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SWIMMING MOTION CLASSIFICATION FOR COACHING SYSTEM BY USING A SENSOR DEVICE

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Abstract. *We are engaged in developing a swimming motion coaching system by using a sensor device. One of the requirements of the system is the process of automatically estimating and dividing the section of swimmer's motions (such as stroke and turn) from the sensor data. In this paper, we proposed a method of estimating the section of each swimming motion in four swimming styles (front crawl, backstroke, breaststroke and butterfly). A classifier of swimming motions based on decision tree was constructed by learning data. As a verification in the generalization ability of the classifier by test data, F-measure was $\geq$ .713 for all swimming styles. We also estimated the start and end points of the section of swimming motions. The estimated mean errors of the start and end points of turn in all swimming styles were $\leq$ .488 seconds (except for backstroke) and $\leq$ .514 seconds, respectively. From the pattern recognition point of view, we found that we could classify the features of stroke and turn in four swimming styles. However, from the user's point of view, we should aim to achieve much higher accuracies.*
Keywords: Sports engineering, Sensor, Machine learning, Decision tree

1. **Introduction.** Swimming is a sport that Japanese players have been acquiring many medals in international competition, and it is also expected that medals including gold medals will be acquired in the future. The Ministry of Education, Culture, Sports, Science and Technology (MEXT) designates it as "target A", which means "a sport that Japanese players can expect to have many medals including gold medal". MEXT is supporting the training and strengthening of players [1]. It is important to improve technics of such

advanced players, but it is also important to elevate the beginners and intermediate players to the advanced players.

It is desirable to improve technics of the players by estimating the performance such as strokes, turns, and start diving (hereinafter called "swimming motions"). The teaching and evaluation by a coach are common. It is sometimes difficult to exactly estimate and evaluate the swimming motions of the player underwater. It is possible to estimate the swimming motions by using motion capture system. However, since such system is an expensive and large scale device, it is not realistic for the beginners and intermediate players to easily use it to evaluate the performance of their swimming motions.

From these backgrounds and the point of view of sports engineering, we have proposed a swimming motion coaching system [2] by using only one compact and waterproofed sensor that can measure 3-axial acceleration and angular velocity (hereinafter called "sensor data"). We attach one sensor on the back of the waist (see Figure 1(a)). It would be desirable to use many sensors but we considered that it could be easily used for beginners and intermediate players and could reduce uncomfortable feeling. First, from only sensor data, the system automatically determines which swimming style (front crawl, backstroke, breaststroke and butterfly) is performing. Next, it automatically detects the sections of each swimming motion. Finally, it estimates and provides the information such as speed and lap time during detection of each swimming motion to the coach and/or players.

To develop the systems, it is necessary to solve some issues: (1) automatic classification of four swimming styles, (2) automatic classification of swimming motions and estimation of the sections of swimming motions, (3) evaluation of the performance of swimming motions such as speed and lap time, and (4) how to provide information to the coach and/or players. Omae et al. [3] proposed a classifier of four swimming styles with good accuracy and at a high speed. In this paper, suppose that we know which swimming styles the players are performing, we focus on issue (2). Jensen et al. [4] attached a sensor to the back of swimmer's head. From the acquired data, they quantified the features of strokes and turns, and constructed a classifier by a linear regression model. The feature values used were mean, standard deviation, variance, energy, kurtosis, skewness, maximum and minimum value of 3-axial acceleration and angular velocity. In their result, the turn was detected with good accuracy. However, the start and end points of the turn were not determined with enough accuracy.

In this paper, by using the machine learning technique and only sensor data, we construct a classifier and propose a data processing method of estimating the section where each swimming motion is performed.

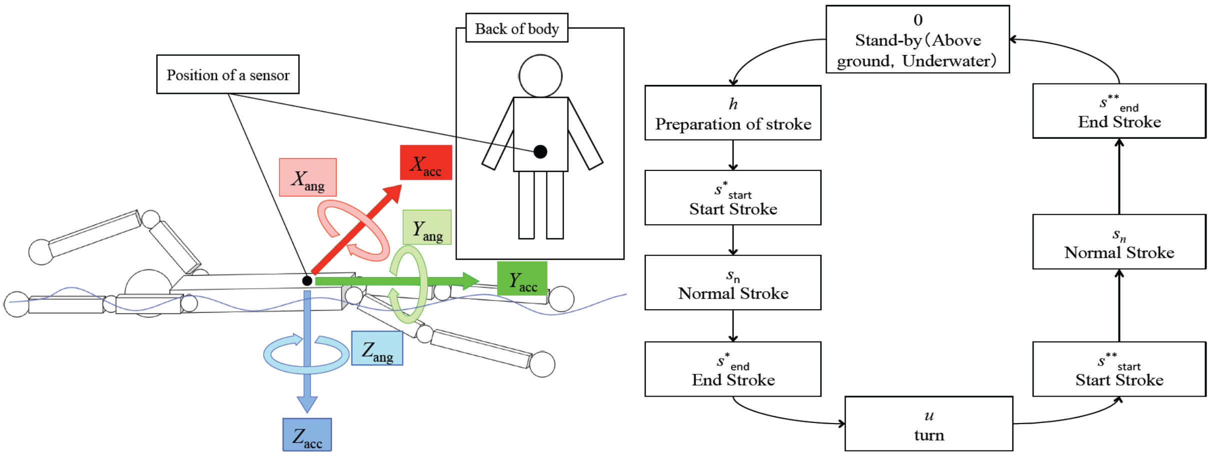
The paper is organized as follows. In Section 2, we give an overview of the experiment and data processing. In Section 3, we explain the method of the construction of classifier and estimation of swimming motions section. In Section 4, the experimental results and discussion are presented. Section 5 is devoted to a summary.

2. Overview of Experiment and Data Processing.

To construct swimming motion classifier, learning data are required and test data are also required to verify generalization ability of the constructed classifier. In this section, we describe the experiments to acquire data necessary for the construction of classifier as well as the processes for constructing learning and test data.

2.1. Experiment of data collection.

We conducted experiments with 19 subjects (16 males, 3 females) of university students who belong to swimming clubs in the university. The attributes of the subjects were 19.5 ± 1.7 years of age, 169.6 ± 7.0cm in height, 64.2 ± 5.6kg in weight, and 13.1 ± 4.1 years of swimming history. The sensor we used is a waterproofed 9-axis wireless motion sensor with a weight of 20g, 67mm $\times$ 26mm $\times$ 8mm size, made by Sports Sensing Co., Ltd. (former Logical Product Co., Ltd.) [5]. This sensor



(a) Position of a sensor and axial setting (b) Swimmer's state transition diagram

FIGURE 1. Status of the subject during the experiment

has built in an acceleration sensor (±5G) and an angular velocity sensor (±1500dps), and it can record each element in memory of the sensor with sampling frequency of 100Hz. Setting of the sensor position and the axis with the positive direction of arrow direction of acceleration and angular velocity sensors are shown in Figure 1(a). Here, X_{acc} denotes X-axis acceleration, X_{ang} denotes X-axis angular velocity, and Y and Z axes are the same. In order to compare sensor data waveforms with actual swimmer's motion, we took movies at 30fps using Sony's HDR-CX720 [6] from the poolside.

We instructed subjects to select two swimming styles that were good at four swimming styles, and to swim a lap (50m) in the 25m pool with full power without start diving. We acquired the data for two swimming styles from 19 subjects. However, there were 5 missing data because of falling of the sensor and the defect of taking movies. The total number of acquired data was 33 (for 12 swims in front crawl, 11 swims in butterfly, 5 swims in breaststroke and 5 swims in backstroke). We divided these data into learning data and test data for each swimming style. Since it is necessary to learn the common features of swimming motion for each swimming style and to remove the individual features of swimming motion, it is better to have as much learning data as possible. Thus, the distributions were for front crawl: 8 learning data and 4 test data, butterfly: 6 learning data and 5 test data, breaststroke: 4 learning data and 1 test data, backstroke: 3 learning data and 2 test data, respectively.

2.2. **Definition of swimming motion.** It is necessary to clear the definitions of each swimming motion to add the motion tags to the sensor data. Swimming motions strongly depend on swimming styles. However, if we know which swimming styles the subjects are performing, we can depict the swimmer's state transition diagram of swimming motions in Figure 1(b). From Figure 1(b), in this paper, we define the swimming motions as Table 1.

2.3. **Data processing.** In order to learn swimming motions from the sensor data, it is necessary to add the motion tags of swimming motions to be an objective variable for each time. Therefore, we synchronized the acquired sensor data and the movies. After that, based on the definition of swimming motions shown in Table 1, the motion tags were added to the sensor data.

To understand human motions, instead of using the raw sensor data, we generally use the converted values that represent the features of objects (hereinafter called "feature values") [7]. The sliding window method [7, 8] is one of the conversion methods. By using the sliding window method, the start and end points of human motions can be detected

Table 1. Definition of subject's motions

Motions	Motion tags	Definition
Stand-by	0	State before the start and after swimming.
Preparation of stroke	h	State from the start of trial until the start of stroke.
Normal stroke	s_n	Series of motions from the start of thrusting one's hands in water to end of motions are defined as one stroke. n $(= 1, 2, 3, \ldots)$ denotes the n-th normal stroke.
Start and end stroke	s^*, s^{**}	State of the stroke immediately after start of stroke (s^*_{start}), before the start of turn (s^*_{end}), after the end of turn (s^{**}_{start}) and just before the goal (s^{**}_{end}). * and ** show 25m in the first half and 25m in the second half, respectively.
Turn	u	State of turn. Definition of start timing of turn for each swimming style: front crawl is lowering head, backstroke is twisting waist, and breaststroke and butterfly are touching the wall. The end timing of turn is until the start of stroke in each swimming style.

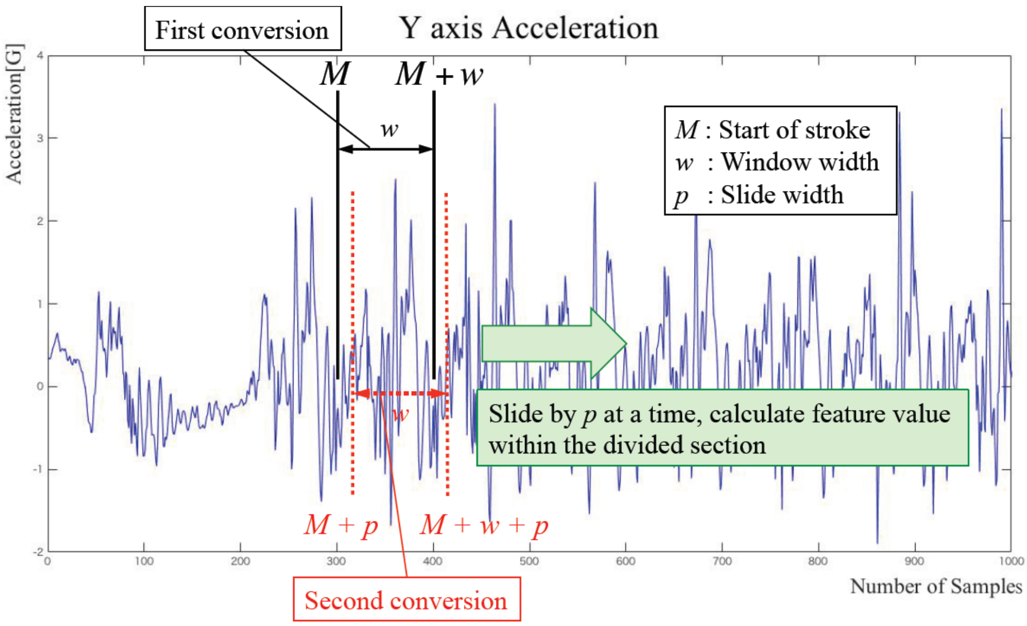


Figure 2. Schematic view of the sliding window method

sensitively. For this reason, we use the sliding window as the conversion method in this paper. The schematic view of the sliding window method is shown in Figure 2. First, the feature values are calculated by using the data within a range of window width w from starting point M. The time stamp of the starting time M is added to these calculated feature values. Then, the start point M is slid by the slide width p: $M = M + p$, and the feature values are calculated in the data range that is the window width w. These processes are repeated until the end of data.

The processed feature values are shown in Table 2, where Mean denotes mean value; Var variance; Skew skewness; Kurt kurtosis; Max maximum value; Min minimum value; Ent frequency domain entropy; Med median. We decided these feature values by referring to the previous research [3]. We calculate these 8 kinds of values for the three-axial

Table 2. Adopted feature values

Definition	Acceleration j	Acceleration r	Ang. velocity j	Ang. velocity r	Definition	Acceleration j	Acceleration r	Ang. velocity j	Ang. velocity r
$a_j = \text{Mean}(r)$	1	X_{acc}	25	X_{ang}	$a_j = \text{Max}(r)$	13	X_{acc}	37	X_{ang}
	2	Y_{acc}	26	Y_{ang}		14	Y_{acc}	38	Y_{ang}
	3	Z_{acc}	27	Z_{ang}		15	Z_{acc}	39	Z_{ang}
$a_j = \text{Var}(r)$	4	X_{acc}	28	X_{ang}	$a_j = \text{Min}(r)$	16	X_{acc}	40	X_{ang}
	5	Y_{acc}	29	Y_{ang}		17	Y_{acc}	41	Y_{ang}
	6	Z_{acc}	30	Z_{ang}		18	Z_{acc}	42	Z_{ang}
$a_j = \text{Skew}(r)$	7	X_{acc}	31	X_{ang}	$a_j = \text{Ent}(r)$	19	X_{acc}	43	X_{ang}
	8	Y_{acc}	32	Y_{ang}		20	Y_{acc}	44	Y_{ang}
	9	Z_{acc}	33	Z_{ang}		21	Z_{acc}	45	Z_{ang}
$a_j = \text{Kurt}(r)$	10	X_{acc}	34	X_{ang}	$a_j = \text{Med}(r)$	22	X_{acc}	46	X_{ang}
	11	Y_{acc}	35	Y_{ang}		23	Y_{acc}	47	Y_{ang}
	12	Z_{acc}	36	Z_{ang}		24	Z_{acc}	48	Z_{ang}

accelerations and angular velocities and adopt them as feature values a_j $(j = 1, \ldots, 48)$ by which swimming motions are classified.

To use the method, it is necessary to set the parameters of window width w and slide width p. It is desirable that the time for dividing the sensor data is the time for one cycle of swimming motions. Therefore, to focus on strokes, we set window width w as the mean time taken for one stroke for each swimming style. As the result from learning data, the window width w_k for each swimming style k became front crawl (k = Fr): 1.15s, butterfly (k = Bu): 1.09s, breaststroke (k = Br): 1.31s, backstroke (k = Ba): 1.27s, respectively. We also set slide width p as 1/100s (= 1 sample) so that it can respond sensitively to switching of swimming motions.

It is also necessary to set the objective variable for the calculated feature values. It is natural to set the majority of swimming motion tag in the data range w as the objective variable of the feature values. Then, we can create data set of feature values (explanation variables) and swimming motion tag (objective variable).

3. Construction of Classifier and Estimation of Swimming Motions Section.

3.1. **Classification algorithm.** We use a decision tree as a classifier of swimming motions. In the decision tree, we use information entropy to search for the effective classification trees. To construct a classifier, classification tree creation processing of optimal feature values is repeated by using the learning data. If this process is repeated until the objective variable is completely classified, the classification accuracy of the learning data is increased. However, there is a possibility that over-fitting may lead to a decrease in generalization ability. Especially, in analysis of motions, noise depending on the individual feature differences tends to occur. If classifier reacts sensitively to its noise and creates classification rules, it becomes over-fitting. So it is necessary to optimize the learning depth from the viewpoint of improving generalization ability and suppressing over-fitting. In the decision tree, learning depth can be indirectly manipulated by adjusting the minimum number of samples per leaf node (hereinafter called "MLS"). Therefore, by doing cross validation (hereinafter called "CV") in the learning data, we search for MLS that is optimal for constructing a classifier.

3.2. **Examination on the improvement of generalization ability.** MLS is searched by using CV in order to construct a classifier which is excellent in generalization ability and not over-fitting. Especially, we use the Leave-one-subject-out Cross Validation (LCV) [9].

LCV constructs the classifiers by using the $B-1$ trial data out of learning data for B trial data. Then, accuracy of the classifier is evaluated by using the data of remaining one trial data which is not involved in construction as a test data. This process is repeated B times so that each data set becomes a test data. Since LCV evaluates the accuracy of classifiers constructed without using the test data, it is possible to verify the robustness of classifiers against the unknown data. In order to search for the optimum MLS in this verification, a classifier with MLS m changed from 1 to 1000 in each data set is constructed and accuracy evaluation is performed for each different MLS. The most accurate MLS is set as the optimum MLS for each swimming style.

If we set that positive case is turn and negative case is stroke, we can count $TP^m_{k,v}$, $TN^m_{k,v}$, $FP^m_{k,v}$ and $FN^m_{k,v}$ for MLS m, v-th verification result in swimming style k. Here, TP is a number of classified turn as turn, TN is a number of classified stroke as stroke, FP is a number of classified stroke as turn, and FN is a number of classified turn as stroke, respectively. In the data of one trial, the ratio of the number of sample data of stroke and turn is generally more in stroke data. In order to evaluate the classification accuracy in the same way, we normalize:

$$TN'^m_{k,v} = \alpha^m_{k,v} TN^m_{k,v}, \quad FP'^m_{k,v} = \alpha^m_{k,v} FP^m_{k,v}, \quad \alpha^m_{k,v} = \frac{TP^m_{k,v} + FN^m_{k,v}}{TN^m_{k,v} + FP^m_{k,v}}, \tag{1}$$

where $\alpha^m_{k,v}$ is the normalization constant that makes the data number ratio of stroke and turn uniform. We calculate the classification accuracy by:

$$A^m_{k,v} = \frac{TP^m_{k,v} + TN'^m_{k,v}}{TP^m_{k,v} + TN'^m_{k,v} + FP'^m_{k,v} + FN^m_{k,v}}, \quad P^m_{k,v} = \frac{TP^m_{k,v}}{TP^m_{k,v} + FP'^m_{k,v}}, \tag{2}$$

$$R^m_{k,v} = \frac{TP^m_{k,v}}{TP^m_{k,v} + FN^m_{k,v}}, \quad F^m_{k,v} = \frac{2P^m_{k,v} R^m_{k,v}}{P^m_{k,v} + R^m_{k,v}}. \tag{3}$$

We also calculate the mean value of F-measure in MLS m:

$$F^m_k = \frac{1}{B_k} \sum_{v=1}^{B_k} F^m_{k,v}, \tag{4}$$

where B_k is the number of trials B in swimming style k. The optimal MLS m^{fit}_k for classifier in swimming style k is obtained:

$$m^{\text{fit}}_k = \underset{m}{\operatorname{argmax}}\, F^m_k. \tag{5}$$

3.3. **Estimation of swimming motions section.** Since in a practical system it is required that the information, such as speed and lap time, is provided after the classification of stroke and turn, the correct estimation of the swimming motions is important.

Since the feature values are characterized by the start time, which is explained in Section 2.3, the results of the classification are also characterized by its time. Therefore, based on the classification result, we can detect the change point of the swimming motions. There may be some miss-classifications of the swimming motions. In order to exclude it from the estimation of the start and end points of the turn, we consider the section where the classification results of stroke/turn continue during a few samples as the actually stroke/turn section.

4. **Results.**

4.1. **Classification accuracy of learning data and test data.** By using learning data of each swimming style, we construct the classifiers of the swimming motion (positive case: turn and negative case: stroke), for each swimming style. The B_k is equal to the number of learning data in each swimming style, which was explained in Section 2.1. The obtained optimal MLS m_k^{fit} discussed in Section 3.2 and the classification results of the constructed classifiers are shown in the left side of Table 3. The classification accuracy is evaluated by accuracy A_k, precision P_k, recall R_k, and F-measure F_k. The evaluation results show that all swimming motions are almost correctly classified: F-measure $F_k \geq .886$.

Table 3. Classification accuracy of the constructed classifier

Style	Optimal MLS	Learning data				Test data			
k	m_k^{fit}	A_k	P_k	R_k	F_k	A_k	P_k	R_k	F_k
Fr	42	.978	.992	.963	.978	.785	.975	.585	.731
Bu	152	.949	.990	.906	.946	.790	.947	.615	.746
Br	473	.903	.959	.842	.897	.816	.951	.668	.784
Ba	556	.896	.974	.813	.886	.769	.943	.573	.713

Since the learning depth is adjusted by CV, there is a possibility that the similar accuracy will be obtained for unknown data. On the other hand, they just represent classification accuracies of learning data and do not guarantee classification accuracies of unknown data. Therefore, we need to verify the classifier's generalization performance for test data that are not involved in learning.

The classification results of the test data are shown in the right side of Table 3. Although accuracies and recalls are not so high ($A_k \sim .769$ and $R_k \sim .573$), precisions are still high ($P_k \geq .943$). F-measures of all swimming styles are $F_k \sim .713$.

4.2. **Estimation of swimming motions section.** We estimated the start and end points of turn based on the results of the classification of the test data. From the estimated results $U'^{k,i}$ and the changing point of the original motion tag $U^{k,i}$ for subject i data of the turn start and end points in swimming style k, we calculated:

$$E_{\text{start}}^{k,i} = \left| U_{\text{start}}^{k,i} - U_{\text{start}}'^{k,i} \right|, \quad E_{\text{end}}^{k,i} = \left| U_{\text{end}}^{k,i} - U_{\text{end}}'^{k,i} \right|. \tag{6}$$

The average value $\overline{E_{\text{start}}^k}$ and $\overline{E_{\text{end}}^k}$, and its standard deviation $\text{Sd}(E_{\text{start}}^k)$, $\text{Sd}(E_{\text{end}}^k)$ were calculated for swimming style k. The results are shown in Table 4. Note that since there is only one subject of the breaststroke in test data, we only show the mean values.

Table 4. Estimation error of the start and end point of turn motion

Style	Estimation error			
k	$\overline{E_{\text{start}}^k}$[s]	$\text{Sd}(E_{\text{start}}^k)$	$\overline{E_{\text{end}}^k}$[s]	$\text{Sd}(E_{\text{end}}^k)$
Fr	.403	.179	.283	.167
Bu	.488	.291	.514	.376
Br	.240	–	.170	–
Ba	1.55	.430	.405	.205

From Table 4, it can be seen that both the starting point and the end point of the turn are largely deviated. This is because the behavior of elongation before and after kicking the wall is confused with motion of stroke. In order to avoid the confusion between this stroke and the extension during turn it is considered that it is necessary to separate turn and elongation motion from the definition of turn motion. Although it is necessary to classify new motion of elongation, this definition narrows target motion section of learning and can adopt feature values specialized for classifying motion of elongation as classification rules.

4.3. **Discussion.** We discuss first the generalization ability. In the process of constructing classifier, in order to obtain the optimal learning depth that did not become over-fitting for each swimming style, MLS calculated by CV for each swimming style was used. Generally, for unknown data, the effective classifier could be made by the optimal learning depth. However, the F-measure of the test data was much lower than that of the learning data. For constructing classifiers, it is desirable that the error of learning model is low and the classification accuracy of the learning data is high. This means that learning model with low bias and low variance is desirable. Since the decision tree is learning model with low bias and high variance, in this paper, we tried to constrain the over-fitting of classifiers by CV and reduce the variance. However, the results shown in Table 3 showed that we could not obtain the desirable results. Therefore, in order to improve the generalization ability, it is necessary to adopt a data processing method and/or learning model that can further reduce the variance.

In the motion tags defined in Table 1, there was the case that all data samples were defined as turn from s^{*}_{end} until s^{**}_{start}. In the definition of Table 1, the turn motion before kicking the wall and the motion of elongation immediately after kicking the wall were also defined as the same turn. In the swimming styles with less shaking of the trunk during strokes, it is possible that the motion of elongation and stroke are confused. We have to change the definition of the swimming motions.

In this paper, we show that we can classify the features of stroke and turn in four swimming styles. From the pattern recognition point of view, the precision rate should be determined as good result. However, as mentioned in Section 1, the system to be constructed in the research [2] aims at feeding back swimmer's performance in real time to swimmers. Therefore, from the user's point of view, we should aim to achieve much higher accuracies.

5. **Summary.** In this paper, we used the decision tree as learning model and constructed a classifier that learned features of swimming motions by converting sensor data into feature values. For constructing classifier, we set the optimum learning depth by LCV. After that, by using the constructed classifier, we estimated the sections in which each swimming motion is performed, and estimated the accuracy.

As the result of verifying the generalization ability of the classifier by test data, it was possible to construct a classifier that captured the features for each swimming motion, although F-measure decreased by more than .113 than that of learning data classification in each swimming style. As the result of estimating section of the turn from the data, the estimated mean errors of the start and end points of turn in all swimming styles were $\leq .488$ seconds (except for backstroke) and $\leq .514$ seconds, respectively. Then, we discussed a cause of such classification accuracy and estimation error from the viewpoint of classifier creation algorithm and swimming motion definition.

It is possible to construct classifiers that classify swimming motions with the accuracy that can use practical system, but the accuracy has to be improved by solving the problems which we found in this paper. In the future, we plan to improve the estimation accuracy by introducing a data processing method and/or learning model that further reduces variance. We will also plan to redefine the optimal window width and swimming motion.

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