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Sport Skill Analysis with Time Series Data

Toshiyuki MAEDA[1], Masanori FUJII[1], Isao HAYASHI[2], and Masumi YAJIMA[3]

[1] Faculty of Management Information, Hannan University,
5-4-33 Amami-higashi, Matsubara-shi, Osaka 580-8502, Japan
{maechan,fujii}@hannan-u.ac.jp

[2] Faculty of Informatics, Kansai University,
2-1-1 Ryozenji-cho, Takatsuki-shi, Osaka 569-1095, Japan
ihaya@cbii.kutc.kansai-u.ac.jp

[3] Faculty of Economics, Meikai University,
1 Akemi, Urayasu-shi, Chiba 279-8550, Japan
myajima@meikai.ac.jp

Abstract— ***We present sport skill data analysis with time series data from motion pictures, focused on table tennis. We use neither body nor skeleton model, but use only hi-speed motion pictures, from which time series data are obtained and analyzed using data mining methods such as C4.5 and so on. We identify internal models for technical skills as evaluation skillfulness for forehand stroke of table tennis, and discuss mono and meta-functional skills for improving skills.***

Keywords**:** Time Series Data, Sport Skill, Data Mining, Motion Picture, Knowledge Acquisition

I. Introduction

As for human action and skill, internal structure of technical skill is layered with mono-functional skill which is generated by human intention, and meta-functional skill which is adjusted with environmental variation [15, 10]. Matsumoto et al. discuss that highly skilled workers in companies have internal models of the layered skill structures and they select an action process from internal models in compliance with situations [10].

It is even difficult, however, for skilled workers to understand internal models completely by themselves. They usually observe objectively their own represented actions, and achieve highly technical skills with internal models. High level skill is emerged with refinement of internal models, where some processes are smoothly collaborated such as bottom-up process from mono-functional skill into meta-functional skill, and as top-down process of arrangement from represented actions into mono and meta-functional skills [4]. On the contrary, in the field of sport skill analysis, many researches are based on body structure model and/or skeleton structure model introduced from action measurement or biomechatronical measurement [12, 5, 11]. In our research, we assume that forehand strokes[5,11] of table tennis play exemplifies sport action, and then identify internal models using data mining methods without body structure model nor skeleton structure model. We focus on technical skill of table tennis [8], and analyze forehand strokes from motion pictures. We evaluate those into three play levels as high/middle/low, and identify internal models using data mining methods [9].

II. Analysis for Table Tennis Forehand Strokes

In researches of sports motion analysis, [14] records excited active voltage of muscle fiber using on-body needle electromyography, and [13] uses marking observation method with on-body multiple marking points, where their objects are to clarify body structure and skeleton structure.

In our research, we assume that technical skills consist of internal models of layered structure as;

- Mono-functional skills corresponding to each body part, and
- Meta-functional skills as upper layer.

We thus identify internal models from observed motion picture data and skill evaluation with represented actions, without discussing body structure or skeleton structure. Figure 1 shows our system structure.

In this paper, we focus on table tennis among various sports, and analyze table tennis skills of forehand strokes from observed motion picture data and skill evaluation with represented actions.

A. Experiments

In our experiments, there are 15 subjects who are university male students. At first, we have recorded moving pictures of 15 subjects who are 7 high / 3 middle / 5 low-level university students. As skill evaluation of represented action, we classify as;

- Expert class: members of table tennis club at university,
- Intermediate class: student who used to be members of table tennis club at junior high or high school, and
- Novice class: inexperienced students.

Each player is marked 9 points on the right arm as;

1) Acromioclaviclar joint point,
2) Acromiale point,
3) Radiale,
4) Ulna point,

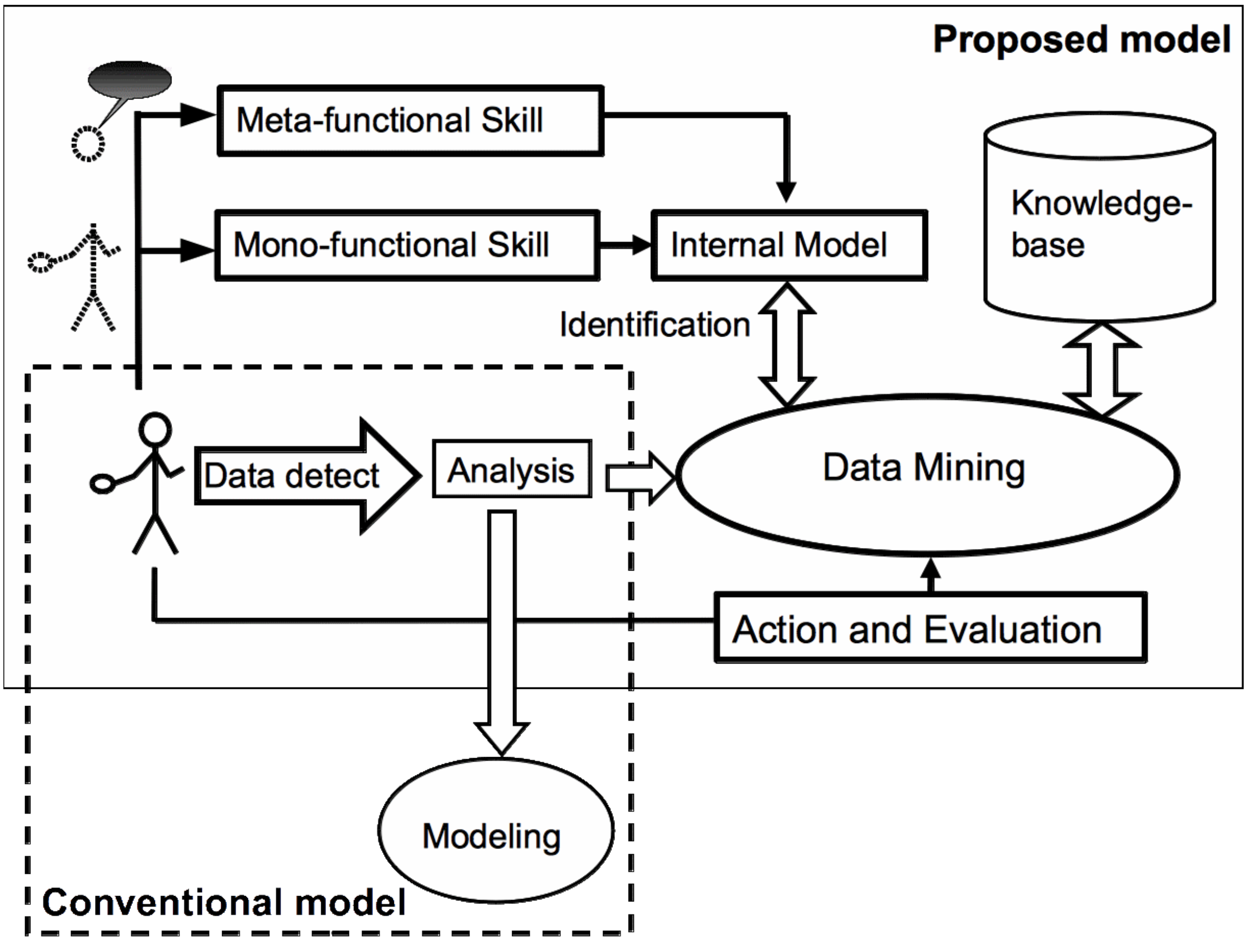

Figure 1. Concept models.

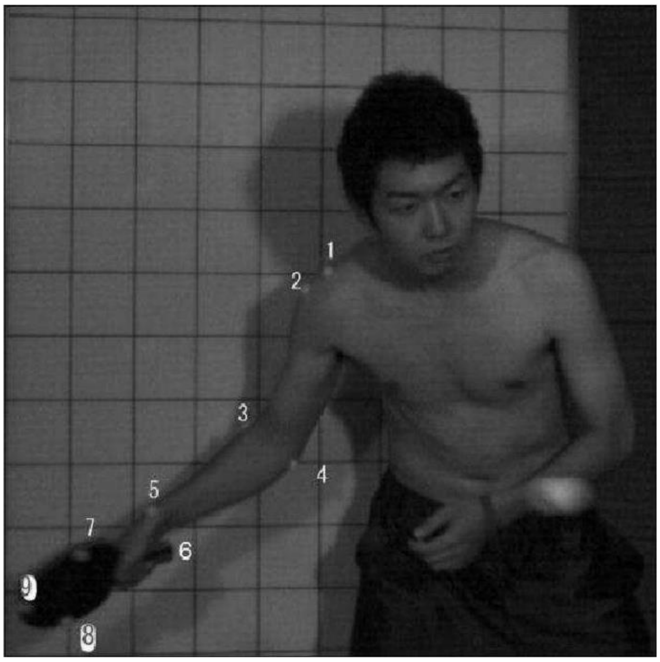

Figure 2. Measurement markings.

5) Stylion,
6) Stylion ulnae,
7) Inner side of racket,
8) Outer side of racket, and
9) Top of racket.

Figure 2 shows positions of marking settings. The ball delivery machine (TSP52050, YAMATO Table Tennis Inc.) is installed around 30 cm from the end line of the table on the extension of the diagonal line. Balls are delivered on 20-degree elevation angle, 25 of speed level, and 30 of pitch level at that machine. A subject player returns the delivered ball in fore-cross way, where the all is bounded 75 cm inside from the end line. We have recorded the moving traces of forehand strokes using a high-speed camcorder (VCC-H300 by Digimo Inc., resolution: 512 x 512 pixel and frame-rate: 90 fps) installed 130 cm tall and 360 cm ahead from the player. While returning the player in 10 minutes, several forehand strokes are recorded for each player (See Figure 3).

B. Position Data Analysis

From recorded motion pictures, 40 to 120 frames are retrieved from the beginning of take-back to the ball, until the end of the forehand stroke. After that, we have retrieved two-dimensional axes of 9 marking points for each frame, where the starting point is set to the shoulder position of the first frame. For instance, two-dimensional axes and horizontal speeds of markings for expert / intermediate / novice players are shown in Figure 4 and Figure 5.

Furthermore, Table 1 shows maximal and minimal values of the horizontal axes for the mark 1(M 1), mark 4(M 4), mark 9(M 9) in Figure 4.

Figure 4, Figure 5, and Table 1 imply as follows:

Figure 3. Pictures of a subject.

	*M*1		*M*4		*M*9	
	Min.	Max.	Min.	Max.	Min.	Max.
Expert	-3	114	-29	254	-267	372
Intermediate	-10	116	-25	236	-218	577
Novice	-33	152	-50	239	-214	697

Table 1. Min. and Max. positions of x-markings.

- Among expert players, there is high correlation for marking position of M 1 ~ M 9, where correlation coefficient are x = 0.985, y = 0.790. That indicates expert players have technical skills for same trajectory of swings. The trajectory, Moreover, looks less fluctuation, which indicates expert players swing more smoothly.
- Swing speeds of expert players show maximal at the impact of ball-racket contact for all marking points, and that implies they have learned the technical skill of max-speed impact.
- Marking positions of novice players have less correlations (correlation coefficient: x = 0.073, y = -0.04), especially position M 1 differs much from each novice player, and that indicates novice players tend to move shoulders. Furthermore, position axes for M 7 and M 9 differ for novice players and thus there is no swing trajectory. From those, there are many variations for swings for novice players.
- All results imply that expert or intermediate players can make some categorical groups for technical skills, but there seems not to be a category for novice players because of various individual technical skills.

III. Skill Class Identification Using Data Mining Techniques

A. Three-class identification

In our experiments, technical skills for table tennis depend on trajectories rather than axes of observed making points. The skill evaluation of represented action consists of three classes such as Expert, Intermediate, and Novice. Each marking position is represented two-dimensional and so the observed data are reconstructed into 90-input / 3-class output. As for expert players, data of two players, which have high correlation coefficient, are used as learning data, and the rest (one player) for the evaluation. For applying observed data of forehand strokes of 9 subject players, we reconstruct time series data from the original data. One datum is a set of 90-tuple numbers (9markings × 2axis(x, y) × 5frames), and each datum is overlapped with 3 frames data (from the third to the fifth frame) of the next datum for presenting linkage of each datum (See Fig 6).

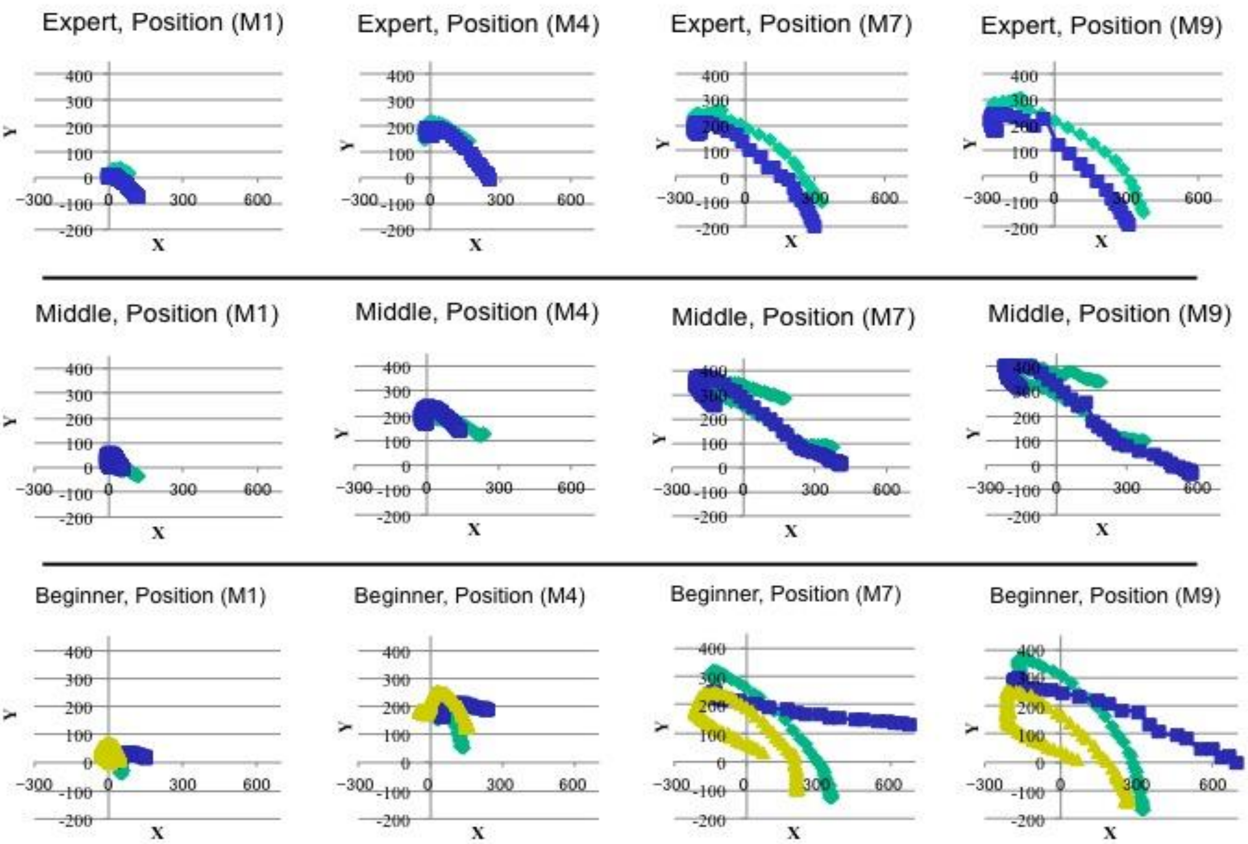

Figure 4. Position of markings.

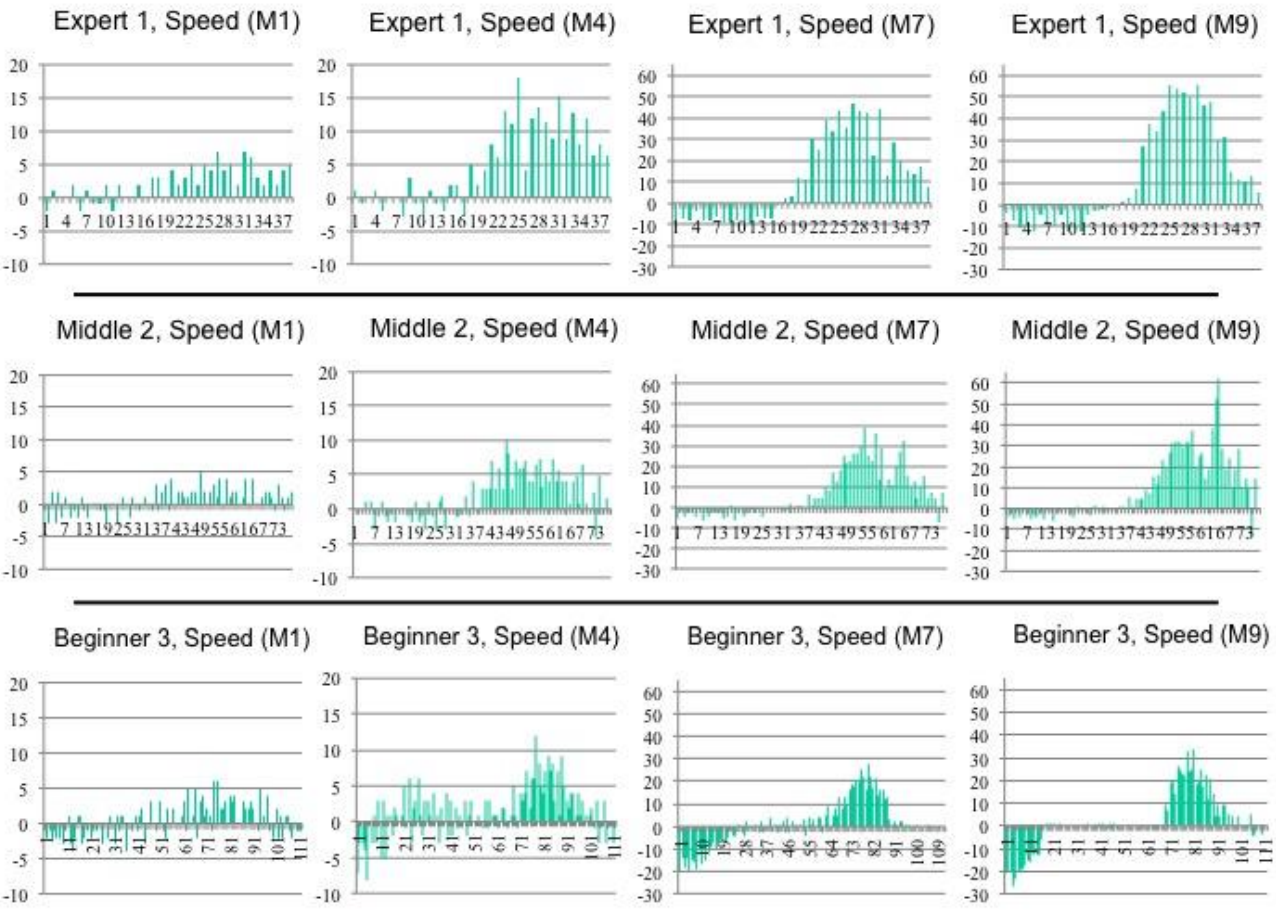

Figure 5. Speed of markings.

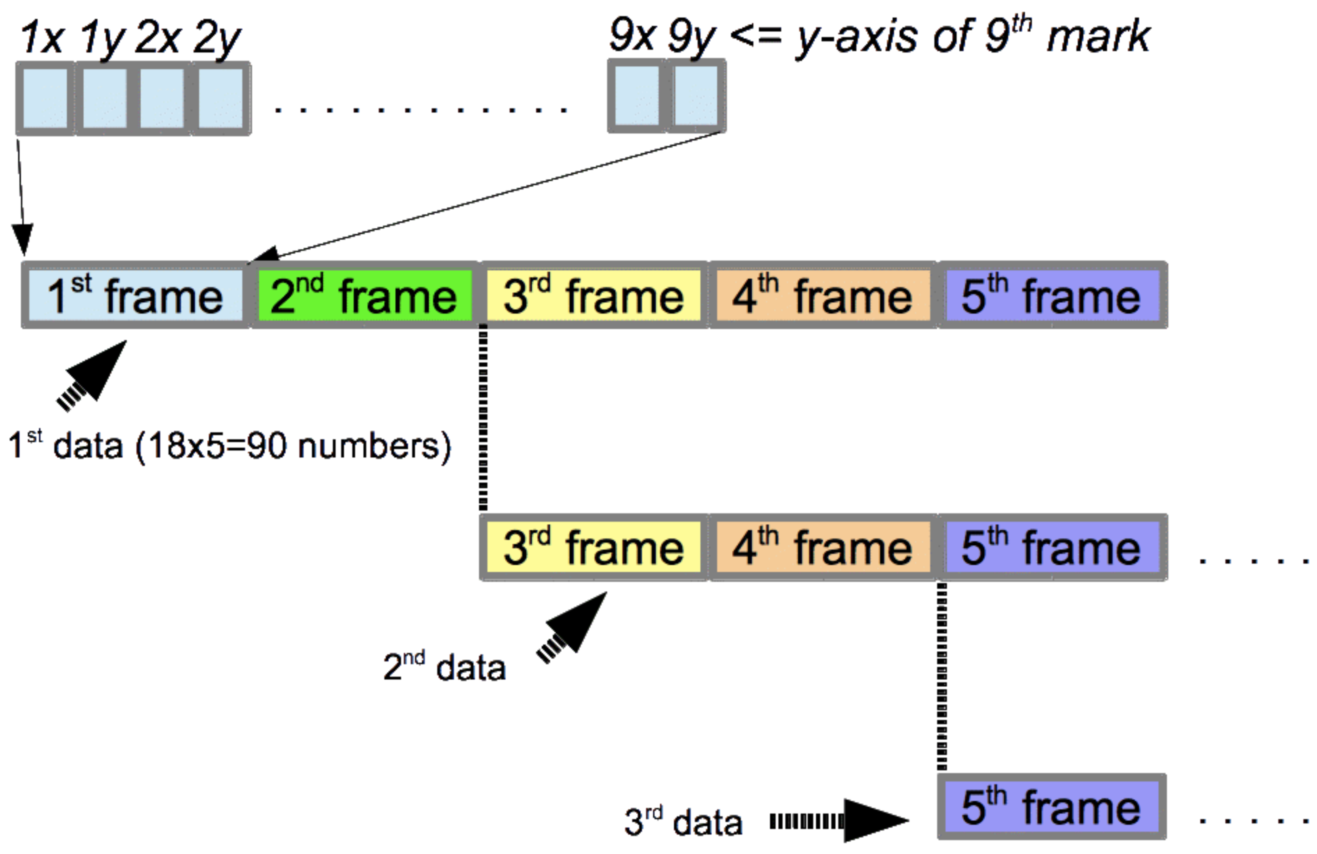

Figure 6. Data structure from isolated pictures.

	Recognition Rate(%)	
	Learning data	Evaluation data
C4.5	98.1	43.3
NBT	100.0	32.8
RF	100.0	25.4

Table 2. Recognition rate of modified data sets.

	Output class	Number of classes for learning data		
		Expert	Intermediate	Novice
C4.5	Expert	14	0	2
	Intermediate	2	0	23
	Novice	11	0	15
NBT	Expert	1	0	2
	Intermediate	14	0	17
	Novice	12	0	21
RF	Expert	6	0	4
	Intermediate	13	0	25
	Novice	8	0	11

Table 3. Discrimination of classes.

We use an integrated data-mining environment "weka" [19] and analyze the data by C4.5, Native Bayes Tree (NBT), Random Forest (RF). Table 2 shows the recognition rate of modified data sets. Table 3 also shows the discrimination of classes for each analyzing method for evaluation data.

In those results, recognition rates of NBT and RF for learning data are 100%, which may be over-learned. The rates for evaluation data are not so good, though C4.5 makes good results for both of learning and evaluation data. On the contrary, the result for the number of class recognition for each method in Table 3 implies that NBT and RF tend to recognize Expert as Intermediate as well as Novice as Intermediate, and furthermore, fail to evaluate Intermediate for Expert and Novice evaluation data. C4.5 recognizes

	Recognition Rate(%)	
	Learning data	Evaluation data
C4.5(Difference)	97.1	48.9
C4.5(Original)	98.1	43.3

Table 4. Recognition rate of differential data sets.

	Recognition Rate(%)		
	Cross Validation	Learning data	Evaluation data
C4.5	95.6	98.1	81.2
NBT	58.9	58.9	52.8

Table 5.Recognition rate of modified data sets for two classes.

Expert as Novice, and Novice as Intermediate. All recognition methods tend to select Intermediate in general.

We thus make new data sets, which consist of differences of marking data for each frame from the modified data, and apply C4.5 into the new data. Figure 4 shows the result. This difference data can be regarded as acceleration rate approximately. This result shows a little improvement for recognition rate, which may suggest that the acceleration value is more important to recognize than the time series data.

B. Two class identification

As mentioned above, one reason for decreasing classification rate may be the existence of Middle class, as the features are not specific rather than other two classes. The skill evaluation of represented action consists of two classes (expert / novice).

Each marking position is represented two-dimensional and so the observed data are reconstructed into 90-input / 2-class output. As for expert players, data of two players, which have high correlation coefficient, are used as learning data, and the rest (one player) for the evaluation.

	Output class	Number of classes for learning data	
		Expert	Novice
C4.5	Expert	40	0
	Novice	26	72

Table 6: Discrimination of classes on C4.5.

In those results, recognition rates of NBT for cross validation and learning data are not so good. The recognition rate for evaluation data on C4.5 is quite good, though NBT makes poor results as for all data.

We investigate further for C4.5 analysis so that novice player classification is perfect, though some of expert players are classified into novice, which might be because of some subtle differences of swings, though they should be more investigated.

IV. Related Work

In [6], on the basis of laboratory research on self-regulation, it was hypothesized that positive self-monitoring, more than negative self-monitoring or comparison and control procedures, would improve the bowling averages of unskilled league bowlers (N=60). Conversely, negative self-monitoring was expected to produce the best outcome for relatively skillful league bowlers (N=67). In partial support of these hypotheses, positive self-monitors significantly improved their bowling averages from the 90-game baseline to the 9- to 15-game post intervention assessment (X improvement = 11 pins) more than all other groups of low-skilled bowlers; higher skilled bowlers' groups did not change differentially. In conjunction with other findings in cognitive behavior therapy and sports psychology, the implications of these results for delineating the circumstances under which positive self-monitoring facilitates self-regulation are discussed.

In [2], biomechanical data on most bracing and protective equipment systems is lacking. To better understand the clinical success of counterforce bracing, a biomechanical analysis of braced and unbraced tennis players (serve and backhand strokes) was undertaken. Three-dimensional cinematography and electromyographic techniques were used. Three commonly used counter force braces (lateral elbow, medial elbow, and radial ulnar wrist) were compared with the unbraced condition. The overall results basically reveal positive biomechanical alterations in forearm muscle activity and angular joint acceleration dependent upon the brace and joint area analyzed.

In [1], comparison of initial and terminal temporal accuracy of 5 male top table tennis players performing attacking forehand drives led to the conclusion that because of a higher temporal accuracy at the moment of ball/bat contact than at initiation the players did not fully rely on a consistent movement production strategy. Functional trial-to-trial variation was evidenced by negative correlations between the perceptually specified time-to-contact at the moment of initiation and the mean acceleration during the drive; within-trial adaptation was also evident for two of the Ss. It is argued that task constraints provide the organizing principles for perception and action at the same time, thereby establishing a mutual dependency between the two. Allowing for changes in these parameters over time, a unified explanation is suggested that does not take recourse to large amounts of (tacit) knowledge on the part of the S.

In [17], in the present studies, the Leuven Tennis Performance Test (LTPT), a newly developed test procedure to measure stroke performance in match-like conditions in elite tennis players, was evaluated as to its value for research purposes. The LTPT is enacted on a regular tennis court. It consists of first and second services, and of returning balls projected by a machine to target zones indicated by a lighted sign. Neutral, defensive, and offensive tactical situations are elicited by appropriately programming the machine. Stroke quality is determined from simultaneous measurements of error rate, ball velocity, and precision of ball placement. A velocity/precision (VP) and a velocity/precision/error (VPE) index are also calculated. The validity and sensitivity of the LTPT were determined by verifying whether LTPT scores reflect minor differences in tennis ranking on the one hand and the effects of fatigue on the other hand. Compared with lower ranked players, higher ones made fewer errors ($P < 0.05$). In addition, stroke velocity was higher ($P < 0.05$), and lateral stroke precision, VP, and VPE scores were better ($P < 0.05$) in the latter. Furthermore, fatigue induced by a prolonged tennis load increased ($P < 0.05$) error rate and decreased ($P < 0.05$) stroke velocity and the VP and VPE indices. It is concluded that the LTPT is an accurate, reliable, and valid instrument for the evaluation of stroke quality in high-level tennis players.

In [20], processing efficiency theory predicts that anxiety reduces the processing capacity of working memory and has detrimental effects on performance. When tasks place little demand on working memory, the negative effects of anxiety can be avoided by increasing effort. When tasks impose a heavy demand on working memory, however, anxiety leads to decrements in efficiency and effectiveness. These presumptions were tested using a modified table tennis task that placed low (LWM) and high (HWM) demands on working memory. Cognitive anxiety was manipulated through a competitive ranking structure and prize money. 10 participants' (mean age 28.9 years) accuracy in hitting concentric circle targets in predetermined sequences was taken as a measure of performance effectiveness, while probe reaction time (PRT), perceived mental effort (RSME), visual search data, and arm kinematics were recorded as measures of efficiency. Anxiety had a negative effect on performance effectiveness in both LWM and HWM tasks. There was an increase in frequency of gaze and in PRT and RSME values in both tasks under high vs. low anxiety conditions, implying decrements in performance efficiency. However, participants spent more time tracking the ball in the HWM task and employed a shorter tau margin when anxious.

[7] critically reviews technique analysis as an analytical method used within sports biomechanics as a part of performance analysis. The concept of technique as 'a specific sequence of movements' appears to be well established in the literature, but the concept of technique analysis is less well developed. Although several descriptive and analytical goals for technique analysis can be identified, the main justification given for its use is to aid in the improvement of performance. However, the conceptual framework underpinning this process is poorly developed with a lack of distinction between technique and performance. The methods of technique

analysis have been divided into qualitative, quantitative and predictive components. Qualitative technique analysis is characterized by observation and subjective judgment. Several aids to observation are identified, including phase analysis, temporal analysis and critical feature analysis. Although biomechanical principles of movement can be used to form judgments about technique, little agreement exists about the number and categories of these principles. A 'deterministic' model can be used to identify factors that affect performance but, in doing so, technique variables are frequently overlooked. Quantitative technique analysis relies on biomechanical data collection methods. The identification of key technique variables that affect performance is a major issue, but these are poorly distinguished from other variables that affect performance. Quantitative analysis is not suitable for establishing the characteristics of the whole skill, but new methods, such as the use of artificial neural networks, are described that may be able to overcome this limitation. Other methods based on modeling and computer simulation also have potential for focusing on the whole skill. Predictive technique analysis encompasses these developments and offers an attractive interface between the scientist and coach through visual animation methods. The authors conclude that biomechanists need to clarify the underpinning rationale, framework and scope for the various approaches to technique analysis.

[18] describes a method for the measurement of sports form. The data obtained can be used for quantitative sports-skill evaluation. Here, they focus on the golf-driver-swing form, which is difficult to measure and also difficult to improve. The measurement method presented was derived by kinematical human-body model analysis. The system was developed using three-dimensional (3-D) rate gyro sensors set at positions on the body that express the 3-D rotations and translations during the golf swing. The system accurately measures the golf-driver-swing form of golfers. Data obtained by this system can be related quantitatively to skill criteria as expressed in respected golf lesson textbooks. Quantitative data for criteria geared toward a novice golfer and a midlevel player are equally useful.

In [16], the ability to recognize patterns of play is fundamental to performance in team sports. While typically assumed to be domain-specific, pattern recognition skills may transfer from one sport to another if similarities exist in the perceptual features and their relations and/or the strategies used to encode and retrieve relevant information. A transfer paradigm was employed to compare skilled and less skilled soccer, field hockey and volleyball players' pattern recognition skills. Participants viewed structured and unstructured action sequences from each sport, half of which were randomly represented with clips not previously seen. The task was to identify previously viewed action sequences quickly and accurately. Transfer of pattern recognition skill was dependent on the participant's skill, sport practiced, nature of the task and degree of structure. The skilled soccer and hockey players were quicker than the skilled volleyball players at recognizing structured soccer and hockey action sequences. Performance differences were not observed on the structured volleyball trials between the skilled soccer, field hockey and volleyball players. The skilled field hockey and soccer players were able to transfer perceptual information or strategies between their respective sports. The less skilled participants' results were less clear. Implications for domain-specific expertise, transfer and diversity across domains are discussed.

[3] denotes as follows; due to complexity, multiplicity and randomness of table tennis matches, it is necessary to develop some skill and tactic diagnostic models especially an efficient scoring model to get some skill and tactics data for table tennis matches. A scoring model is developed for table tennis matches based on video image processing technology. An input match video is used to analysis the skill and tactic of the players. Once the player scored more than some criteria points constantly, it records this particular event either in the notebook or in database to arouse his attention. By playing the fragment of the record video either slow or fast as he likes, the player can know not only the reason why he loses the points, but also knows the skill and tactic of the opponent. Besides it gives a dynamic grow of histogram for every score. The proposal improves the efficiency and quality of the matches. Moreover it provides an efficient guidance in the future's plan making, practice or competition for coaches and athletes.

V. Conclusion

This paper addresses analysis and identification for internal models for technical skills as evaluation skillfulness for forehand stroke motion pictures of table tennis, and discusses mono and meta-functional skills for improving skills. We had some experiments and some results imply that expert or intermediate players can make some categorical groups for technical skills, but there seems not to be a category for novice players because of various individual technical skills. Furthermore, for applying observed data of forehand strokes of players, we reconstruct time series data from the original data and analyze the new data by data mining techniques such as C4.5, NBT, RF, where the recognition rate for evaluation data is not so good, though C4.5 makes good results for both of learning and evaluation data. As future plans, we have to progress further evaluation, and measure more precise data and then analyze if needed.

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Author Biographies

Toshiyuki MAEDA was born in Kyoto, Japan. He graduated from Kyoto University, Faculty of Science in 1984, and graduated with a master degree in chemistry from Graduate School of Science, Kyoto University in 1986. He received his degree of Doctor of Science from Osaka Prefecture University in 2004. After being a research engineer at Matsushita Electric (a.k.a. Panasonic), he was a lecturer at Fukuyama Heisei University, Japan, and was an associate professor at Hannan University. From 2008, he is a professor at Hannan University. He is a member of IEEE, Information Processing Society of Japan, and so on.

Masanori FUJII was graduated from Nippon Sports Science University. He is currently Associate Professor at Hannan University, Faculty of Management Information.

Isao HAYASHI was graduated from Osaka Prefecture University and received his degree of Doctor of Engineering. He is currently Professor at Kansai University, Faculty of Informatics.

Masumi YAJIMA was graduated from Tokyo Gakugei University and received her degree of Master of Education. She is currently Associate Professor at Meikai University, Faculty of Economics.