A Proposal of Adaboost Type TAM Network and Its Application to Sport Skill Analysis

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ABSTRACT

In this paper, we discuss sport technique evaluation of motion analysis modeled by TAM network as a kind of neural networks. We recorded continuous forehand strokes of each table tennis player into video frames, and analyzed the trajectory pattern of nine measurement markers attached at the body of players with the motion analysis model. We extracted input attributes and technique rules in order to classify the skill level of players of table tennis, i.e., expert player, middle level player and beginner. In addition, we analyzed movement of the markers in order to understand how to improve technique skill.

Keywords

Neural Networks, Sports Skill, Knowledge Extraction

1. INTRODUCTION

The Topographic Attentive Mapping (TAM) network [1,2] can date back to the early work of ARTMAP [3] family of models. The network structure consists of four layers: the feature layer, the basis layer, the category layer, and the class layer. A node in the basis layer combines the bottom-input signal propagated from the feature layer via excitatory synapses with the top-down feedback signal controlled from the output layer via inhibitory synapses. After presentation of training pattern, if the network makes inaccurate output, the attentional top-down signal modulates the synaptic weights in the class and basis layers with winner-take-all learning in order to minimize the difference between the network output and the desired output. At the same time, nodes are added incrementally to the category layer until the classification accuracy on the training set reaches a threshold level. However, the recognition rate could become lower since such addition of nodes may lead to overfitting of the training data. In order to address this problem, we propose a new TAM network which incorporated a model of ensemble learning. Ensemble learning models [4] are applied to the pattern classification problems. AdaBoost [5] is a remarkable boosting method [6] of ensemble models. AdaBoost consists of multiple weak classifiers which makes recognition rate high by assigning selection weight to misclassified data. The final output is calculated with majority rule as to evaluation data by the multiple weak classifiers.

On the other hand, in motor skill research for human, the movement skill is constituted by hierarchical cerebellum model with feedback and feedforward functions that can adapt itself to an environmental change [7]. Kawato [8] has proposed a control model of Allen-Tsukahara as internal model. When the difference exists in the desired trajectory and the realized trajectory of the movement, the difference signal is transmitted to purkinje cell of cerebellum and controls the movement output and the starting timing. Purkinje cell in cerebellum organizes forward model and inverse model for voluntary movement. We call the forward model and inverse model internal model. According to the interpretation for cerebellum, we propose to constitute an internal model of cerebellum as neural network through two kinds of processes, which are the bottom-up processing of signal flow to the integral representation of movement from the monofunctional layer, and the top-down processing of the adjustment to the monofunctional layer from external observation.

In this paper, we adopt TAM network as an internal model, and apply it to extraction of sport skill. In particular, we discuss how to acquire technique skill of the forehand stroke of table tennis [9, 10]. Perl [11] employed Kohonen Feature Map as a neural network for analysis of table tennis movement and estimate strategic structure of table tennis from analyzing the trajectory of ball. We extract skill rules and input attributes by multiple functions of TAM network. First, we selected several subjects who were expert table tennis players, middle level players and beginners. We recorded the trajectory pattern of their forehand strokes with a high-speed camera. Next, we constituted the observed data set from position coordinate and its speed of time-series data at nine measurement markers of their right upper arm, and then analyzed the data by TAM network to compare it with C4.5, Native Bayes Tree, and Random Forest. Using the

BICT 2014, December 01-03, Boston, United States

DOI 10.4108/icst.bict.2014.257882

TAM network, we extracted technique rules as fuzzy rules, and estimated necessary attributes from measurement markers of body to distinguish table tennis skill. However, the recognition rate by TAM network is not high enough because the data are partial. To get a solution of the problem, we applied Adaboost type TAM network to the skill data. As a result, we obtained the high recognition rate to classify table tennis skill.

2. INTERNAL MODEL FOR SPORTS SKILL ANALYSIS

Figure 1 shows the concept of internal model. When the difference exists in the desired trajectory and the realized trajectory of the movement, the difference signal is transmitted to purkinje cell of cerebellum and controls the movement output and the starting timing. The cerebellum structures forward model and inverse model for voluntary movement. We call the model internal model. The forward model assumes the movement signal as the input and assumes the movement trajectory as the output. The inverse model assumes the desired trajectory and the error signal the input of mossy fibers and the input of climbing fibers respectively, and assumes the movement signal the output. At a start of the movement, the feedback model is not able to control the trajectory movement smoothly. Gradually, the movement is controlled well, because the inverse model reduces the error between the desired trajectory and the realized trajectory by feedforward function.

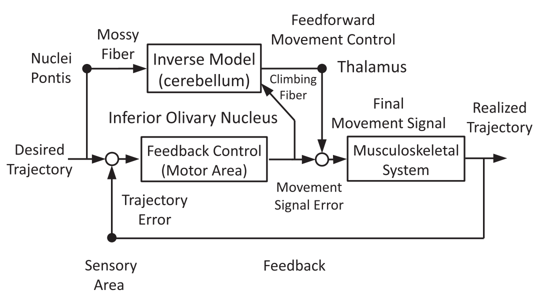

Figure 1: Structure of Internal Model

In the analysis of sport skill, the physical structure and the frame structure are usually used by the electromyography method, which records action potentials when muscular fibers are excited. Alternatevely, an observation method with measurement markers attached to the body to detect the coordinate position and speed of each was addopted.

In this paper, we discuss neural network as an internal model which consists of hierarchical internal structure with a monofunctional layer to generate the single function result and a meta layer that adapted itself to an environmental change. Using TAM network as a kind of internal model, we extract table tennis skill from the trajectory data of forehand strokes and coach's technique evaluation. Figure 2 shows the structure of the proposed structure model.

3. TAM NETWORK

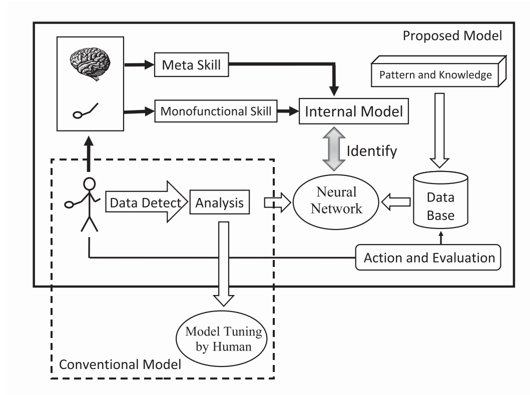

Figure 2: Proposed Structure Model

A Topographic Attentive Mapping (TAM) network is a biologically-inspired model, and consists of four layers: the feature layer, the basis layer, the category layer, and the class layer. If the network produces inaccurate output, the attentional top-down signal modulates the synaptic weight in the class and basis layers in order to minimize the difference between the output and the supervised data by a winner-takes-all algorithm. Simultaneously, a node is added to the category layer until the output accuracy is improved. The structure of the TAM network is shown in Figure 3.

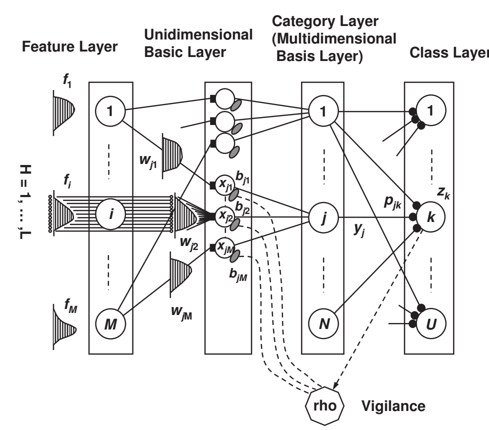

Figure 3: TAM Network

We assume that observation data of the R unit were given in M inputs and one output as data set D. The s-th data of the i-th input variable is denoted as v_{si}, $s = 1, 2, \cdots, R$, and the output data is represented by O_s.

Each data point is rank-ordered in the feature layer. In the i-th input feature, we sort the input data of the R unit in ascending order again, and the input data, I_{si}, is normalized. By way of input data I_{si}, the distributed data in the feature layer is provided as f_{sih}.

$$I_{si} = \frac{s-0.5}{R}, \qquad i = 1, 2, \cdots, M. \tag{1}$$

$$f_{sih} = \frac{exp[-0.5(LI_{si} - h + 0.5)^2]}{\sum_{h'=1}^{L} exp[-0.5(LI_{si} - h' + 0.5)^2]} \tag{2}$$

where L is the number of the discrete quantity of distributed input data, and h is the suffix, $h = 1, 2, \cdots, L$. We simplify by replacing f_{sih} by f_{ih} because we are only handling one data process in the processing algorithm at a time.

The activity value x_{ji} of each node of the unidimensional basis layer is calculated by the distributed synapse weight w_{jih} between the feature layer and the inhibitory synapse weight b_{ji} by the vigilance parameter ρ between the class layer. Output y_j from the category node to the class layer is calculated as follows:

$$y_j = \prod_{i=1}^{M} x_{ji} = \prod_{i=1}^{M} \frac{\sum_{h=1}^{L} f_{ih} w_{jih}}{1 + \rho^2 b_{ji}}. \tag{3}$$

In the class layer, the maximum value of each node output is adopted as the output of the TAM network.

$$K = \{k | \max_k z_k\} = \{k | \max_k \sum_{j=1}^{N} y_j p_{jk}\} \tag{4}$$

where $p_{jk},\ k = 1, 2, \cdots, U$ is the synapse weight between a class node and a category node.

Now, let K^* denote the "correct" supervised output. If the output K of the TAM network does not correspond with the supervised output class K^*, the "attention" mechanism is invoked, and the vigilance parameter ρ increases to the subject level of $z_{K^*}/z_K \geq OC$ or the maximal vigilance level $\rho^{(max)}$, where OC is the threshold.

If $z_{K^*}/z_K < OC$ then repeat
  (a) $\rho = \rho + \rho^{(step)}$
  (b) equation (1) *and* (2)
until either $z_{K^*}/z_K \geq OC$ or $\rho \geq \rho^{(max)}$.

If the vigilance parameter ρ reaches its maximum level, $\rho^{(max)}$, one new node is added to the category layer. However, if the constraint $z_{K^*}/z_K \geq OC$ is satisfied, weight adaptation occurs using a feedback signal, y_j^*, from the class layer to the category layer, computed as follows:

$$z_k^* = \begin{cases} 1 & ; \ \text{if } k = K^* \\ 0 & ; \ \text{otherwise} \end{cases} \tag{5}$$

$$y_j^* = \frac{\prod_{i=1}^{M} x_{ji} \times \sum_{k=1}^{U} z_k^* p_{jk}}{\sum_{j'=1}^{N} \prod_{i=1}^{M} x_{j'i} \times \sum_{k=1}^{U} z_k^* p_{j'k}} \tag{6}$$

The feedback signal is then used to govern learning:

$$\triangle b_{ji} = b_j^{(rate)} y_j^* (x_{ji} - b_{ji}) \tag{7}$$

$$\triangle p_{jk} = p_j^{(rate)} y_j^* (z_k^* - p_{jk})$$

$$\triangle w_{jih} = w_j^{(rate)} y_j^* (f_{ih} - w_{jih})$$

$$p_j^{(rate)} = \frac{\alpha}{\alpha + n_j} \tag{8}$$

$$w_j^{(rate)} = \frac{\alpha}{\alpha\beta(M) + n_j} \tag{9}$$

where

$$\beta(M) = \frac{\lambda^{1/M}}{1 - \lambda^{1/M}}, \qquad \lambda \in (0, 1) \tag{10}$$

$$\triangle n_j = \alpha y_j^* (1 - n_j) \tag{11}$$

and α, λ and $b_j^{(rate)}$ are constant parameters. Parameter $p_j^{(rate)}$ acts as the revision parameter in Simulated Annealing while $w_j^{(rate)}$ is the revised value of the bias $\beta(M)$ of the M dimensional inputs.

In the training phase, learning of w_{jih}, p_{jk} and b_{ji} proceeds upon presentation of each input datum. Each presentation of the whole training set is called and "epoch", and training consists of multiple epochs. When the learning is completed, the values of w_{jih}, p_{jk} and b_{ji} should be close to f_{ih}, z_k^* and x_{ji} respectively, due to winner-takes-all as well as adaptive learning [3].

4. APPLICATION OF TAM NETWORK TO SKILL ANALYSIS OF TABLE TENNIS

In the experiment, we selected fifteen students of Hannan University as subjects. Fifteen subjects are divided by three groups, i.e., seven subjects who belong to the table tennis club of Hannan University as expert players, three subjects who have belonged to table tennis club of junior high school or high school as middle-level players, and five subjects without experience of the table tennis as the beginners. We set nine measurement markers to detect movement on their right upper arm, which are 1)the acromioclavicular joint, 2)the acromion, 3)the head of radius, 4)the head of ulna, 5)the styloid process of radius, 6)the styloid process of ulna, 7)the right apex marker in the racket edge, 8)the left apex marker in the racket edge, and 9)the upper apex marker in the racket.

A pitching machine (Yamato table tennis Co., Ltd., TSP52050) were set at about $30cm$ distance from the end line of the table diagonally in the extended line of subject, and a ball was distributed to throw at elevation of 20 degrees, 25 speed levels, and 30 pace levels. The subject returns a ball which bounded in the $75cm$ inside from the end of the table to the opposite side in the forehand cross. For tracing the trajectory of subject's movement, we recorded subject's forehand strokes for $10min$ by a high-speed camera (Digimo Company, VCC-H300, resolution: $512 \times 512 pixel$, frame rate: $90fps$) placed in front $360cm$ of the subject and $130cm$ in height.

We extracted still images of 40 to 120 frames from video memory. In each frame image, we obtained two-dimensional (x, y) coordinate of nine measurement markers as the original position at the subject's shoulder of the first frame. As an example, we show the observation position of markers in Figure 4, and the speed of the horizontal direction (x) in Figure 5.

In these results, we should notice the following characteristics.

- By comparison with two expert players, the coordinates of positions from M_1 to M_9 were fitted close together for all of the players. The correlation coefficients were obtained as $x = 0.985$, $y = 0.790$. That means the expert players have acquired a common motion to swing the racket.

- From the data of the expert player, the speed of the moment hitting a ball was maximum at all measurement markers. They acquire a technique skill to be the maximum speed in the impact hitting a ball.

- By comparison with two middle level players, the coordinates of positions from M_1 to M_9 were partly fitted for the different players. The correlation coefficients were $x = 0.919, y = 0.607$. The middle level player acquires an expertise skill well, however their trajectory doesn't trace an oval smooth forehand drive.

- From the data of the middle level player, the speed of M_7 and M_9 becomes the two peaks form. We should notice that they have adjusted speed at the moment of the impact to hit a ball with the racket.

- By comparison with three beginners, the coordinates of positions from M_1 to M_9 were quite different for each player. The correlation coefficients were $x = 0.073, y = -0.04$. There is no category of the same technique pattern for beginners. The beginner shoulder(M_1) is moving in comparison with expert player and middle level player. In addition, the position coordinate of M_7 and M_9 is quite different in each player.

- From the speed data of M_3 to M_9 of beginner, they reduced the speed just before hitting a ball, and waited until the ball comes. It is so-called "a movement to meet a ball by racket". In addition, it is so-called "a movement to delay the body", that is to much movement of the shoulder and the elbow compared with the movement of racket. The speed at frames of M_1 and M_4 is detected, even if the speed of M_7 and M_9 at the same frame is zero.

- From the discussion about the minimum and the maximum value of the coordinate position of horizontal direction (x) at the first marker (M_1), the fourth marker (M_4), and the ninth marker (M_9), the expert player swings a racket compactly in the horizontal direction. The beginner swings big width in the horizontal direction.

We analyzed the data of two-dimensional (x, y) coordinate of nine markers by TAM network. However, the technique skill of the table tennis depends on the time-series of position coordinate. Therefore we constituted the data sets by adding five consecutive frames from the second frame to the sixth frame to each frame data. The output is skill evaluation of three classes of the expert player, the middle level player, and the beginner. As a result, a data set consists of ninety input variables and three classes as output because each measurement marker is two-dimensional.

The training data (TRD) consists of three kinds of players, i.e., two expert players who are selected from three expert players, two middle level players, and two beginners who are selected from four beginners, and the checking data (CHD) is constituted with one expert player and one beginner. The result is strongly depending on which kind of data is used for learning or evaluation data. Therefore, for the beginner, we calculated the correlation coefficient of the position coordinate at each marker, and constituted a data set D which included high two subjects of the correlation coefficient among four beginners in TRD and CHD, respectively.

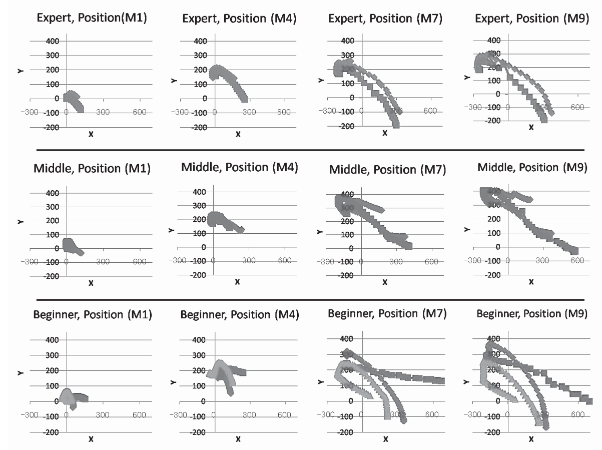

Figure 4: Position of Markers

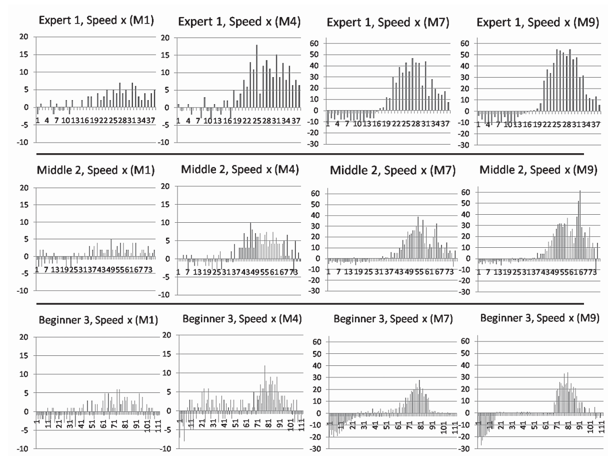

Figure 5: Speed of Markers

The recognition rate of TRD was 53.7%, and the recognition rate of CHD was 57.5%. This is a reason there is a difference in the number of the observation data of each class. Therefore, for data set D, we constituted the data sets by adding five consecutive frames from the first frame to the fifth frame to each frame data, and we let the number of data set increase by the adding data. The result is shown in Table 1. TAM(D) means recognition rate of data set D, and TAM($D+$) shows recognition rate of the revised data set D by adding data. Simultaneously, we show recognition rates of C4.5, Native Bayes Tree(NBT), Random Forest(RF) for comparing TAM network with their data mining methods for data set D.

We should notice that the recognition rate of TAM network as to the data set $D+$ improved than D. On the other hand, the recognition rate of NBT and RF as to TRD is 100%, but we should indicate that it is too much overlearning for TRD because the recognition rate as to CHD is extremely low. The C4.5 showed good recognition results as

Table 1: Recognition Rate of Revised Data Sets

	Recoginiton Rate(%)		
	TRD	CHD	Ave.
TAM(D+)	61.2	43.0	52.1
TAM(D)	53.7	57.5	55.6
C4.5	98.1	43.3	70.7
NBT	100.0	32.8	66.4
RF	100.0	25.4	62.7

to TRD and CHD compared with others. Therefore, the recognition rate of the TAM network as to $D+$ showed good result as same as level with C4.5.

Next, we analyzed the sensitivity of characteristic of the markers. We discussed the priority of markers for 18 inputs (90 inputs by adding data) of nine markers as to the data set $D+$. As a method, we get a couple of two markers as a set of four inputs, and we temporarily remove four inputs (20 inputs) from 18 inputs (90 input variables) for comparing recognition rates in each couples. If the recognition rate by removing a set of inputs is the lowest, then that set of input variables included important markers. That is, the recognition rate decreased the most by removing the markers. The result of recognition rate by removing markers is shown in Table 2. We show that the average recognition rate is 10 times of TRD. When M_1 and M_2 were temporarily removed, the recognition rate of TAM network decreased to 42.9% from 61.2% and the recognition rate was the lowest. Therefore, we concluded that the most important markers were M_1 and M_2. By the same procedure, the important inputs were obtained in order of $M_1, M_2 \rightarrow M_7, M_8, M_9 \rightarrow M_5, M_6 \rightarrow M_3, M_4$. We should notice that the recognition rate was conversely increasing when M_5, M_6 and M_3, M_4 were removed.

Table 2: Sensitivity of Input Variables

Number of Input Var.	Omitted Input Var. and R.R.(%)				Selected Input Variables
	M_1, M_2	M_3, M_4	M_5, M_6	M_7-M_9	
18	-	-	-	-	-
12-14	42.9	57.4	51.1	48.2	M_1, M_2
8-10	-	45.9	48.4	41.6	M_7 - M_9
4	-	42.9	42.0	-	M_5, M_6
-	-	-	-	-	M_3, M_4

From these results, the important items to judge the level of players show firstly 1)the acromioclavicular joint and 2)the acromion, and secondly the markers of 7) to 9) in the racket. The result is consistent with the conclusions of analysis in Figure 4 and Figure 5.

Lastly we extracted the table tennis skill as fuzzy rule. The TAM network consists of four layers of hierarchical structure. The layers of feature and basic level represent the monofunctional mechanism, and the layers of category and class level represent the meta concept. Using the structure of TAM network, we can extract the relationship between the monofunctional skill and the meta skill with fuzzy rule.

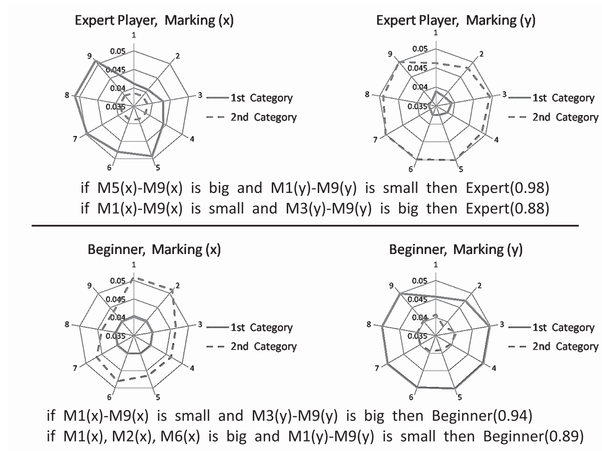

Figure 6: Rules of Table Tennis Skill

We selected first the J-th category node where p_{jk} became the maximum at each class node as to the data set $D+$, and we calculated w_{Ji} of the J-th category node for each input as follows;

$$w_{Ji} = \frac{\sum_{h=1}^{L} w_{Jih}}{L}, \quad for \ \forall i \tag{12}$$

$$J = \{j | \max_{j} p_{jk}, \ \ k = 1, 2, 3\}. \tag{13}$$

The set of linkages represents fuzzy rule when we extract linkages where w_{Ji} represents maximum for each player. We show an example of fuzzy rules in Figure 6. The figures represent fuzzy rules of expert player and beginner. As a result, we could extract the table tennis skill as fuzzy rule format.

5. ADABOOST TYPE TAM NETWORK

The recognition rate of TAM network is better than data mining methods. However we should mention that the recognition rate is not as high as desired. Therefore, we applied Adaboost algorithm which is a kind of ensemble learning models to TAM network, and improve the recognition rate of TAM network. AdaBoost [5,6] is an outstanding boosting method. In each iteration of steps in the Adaboost algorithm we select TRD from the set of misclassified data with higher weights than 50%, and then apply these data to a weak classifier in the consecutive iteration. After the weak classifier is identified, the weights of the data are updated. Until the iteration number becomes equal to the defined times, or while the current recognition rate of CHD is higher than previous recognition rate, the procedure is repeated continually. The joint output is calculated by majority rule decision of the multiple weak classifiers $M_1, M_2, \cdots, M_i, \cdots, M_L$ when CHD is given to these models.

We constituted data set first so that the number of the data of each data set becomes same by adding data. By adjusting, the number of expert players in TRD of the data set $D{++}$ became 78, the number of middle level players became 73, and the number of beginner became 98. On the other hand, as to CHD of data set D++, the numbers of expert players and beginner were 54 and 40 respectively. The recognition rate of TRD was 61.2%, and the recognition rate of CHD was 43.0%. The recognition rate is the average of 10 times experiments. For the data set D++, we constructed three kinds of data group for the data set D++ because Adaboost is the identification method of two classes. That is that the data set D++ was divided to three groups with two classes, i.e., D_1 which includes the beginners and others, D_2 which includes the middle level players and others, and D_3 which is the expert players and others. These data sets were analyzed by the Adaboost type TAM network with $epoch = 3$, $\alpha = 0.0000001$, $\lambda = 0.33$.

Table 3: Recognition Rate by Adaboost Type TAM Network

	TRD				
	TAM	Adaboost Type TAM Network			
	Network	M_1	M_2	M_3	Ave.
D_1	67.0	67.0	70.2	75.0	70.7
D_2	71.0	71.0	74.0	80.6	75.2
D_3	70.0	70.0	72.7	77.5	73.4
Ave.	69.3	69.3	72.3	77.7	73.1

	CHD					
	TAM	Adaboost Type TAM Network				
	Network	M_1	M_2	M_3	Ave.	Majority Result
D_1	58.5	58.5	64.6	(56.9)	61.6	58.5
D_2	58.0	58.0	69.0	(42.0)	63.5	69.0
D_3	58.0	58.0	69.0	(42.0)	63.5	69.0
Ave.	58.2	58.2	67.5	47.0	62.9	65.5

The results are summarized in Table 3. We show that the average recognition rate is 10 times of the data sets. As to TRD of the data set D_1, Adaboost algorithm was repeated three times, and 149 data were selected as misclassified TRD at the first step of algorithm, and 42 data were selected as misclassified TRD at the second step. In the same way as to the data set D_2, 149 data were selected as the misclassified TRD in the first step of algorithm, and 44 data were selected as the misclassified TRD in the second step. As to the data set D_3, 149 data were selected as the misclassified TRD in the first step, and 42 data were selected as the misclassified TRD in the second step. As these result, the average recognition rate of Adaboost type TAM network for TRD was improved to 73.1%, which is better than 69.3% of the TAM network. As to CHD, the recognition rate of Adaboost type TAM network became 65.5% whereas the recognition rate of the TAM network was 58.2%. As a result, we should notice that Adaboost type TAM network is better than normal TAM network because a significant difference was $p = 0.014396414$ compared with the t-test with significance level 0.05%.

6. CONCLUSION

In this paper, we analyzed the data set of the forehand strokes of table tennis with TAM network and Adaboost type TAM network, and we extracted technique skill of forehand stroke depending on player level. In the near future, we should explore the structure of the internal model which has the monofunctional skill and the meta skill in order to better understand how to improve techniques of table tennis for players who want to improve.

7. ACKNOWLEDGMENTS

This work was financially supported in the part by the Kansai University Expenditures for Support of Establishing Research Centers, "Construction of Bridge Diagnosis Scheme by Brain Recognition Robotics" 2013.

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