Sport Skill Classification Using Time Series Motion Picture Data

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***Abstract*—We present a sport skill classification using time series motion picture data, focused on table tennis. We do not use 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.**

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

I. Introduction

As for human skill, internal structure of technical skill is layered with mono-functional, or lower level skill which is generated by human intention, and meta-functional, or upper level skill which is adjusted with environmental variation [1].

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 [2].

It is even difficult, however, for skilled workers to understand internal models completely by themselves. They usually introspect objectively their own represented actions, and achieve highly technical skills with internal models.

In the field of sport skill analysis, many researches are based on the body structure model and/or skeleton structure model introduced from activity measurement or biomechatronical measurement [3], [4], [5].

We assume that forehand strokes of table tennis play exemplify sport action, and classify skill models using motion picture data analysis without body structure model nor skeleton structure model. We evaluate those into three play levels as expert/intermediate/novice, and classify the models using data mining methods [6].

II. Related Works

In Bootsma et al.[7], 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 that 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 in two of the subjects. It is argued that task constraints provide the organizing principles of 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.

Watanabe et al.[8] 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 of 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 researches of sports motion analysis, Oka et al.[9] records excited active voltage of muscle fiber using on-body needle electromyography, and Moribe et al.[10] uses a marking observation method with on-body multiple marking points, where their objects are to clarify body structure and skeleton structure.

III. Experiments

Our research is to identify internal models from observed motion picture data and skill evaluation with represented actions, without measurement of the body structure or the skeleton structure.

In our research, 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.

At first, we have recorded motion pictures of 15 subjects who are 7 expert / 3 intermediate / 5 novice-level university students. As skill evaluation of representing action, We classify the levels as follows;

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- Expert class: high level 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: low level inexperienced students.

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

1) Acromioclaviclar joint point,
2) Acromiale point,
3) Radiale,
4) Ulna point,
5) Stylion,
6) Stylion ulnae,
7) Inner side of racket,
8) Outer side of racket, and
9) Top of racket.

Figure 1 shows positions of marking setting.

The ball delivery machine is installed around 30 centimeters (cm) from the end line of the table on the extension of the diagonal line. Balls are delivered on 20 degree elevation angle of the machine. A subject player returns the delivered ball in a fore-cross way, where the ball is bounded 75 centimeters inside from the end line. We have recorded swing traces of forehand strokes using a high-speed camcorder (resolution: 512 $\times$ 512 pixel and frame-rate: 90 frames per seconds) installed 130 cm tall and 360 cm ahead of the players.

On playing in 10 minutes, several forehand strokes are recorded for each player (see Figure 2).

IV. Skill Classification

A. Data Correlation Analysis

From the recorded motion pictures, 40 to 120 frames are retrieved from the beginning of take-back to the ball until the end of forehand stroke. We have then distributed two dimensional axes positions (pixel values) of 9 marking points for each frame, where the starting point is set at the shoulder position of the first frame. For instance, two dimensional axes, as shown in Figure 3, and horizontal speeds of markings for expert / intermediate / novice players are shown in Figure 4.

Furthermore, Table I shows minimal (Min.) and maximum (Max.) values of the horizontal axes for the marking point 1($M1$), mark 4($M4$), and mark 9($M9$) respectively in Figure 3 .

TABLE I
Min. and Max. Position of x-Direction of Markings.

	$M1$		$M4$		$M9$	
	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

Figure 3, Figure 4, and Table I imply as follows:

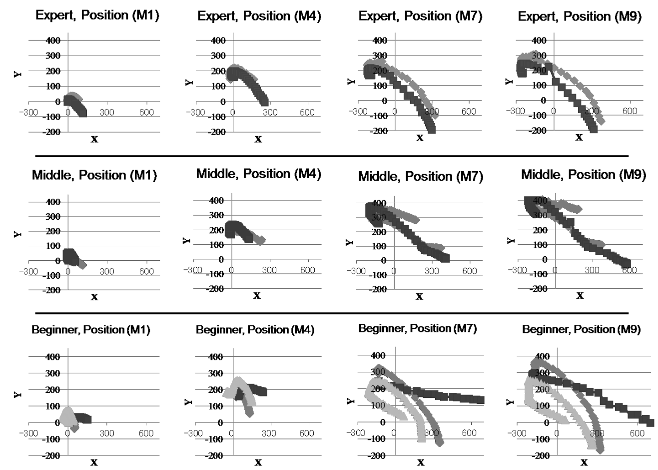

FIGURE 3. Position of Markings.

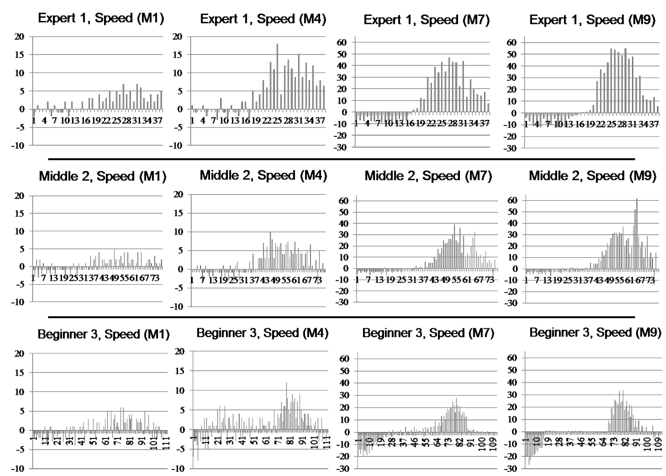

FIGURE 4. Speed of Markings.

- Among expert players, there is a strong correlation for marking position of $M1 \sim M9$, where the correlation coefficient are $x = 0.985, y = 0.790$. Those indicate that expert players have actual technical skills because of the similar trajectory of swings. The trajectory, moreover, looks less fluctuation which suggests expert players swing more smoothly. Swing speeds of expert players raise maximum at the impact of ball-racket contact for all marking points, and that implies that 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 at the position $M1$ which differs much from that of each novice player, and that indicates novice players tend to move shoulders. Furthermore, axes position for $M7$ and $M9$ differ some as well as $M1$ and so there

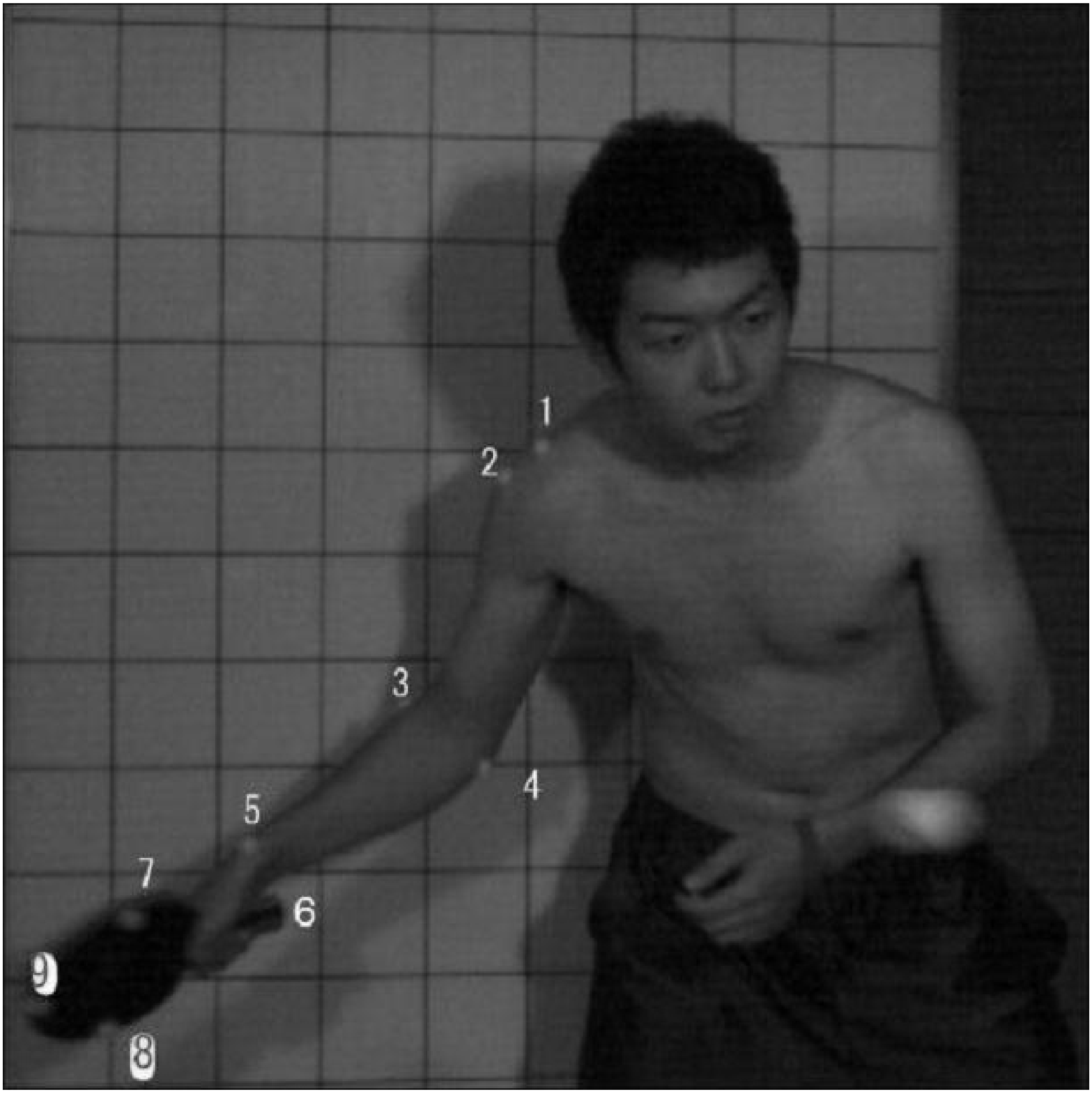

FIGURE 1. Measurement markings.

FIGURE 2. Pictures of subject.

is no typical swing trajectory. From those results, there are many variations for swings for novice players. As a summary, 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.

B. Three-class Classification

The above analysis shows the technical skills of table tennis depend on trajectories rather than axes positions of observed making points. We thus attempt further investigation using data mining technique. The skill evaluation of representing 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 in 90-input / 3-class output.

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 such as 9 markings $\times$ 2 axis $(x, y) \times 5$ frames, and each datum is overlapped with 3 frames data (from third to fifth frame) of the next datum for presenting linkage of each datum (see Fig 5).

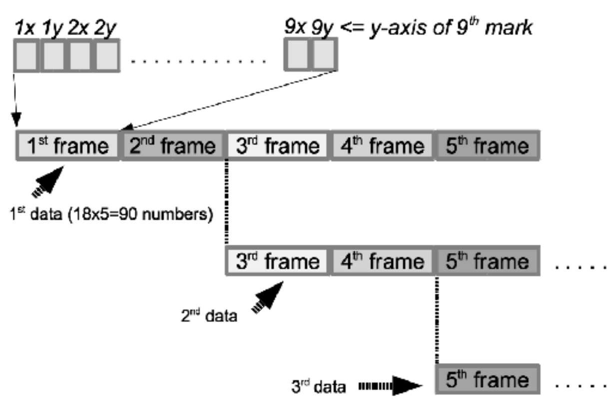

FIGURE 5. Data structure from isolated pictures.

We use an integrated data mining environment "weka"

[11] and analyze the data by analyzing methods of J48 (an implementation of C4.5), Native Bayes Tree (NBT), Random Forest (RF). Table II shows the recognition rate of the data sets. As for expert players, data on two players, which have a high correlation coefficient, are used as learning data, and the rest (one player) for evaluation. Table III also shows the discrimination of classes for evaluation data.

TABLE II
RECOGNITION RATE OF MODIFIED DATA SETS FOR THREE CLASSES.

	Recognition Rate(%)	
	Learning data	Evaluation data
J48	98.1	43.3
NBT	100.0	32.8
RF	100.0	25.4

TABLE III
DISCRIMINATION OF CLASSES.

		Number of classes for learning data		
	Output class	Expert	Intermediate	Novice
J48	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

In those results, recognition rates of NBT and RF for learning data are 100%, which may be over-learned. The recognition rates for evaluation data are not so good, though J48 makes better results for evaluation data. On the contrary, the result of the number of class recognition for each method in Table III 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. J48 recognizes Expert as Novice, and Novice as Intermediate. All recognition methods generally tend to select Intermediate.

C. Two-class Classification

As mentioned above, one reason for the low rate of the classification rate may be the existence of Intermediate class, as the features are not specific rather than the other two classes. We then set up a hypothesis that Intermediate class may be similar to another class. We thus analyze two cases, where Intermediate data is combined to Expert class and Novice class. The skill evaluation of representing action consists of two classes (Expert / Novice). Table IV shows the recognition rate using J48. In this table "IaE" represents "Intermediate as Expert," and "IaN" represents "Intermediate as Novice" respectively.

The recognition rate for "IaE" is very bad and that implies Intermediate is not similar to Expert, and the recognition rate for "IaN" is rather good. Those results suggest Intermediate class skill may be similar to Novice, though we need further investigation.

TABLE IV
RECOGNITION RATE OF MODIFIED DATA SETS FOR TWO CLASSES.

	Recognition Rate(%)		
	Cross Validation	Learning data	Evaluation data
IaE	86.7	99.1	25.8
IaN	90.0	99.1	68.2

V. CONCLUSION

This paper addresses analysis and classification for internal models for technical skills as evaluation skillfulness for forehand stroke motion pictures of table tennis, and discuss 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. Futhremore, 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 J48, NBT, RF, where the recognition rate for evaluation data is not so good, though J48 makes better results for learning and evaluation data. Two-class analysis furthermore suggests Intermediate class may be categorized as Novice class.

As future plans, we have to progress further experiments, and measure more precise data and then analyze if needed.

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REFERENCES

[1] T. Shiose, T. Sawaragi, K. Kawakami, and O. Katai: Technological Scheme for the Preservation of Technique from Ecological Psychological Approach. (in Japanese), *Ecological Psychology Research*, Vol.1, No.1, pp.11-18 (2004)

[2] Y. Matsumoto: *Organization and Skill – Organization Theory of Preservation of Technique* (in Japanese), Hakuto Shobo (2003)

[3] Y, Mochizuki, R. Himeno, and K. Omura: Artificial Skill and a New Principle in Sports(Special Issue on Digital Human : Measurement and Modeling of Human Functions. (in Japanese) *System, Control, and Information*, Vol.46, No.8, pp.498-505 (2002)

[4] J. Kasai, T. Mori, T. Yoshimura, and A. Ohta: Studies of Forehand Strokes in Table Tennis by 3 Dimensional Analysis Using the DLT Method. (in Japanese) *Waseda Journal of Human Sciences*, Vol.7, No.1, pp.119-127 (1994)

[5] M. Miyaki, N. Ashida, T. Takashima, T. Azuma, and K. Tsuruta: Motion Analysis of Forehand Stroke in Table Tennis Play. (in Japanese) *In Proceedings on 42nd Conference of Japanese Society of Physical Education* , pp.681 (1991)

[6] T. Maeda, I. Hayashi, M. Fujii: Time Series Data Analysis for Sport Skill. *Proceedings of the 2012 12th International Conference on Intelligent Systems Design and Applications* , pp.392–397, Kochi, India (2012)

[7] R. J. Bootsma, and P. C. Van Wieringen: Timing an attacking forehand drive in table tennis. *Journal of Experimental Psychology: Human Perception and Performance*, Vol.16, No.1, pp.21–29 (1990)

[8] K.Watanabe, and M. Hokari: Kinematical analysis and measurement of sports form. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, Vol.36, Iss. 3, pp.549–557 (2006)

[9] H. Oka, A. Ikuta, and A. Nishira: Electromyographic Study of Forehand Skill in Table Tennis. *Hyogo University of Teacher Education Journal*, Vol.20, pp.19-27 (2000)

[10] A. Moribe, M. Ae, N. Fujii, K. Hougen, and A. Yuda: Study of Forehand Attack in Table Tennis Play – Focus on reaction to variation of rallies –. *In Proceedings on 54th Conference of Japanese Society of Physical Education* , pp.377 (2003)

[11] http://www.cs.waikato.ac.nz/ml/weka/ (2014)