Extraction of Attributes and Knowledge Rules for Sport Skill by TAM Network

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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 skill in table tennis technique.**

I. Introduction

In motor skill research for human, the movement skill is constituted by hierarchical internal structure with feedback and feedforward functions that can adapt itself to an environmental change [1]. Kawato [2], [3] has proposed a control model of Allen-Tsukahara as internal model. When a motor signal is propagated to cerebellum, the desired trajectory is transmitted to musculoskeletal system from motor area via medulla spinalis. 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. 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. 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.

On the other hand, in the research of extraction of sport skill, physical structured model and frame structured model by movement analysis and physiologic measurement analysis have been proposed [4]–[6]. In the paper [4], Mochizuki defines skill reproduced on an artifact as “artificial skill”. They have proposed physical structured model with three-dimensional movement measurement technique by DLT(Direct Linear Transformation) method and estimate the mechanism of the most suitable throw movement of the pitcher of professional baseball. Kasai [5] applied the DLT method to forehand movement of table tennis, and observed the trajectory of stroke movement by three dimensional analysis. Miyaki [6] discussed experiential “use of motion-dependent forces” of forehand stroke of table tennis using movement analysis.

In this paper, we discuss the forehand stroke of table tennis as sport technique skill, and extract the skill by TAM network [7] modeled as an internal model without using physical structured model and frame structured model. Perl [8] 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. On the other hand, 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 TAM network, we obtained 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 propose a new TAM network which incorporated a model of ensemble learning. Ensemble learning models [9], [10] are applied to the pattern classification problems. AdaBoost [11], [12] is a remarkable boosting method [13] of ensemble models. AdaBoost consists of multiple weak classifiers which update recognition rate by assigning weight high degree to misclassified data. The final output is calculated with majority rule as to evaluation data by the multiple weak classifiers. Using the Adaboost type TAM network, we obtained the high recognition rate to classify table tennis skill.

II. Analysis of forehand stroke of table tennis

Figure 1 shows the concept of internal model. The cerebellum is composed with molecular layer, purkinje cell layer, and granule cells layer. When a motor signal is propagated

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to cerebellum, the desired trajectory is transmitted to musculoskeletal system from motor area via medulla spinalis. 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. Two kinds of input signals are transmitted to cerebellum in mossy fibers and climbing fibers, and the cerebellum structures forward model and inverse model for voluntary movement. We call the forward model and inverse 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. However, the movement is controlled well gradually, because the inverse model can reduce an error between the desired trajectory and the realized trajectory by feedforward function.

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 (x, y) 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. We have already developed TAM network as a classifier model. SVM and SOM are used for as classifier models of neural network well, but we have reported that TAM network is useful when there exist only few learning data [7]. Therefore, 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.

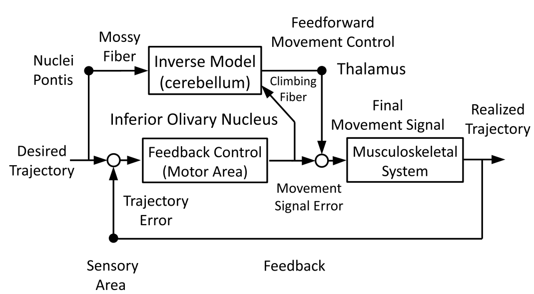

Fig. 1. Structure of Internal Model

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

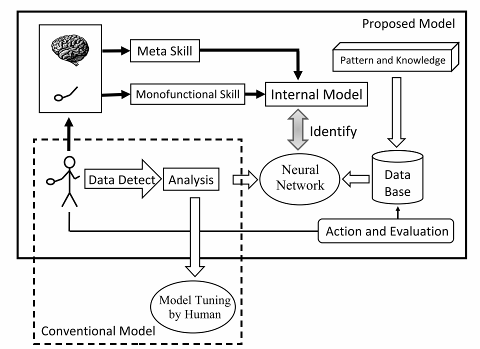

Fig. 2. Proposed Structure Model

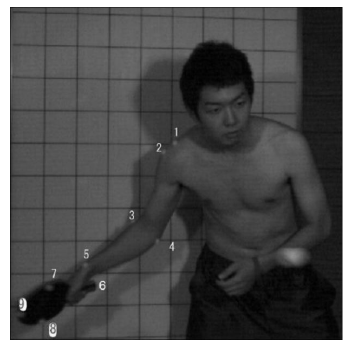

Fig. 3. Mesurement Markers

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. Figure 3 shows nine measurement markers.

A pitching machine (Yamato table tennis Co., Ltd., TSP52050) were set at about cm 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 cm 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 min by a high-speed camera (Digimo Company, VCC-H300, resolution: $\times$ $pixel$, 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 addition, we show 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) in Table I.

TABLE I. MIN AND MAX POSITION OF X-DIRECTION OF MARKERS

	M_1		M_4		M_9	
	Min	Max	Min	Max	Min	Max
Expert	-3	114	-29	254	-267	372
Middle	-10	116	-25	236	-218	577
Beginner	-33	152	-50	239	-214	697

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 . , y . . 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 . , y . . 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 . , y $-$ . . 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 Table I, the expert player swings a racket compactly in the horizontal direction. The beginner swings big width in the horizontal direction.

III. ANALYSIS BY TAM NETWORK

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

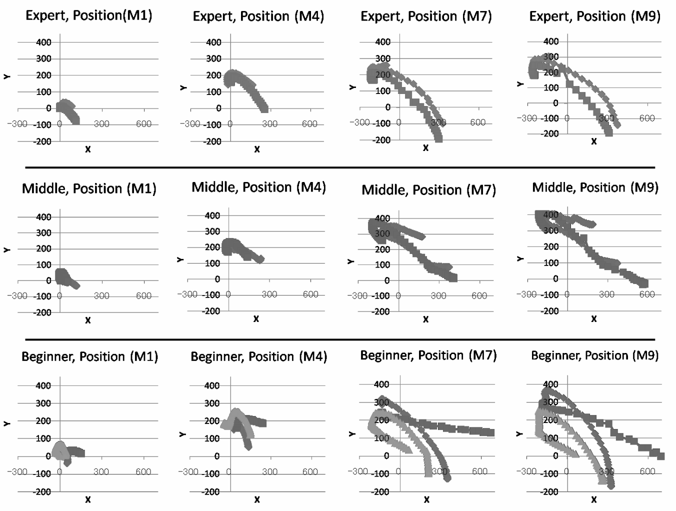

Fig. 4. Position of Markers

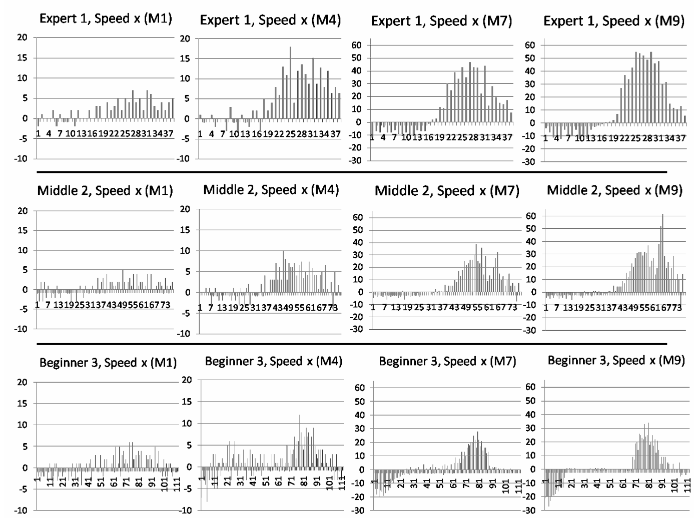

Fig. 5. Speed of Markers

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 6.

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:

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

In the class layer, the maximum value of each node output

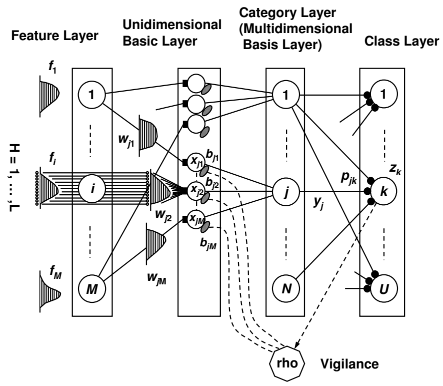

Fig. 6. TAM Network

is adopted as the output of the TAM network.

$$K \quad \{k|\,\mathrm{ma}_{k}\ z_k\} \quad \{k|\,\mathrm{ma}_{k} \sum_{j=1}^{N} y_j p_{jk}\} \tag{2}$$

where $p_{jk},\ k \quad ,\ ,\cdots,U$ 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 $z_{K^*}/z_K < OC$ th n r at
$a \quad \rho \quad \rho \quad \rho^{(step)}$
b quati n and
unti ith r $z_{K^*}/z_K \geq OC$ r $\rho \geq \rho^{(max)}$.

When the vigilance parameter ρ reaches its maximum level $\rho^{(max)}$, one new node is added to the category layer. When the condition of $z_{K^*}/z_K \geq OC$ is satisfied in the interactive processing, the learning process of synapses is started and learning parameters of w_{jih}, p_{jk} and b_{ji} are updated.

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.

Since the data set of the players included loss data, therefore, 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 three kinds of data sets, i.e., a data set A which included high two subjects of the correlation coefficient among four beginners in TRD and CHD, respectively, and the data set B and C which assigned high two subjects of the correlation coefficient among four beginners to TRD. For the expert player, we assign high two subjects of the correlation coefficient as to TRD, and select one subject as to CHD.

TABLE II. RECOGNITION RATE OF DATA SETS

	Recognition Rate(%)		
	TRD	CHD	Ave.
Data Set A	53.7	57.5	55.6
Data Set B	56.9	43.3	50.2
Data Set C	55.2	42.3	48.8

The result of TAM network is shown in Table II. In each data set, the recognition rate of TRD and CHD is not so high. This is a reason there is a difference in the number of the observation data of each class. Therefore, for data set A, 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 III. TAM(A) means recognition rate of data set A, and TAM(A+) shows recognition rate of the revised data set A 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 A.

TABLE III. RECOGNITION RATE OF REVISED DATA SETS

	Recoginiton Rate(%)		
	TRD	CHD	Ave.
TAM(A+)	61.2	43.0	52.1
TAM(A)	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

We should notice that the recognition rate of TAM network as to the data set A+ improved than A. 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 to TRD and CHD compared with others. Therefore, the recognition rate of the TAM network as to A+ 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 A+. 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 IV. 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 . % from . % 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 IV. SENSITIVITY OF INPUT VARIABLES

Number of Input Var.	Omitted Input Var. and Recognition Rate(%) M_1, M_2	M_3, M_4	M_5, M_6	M_7-M_9	Selected Input Variables
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

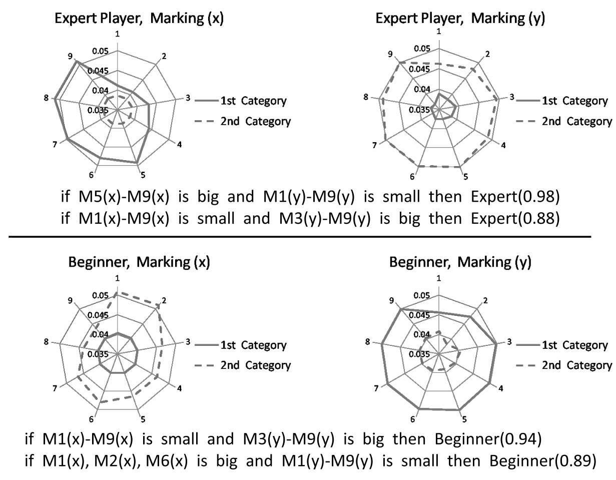

Fig. 7. Rules of Table Tennis Skill

To show the priority of markers, we define the importance of the i-th inputs as the following P_i.

$$P_i \quad \frac{R_i - R_{i-1}}{\sum_i |R_i - R_{i-1}|} \tag{3}$$

where, the recognition rate of the i-th input variable is expressed by R_i. From the result of Table IV, we obtained P_{M_1,M_2} . , $P_{M_7-M_9}$. , P_{M_5,M_6} $-$. , P_{M_3,M_4} $-$ . . Since P_i means the ratio of the deviation rate of recognition in all deviations, it means that we can distinguish the skill level between players when P_i was positive, and we can't distinguish it when P_i was negative.

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.

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

$$w_{Ji} \quad \frac{\sum_{h=1}^{L} w_{Jih}}{L}, \quad for \ \forall i \tag{4}$$

$$J \quad \{j | \max_{j} \ p_{jk}, \ k \quad , \ , \ \}. \tag{5}$$

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 7. The figures represent fuzzy rules of expert player and beginner. As a result, we could extract the table tennis skill as fuzzy rule format.

IV. ANALYSIS BY 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 [11], [12] 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 %, 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 A++ became 78, the number of middle level players became 73, and the number of beginner became 98. As to the data set B++, the number of expert players became 78, the middle level players became 73, and the beginner became 94. In addition, as to TRD of data set C++, the number of expert players, middle level players, and beginner became 78, 73 and 95 respectively. On the other hand, as to CHD of data set A++, the numbers of expert players and beginner were 54 and 40 respectively. The numbers of CHD of data set B++ were 27 for the expert player and 23 for the beginner respectively. As to CHD of data set C++, the numbers of expert players and beginner were 27 and 20 respectively. The result was shown in Table V. The recognition rate is the average of 10 times experiments.

We calculated recognition rate by Adaboost type TAM network for data set A++ in Table V. However, we constructed three kinds of data group for the data set A++ because Adaboost is the identification method of two classes. That is that the data set A++ was divided to three groups with two classes, i.e., D_1 which includes the beginners and others, D_2

TABLE V. DATA SETS FOR ADABOOST TYPE TAM NETWORK

	Recognition Rate(%)		
	TRD	CHD	Ave.
Data Set A++	61.2	43.0	52.1
Data Set B++	59.1	37.4	48.3
Data Set C++	59.1	42.0	50.6

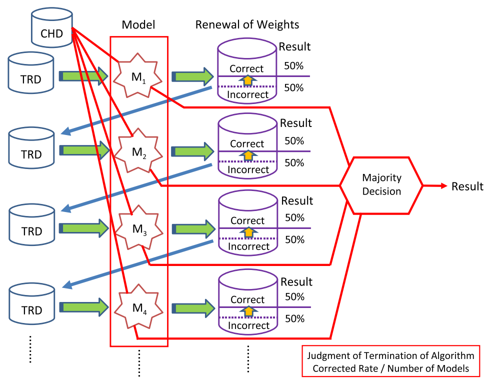

Fig. 8. Conceptual Diagram of AdaBoost

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 $epoch$, α . , λ . .

TABLE VI. RECOGNITION RATE OF ADABOOST TYPE TAM NETWORK

	TRD				
	TAM Network	Adaboost Type TAM 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 Network	Adaboost Type TAM 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 VI. 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 . %, which is better than . % of the TAM network. As to CHD, the recognition rate of Adaboost type TAM network became . % whereas the recognition rate of the TAM network was . %. As a result, we should notice that Adaboost type TAM network is better than normal TAM network because a significant difference was p . compared with the t-test with significance level . %.

V. 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.

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