, MW-SOM and SP-SOM for temporal changing input vector with noises

than or almost equal to that of MW-SOM with supervised incremental learnings for almost all cases. Furthermore, SP-SOM with incremental supervised learning is stable for all cases which are not shown in this paper in contrast to the unstability of WM-SOM.

VII. Conclusion

%vspace-4pt In this paper, we compare the integration methods of multi-modal biometric vectors using Self Organizing Maps(SOM), Multi-Winner Self Organizing Maps (MW-SOM) and Supervised Pareto Learning Self Organizing Map(SP-SOM) and their learning methods for the adaptation to the temporal changes of input vectors. The effectiveness of those methods are examined by the authentication experiments with keystroke timings and key typing sounds using the artificially modified data. From SOM, MW-SOM and MW-SOM SP-SOM with incremental supervised learning shows the best adaptation ability to the temporal changes and robustness to the noises.

As the feature work, SP-SOM and incremental learning method must be tested with another kind of multi-modal vectors. As for the authentication method this method must be tested more broadly with many examines.

References

[1] Fenghua Wang, Jiuqiang Han, Xianghua Yao, Iris Recognition Based on Multialgorithmic Fusion, *WSEAS TRANSACTIONS on INFORMATION SCIENCE & APPLICATIONS*, 12-4, pp.1416-1421,March(2007)

[2] F. Monrose and A.D. Rubin, Keystroke Dynamics as a Biometric for Authentication, *Future Generation Computer Systems*, (March, 2000).

[3] J. J. Brault and R. Plamondon, A Complexity Measure of Handwritten Curves: Modelling of Dynamic Signature Forgery, *IEEE Trans. Systems, Man and Cybernetics*, 23:pp.400-413(1993)

[4] L.C.F.Araujo, L,H,R,Sucupira,et.al, User Authentication Through Typing Biometrics Features, *IEEE TRANS. on Signal Processing*,Vol.53, No.2,pp.851-855(2005)

[5] H. Dozono and M. Nakakuni et.al, The Analysis of Pen Inputs of Handwritten Symbols using Self Organizing Maps and its Application to User Authentication, *Proc. of IJCNN2006*, pp.4884-4889(2006) %vspace-7pt

[6] H. Dozono and M. Nakakuni et.al, The Analysis of Key Stroke Timings using Self Organizing Maps and its Application to Authentication, *Proceedings of The 2006 International Conference on Security and Management*, pp.100-105(2006) %vspace-7pt

[7] S.Dokic,A.Kulesh,et.al, An Overview of Multi-modal Biometrics for Authentication, *Proceedings of The 2007 International Conference on Security and Management*, pp.39-44(2007) %vspace-7pt

[8] M. Nakakuni, H. Dozono,et.al, Application of Self Organizing Maps for the Integrated Authentication using Keystroke Timings and Handwritten Symbols, *WSEAS TRANSACTIONS on INFORMATION SCIENCE & APPLICATIONS*, 2-4:pp.413-420(2006) %vspace-7pt

[9] H. Dozono,M. Nakakuni,et.al, An Integration Method of Multi-Modal Biometrics Using Supervised Pareto Learning Self Organizing Maps. *Proc. of the Internal Joint Conference of Neural Networks 2008*, (2008) %vspace-7pt

[10] H. Dozono and M. Nakakuni et.al, The Analysis of Key Typing Sounds using Self Organizing Maps, *Proceedings of The 2007 International Conference on Security and Management*, pp.337-341(2007) %vspace-7pt

[11] C.C. LOY, C.P. LIM and W. K. LAI, Pressure-Based Typing Biometrics User Authentication Using the Fuzzy ARTMAP Neural Network, *Proceeding of the 12th International Conference on Neural Information Processing*, (2005) %vspace-7pt

[12] T. Kohonen, *Self Organizing Maps, Springer*, ISBN 3-540-67921-9 %vspace-7pt

[13] H. Dozono,et.al, Visual Reinforcement Learning Algorithm using Self Organizing Maps and Its Simulation in OpenGL Environment, *WSEAS TRANSACTIONS on INFORMATION SCIENCE & APPLICATIONS*, 5-5,:pp.685-694(2008) %vspace-7pt

[14] H. Dozono,M. Nakakuni,et.al, Application of Self Organizing Maps to User Authentication Using Combination of Key Stroke Timings and Pen Calligraphy, *Proceedings of the 5th WSEAS Int. Conf. on COMPUTATIONAL INTELLIGENCE*, pp.105-110(2006)