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Application of Machine Learning Technology for Automatic Motion Recognition for Japanese Tea-Making Procedure of CHA-NO-YU

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ABSTRACT

CHA-NO-YU, the Japanese traditional tea-making ceremony, has been a research subject in many academic fields including anthropology, psychology, and engineering. To effectively study the CHA-NO-YU, automatic recognition of motions of the tea-making procedure is desirable. Hence, herein, a method is proposed to recognize 12 motion classes of the tea-making procedure with acceleration, angular velocity, and right-hand tilt angle data. In the experiment, one Japanese subject with 18 years of experience in CHA-NO-YU performed the 12 motion classes repeatedly, and a 99-sensor dataset was obtained for every motion class. In the recognition step, random forest classifier was adopted. Finally, the recognition of the 12 motion classes of the tea-making procedure could be realized with greater than 0.98 accuracy, precision, recall, and F1-score.

KeyWords*:* Motion recognition, Machine learning, CHA-NO-YU, Tea-making procedure.

1. INTRODUCTION

CHA-NO-Yu is a comprehensive art of Japanese traditional culture, which includes both tangible elements such as the utensils to make tea and intangible ones including etiquette and tea-making procedure. The art has also been known in Europe and America since Tenshin Okakura spread it to the world through his book: “The book of tea” [1] written in English in 1906. Subsequently, the west’s interest in CHA-NO-YU increased, and there were many studies on the subject, such as that by Sadler [2]. Even now, the CHA-NO-YU is a research subject in many academic fields: cultural anthropology [3], psychology [4, 5], engineering [6], and so on.

The basic principle of CHA-NO-YU is that a host makes tea for the guests as part of a tea ceremony. At a glance, it appears simple, but the host has to make tea based on a strict etiquette and procedure, which is called *Otemae* in Japanese; the host uses several utensils, as shown in Table 1 (words inside the parentheses are the utensils’ names in Japanese), and makes tea according to a procedure partially shown in Table 2. Table 2 shows steps of the basic tea-making procedure called *Hira-demae* as stipulated by the Sadou-Sekishu-ryu-souke school, a premier CHA-NO-YU school.

In most studies [4, 5], the focus of the research is on the communication between the host and guests. In the tea ceremony, the host and guests communicate depending on progress of the tea-making procedure to build a seated-as-one-experience. Thus, information about when and what motion of the tea-making procedure is performed has to be obtained for communication analysis. Additionally, there are several studies to evaluate the skill of the tea-making procedure by engineering approaches (for example, [6]); even in this case, information about the progress of the tea-making procedure is indispensable. However, visually checking the progress of the tea-making procedure is difficult because of the many steps involved, as indicated by Table 2. Therefore, obtaining such information automatically is beneficial for research. In this study, an acceleration-, angular velocity-, and right-hand tilt angle-based method is proposed to recognize motions of the tea-making procedure.

In previous studies of motion recognition, an accelerometer has often been used. For example, studies [7, 8] attempted to recognize human activities: sitting, walking, running, cycling, transport (while sitting) and so on using acceleration datasets. Furthermore, studies [9, 10] presented some methods to recognize nurses' complex assistance activities: moving patients between wheelchair and bed, turning patients over, and so on. Thus, the accelerometer can be regarded as a practical device to recognize motion. In this study, motions whose start and end times were previously known were selected for simplification.

Table 1: Utensils for tea-making procedure

Utensil	Usage
Tea bowl (Cha-Wan)	Bowl to contain liquid Matcha green tea
Thin tea container (Natsume)	Container for powdered Matcha green tea
Tea scoop (Cha-Shaku)	Spoon to scoop powdered Matcha green tea
Kettle (Kama)	Iron pot for heating water to make tea
Wind Furnace (Furo)	Tool to heat Kama
Fresh water container (Mizu-Sashi)	Vessel holding water for Kama
Bamboo ladle (Yu-Shaku)	Ladle to draw hot and fresh water
Silk cloth (Fukusa)	Cloth to purify utensils such as Natsume and Cha-Shaku
Tea whisk (Cha-Sen)	Whisk to make liquid Matcha
Slop bowl (Ken-Sui)	Bowl to throw away water already used
Lid holder (Futa-Oki)	Tool to put lid of Kama on
Jug (Mizu-Tsugi)	Tool to pour fresh water into Mizu-Sashi
Fan (Sensu)	Tool to be used at the start and end of tea ceremony

Table 2. Parts of tea-making procedure' motions

Motion	Activity
1	Bring Natsume held in right-hand and Cha-Wan held in left hand in front of Mizu-Sashi
2	Return to the entrance of tea-room
3	Put Ken-Sui set with Yu-Shaku and Futa-Oki on the left side of a host with left hand

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-Omitted-	
29	Put Yu-Shaku on top of Kama in the form of “Sute Yu-Shaku”
30	Take Cha-Sen, and perform “Cha-Sen Doushi”
31	Rotate Cha-Wan counterclockwise to warm up Cha-Wan
32	Throw away hot water in Ken-Sui with left hand
-Omitted-	
97	Return the entrance of tea-room holding Mizu-Tsugi
98	Put Mizu-Tsugi on the right side of a host, and put Sensu in front of entrance of tea-room, and bow

2. EXPERIMENTATION

Experiments were conducted with one 43-year-old Japanese male subject with 18 years of experience with CHA-NO-YU. Here, 9 out of 98 motions shown in Table 2 were selected. The abstracts of the 9 motions of the tea-making procedure are shown in Table 3. These 9 motions were selected because they are distinctive and conducted mainly with the right hand (the accelerometer was attached to the right-hand wrist). The 9 motions are shown in Fig. 1. Fig. 2 depicts a schematic of utensils' location in a tea room. In the CHA-NO-YU, utensils are placed on *tatami* mats, and the host makes tea sitting straight on the mat (This sitting style is called *Seiza* in Japanese.). In this experiment, the subject took the required utensils from a fixed place on fixed timing. The utensils were moved following a fixed trajectory, and then used following fixed motions in the same way as an actual tea ceremony. Each of the 9 motions of the tea-making procedure, shown in Table 3, was continuously repeated 99 times, whereas the 98 motions of the tea-making procedure were conducted according to the order shown in Table 2.

This study adopted TSND-151 released by ATR-Promotions to measure three-axis acceleration and angular velocity. Here, sampling rate was 200 Hz, range of acceleration was set to ±8G, and range of angular velocity was set to ±2000 dps. TSND-151 was attached to the right-hand wrist.

In the measurements of each motion shown in Table 3, the subject raised the right arm quickly and vertically before and after each motion of tea-making procedure to detect motion segment from sequential acceleration and angular velocity signals.

Table 3.Nine motions of the tea-making procedure selected for motion recognition

Motion	Activity
15	Take *Fukusa* from right side of kimono sash belt, and fold it (This is called *Fukusa Sabaki*.)
16	Purity front, back and top of *Natsume*'s lid with *Fukusa*
28	Draw hot water from *Kama*, and pour into *Cha-Wan*
29	Put *Yu-Shaku* on top of *Kama* in the form of *Sute Bi-Shaku*
30	I. Stir hot water in a *Cha-Wan* like drawing a semicircle three times to moisten a *Cha-*

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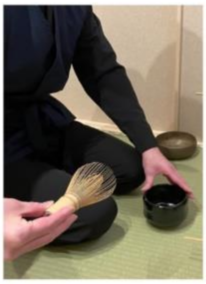
	Sen, and check condition of *Cha-Sen* moving it to the upper right II. Stir hot water like drawing a semicircle one time and check condition of *Cha-Sen* moving it to the upper right III. Repeat Step II. IV. Stir hot water in a *Cha-Wan* like drawing a semicircle three times, then draw a circle in the bottom of a *Cha-Wan* with a *Cha-Sen*, and finally put a *Cha-Sen* on the *tatami* mat
41	I. Take *Cha-Shaku* from the top of *Natsume*'s lid with right hand II. Take *Natsume* with left hand and take off the *Natsume*'s lid with right hand III. Shift two scoops of powdered *Matcha* from *Natsume* to *Cha-Wan* with *Cha-Shaku* held with right hand IV. Flatten scooped powdered *Matcha* in *Cha-Wan* using *Cha-Shaku* with right hand
48	Mix powdered *Matcha* and hot water roughly, and then shake *Cha-Sen* back and forth quickly to whip *Matcha*
49	I. Check condition of liquid *Matcha* by tilting *Cha-Wan* a little toward oneself II. Rotate *Cha-Wan* counterclockwise with right hand and put it on the *tatami* mat to pass it to a guest
57	I. Take off *Mizu-Sashi*'s lid with right hand II. Carry the lid to the position of *Ken-Sui* with right hand III. Switch the lid from right hand to left and wipe off the lid's moisture with right hand IV. Lay the lid against right side body of *Mizu-Sashi* with right hand


Motion 15


Motion 16


Motion 28


Motion 29


Motion 30


Motion 41


Motion 48


Motion 49


Motion 57

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Figure 1: Nine motions of the tea-making procedure

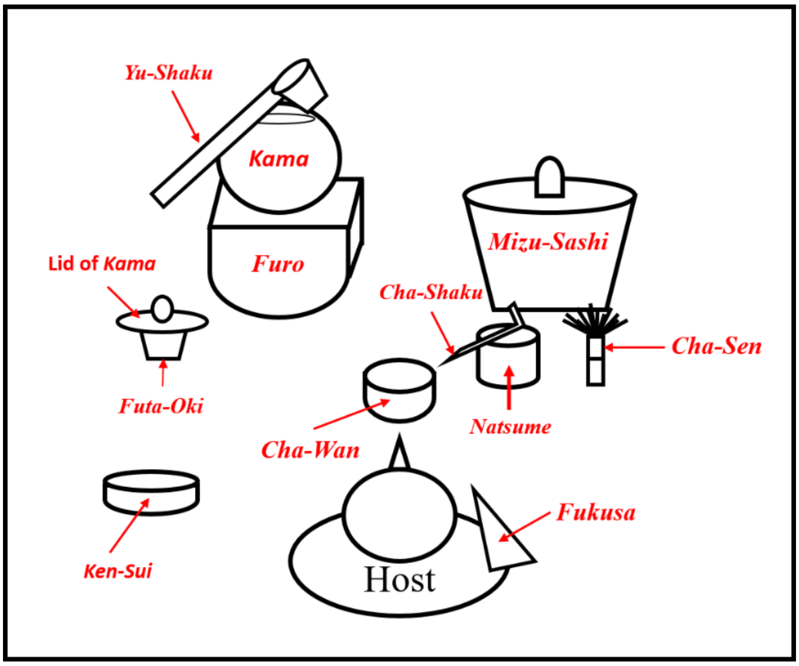

Figure 2: Utensils location in a tea room

3. METHOD

3.1 Unification of length of signal segments

Generally, a motion recognition is performed by moving a fixed-size time-window. Often, the window-size is set to the minimum time-length among those of target motions. Table 4 shows time-lengths of the 9 motions of the tea-making procedure. The lengths of the 9 motions were calculated by detecting large spikes on raising the right arm vertically at start and end of each motion. Here, minimum time-length was 10 s for motions 49 and 57. According to this minimum time-length, data segments from 0 to 10 s were used for motion recognition of motions 15, 16, 28, and 41, and remaining segments were not used. For motion 30, one segment was divided into three parts: 0–10 s, 11–20 s, and 21–30 s. These three parts were renamed as motions 301, 302, and 303, respectively. For motion 48, segment from 0 to 10 s was renamed as motion 481, and that from 8 to 17 s was renamed as motion 482. Motion recognition was performed for the 12 motions (including 301, 302, and 303 and 481 and 482 instead of 30 and 48, respectively) in the following step.

Table 4. Time lengths of the 9 motions of tea-making procedure

Motion	Time-length (s)
15	13
16	13
28	12
29	10
30	35
41	12

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48	17
49	10
57	10

3.2 Features of acceleration, angular velocity, and right-hand tilt angle

Fig. 3 illustrates examples of the 9 motions' right-hand tilt angle waveforms. In the figure, two examples are shown for every motion class; we see that the waveforms of the two examples are similar for all motions. From this, the variability of statistical features of sensor signals may be assumed to be low among the same motion class.

A total of 138 features for the acceleration, angular velocity, and right-hand tilt angle signals were used to recognize the 12 motion classes of the tea-making procedure with reference to [11, 12]. Right-hand tilt angle was calculated from acceleration.

Parts of 138 features were computed for each axis of acceleration, angular velocity, and right-hand tilt angle; and the corresponding vector norms (VN), $\mathrm{VN} = \sqrt{\mathrm{X}^2 + \mathrm{Y}^2 + \mathrm{Z}^2}$. Other features were computed only for three types VNs computed from three axis of acceleration, angular velocity, and right-hand tilt angle.

Features computed for each axis and VNs were mean of signal (MEAN), standard deviation (STD), median (MED), maximum value (MAX), minimum value (MIN), summation (SUM), root mean square (RMS), and curve length (CL) (1), total energy in frequency domain (TEF), differential value between MAX and MIN (RANGE), maximum power in spectral domain (MP), and frequency representing maximum power in spectral domain (FMP).

Other features for VNs were differential entropy of vector norm in time domain (ENTROPYT) (2), entropy of vector norm in frequency domain (ENTROPYF) (3), variance sum ($\mathrm{VAR}[\mathrm{X}+\mathrm{Y}+\mathrm{Z}]$(4), absolute mean value three axes (AMV) (5), interquartile range (IR) (6), kurtosis of vector norm (KURTOSIS), skewness of vector norm (SKEWNESS), and median crossings (MC) (7).

The CL, ENTROPYT, ENTROPYF, $\mathrm{VAR}[\mathrm{X}+\mathrm{Y}+\mathrm{Z}]$, AMV, IR, and MC were calculated using the following formulas (1), (2), (3), (4), (5), (6), and (7), respectively.

$$\mathrm{CL} = \sum_{i=2}^{N} |x_{i-1} - x_i| \quad (1),$$

$$\mathrm{ENTROPYT} = \sum_{i=1}^{N} f(x_i) log f(x_i) \ (2),$$

$$\mathrm{ENTROPYF} = -\sum_{i=1}^{N/2} p_i log_2 p_i \ (3),$$

$$\mathrm{Var}[\mathrm{X}+\mathrm{Y}+\mathrm{Z}] = \mathrm{Var}[\mathrm{X}] + \mathrm{Var}[\mathrm{Y}] + \mathrm{Var}[\mathrm{Z}] + 2\mathrm{Cov}[\mathrm{X},\mathrm{Y}] + 2\mathrm{Cov}[\mathrm{X},\mathrm{Z}] + 2\mathrm{Cov}[\mathrm{Y},\mathrm{Z}] \ (4),$$

$$\mathrm{AMV} = \frac{1}{T}\left(\sum_{i=1}^{N}|x_i| + \sum_{i=1}^{N}|y_i| + \sum_{i=1}^{N}|z_i|\right) \ (5),$$

$$\mathrm{IR} = \mathrm{percentile}(75, \mathrm{VN}) - \mathrm{percentile}(25, \mathrm{VN}) \ (6),$$

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$$\mathrm{MC} = \begin{cases} t = \mathrm{VN} - median(\mathrm{VN}) \\ t = \sum_{i=1}^{N-1} sgn(t_i - t_{i+1}) \\ \sum_{i=1}^{N-1} sgn(t_i - t_{i+1}) \\ sgn(a, b) := \{1\ if (a \times b) < 0, 0\ if (a \times b) > 0\} \end{cases} \quad (7),$$

where N means total number of samples; x_i, y_i, and z_i are i-th samples of x, y, and z axes; X, Y, and Z mean total signals of x, y, and z axes, respectively; p_i means power in frequency domain; and VN means the vector norm of acceleration signal, angular velocity, or right-hand tilt angle.

The aforementioned 138 features were calculated for each data segment with clues to spike signals of acceleration caused by raising right hand vertically before and after each motion of the tea-making procedure.

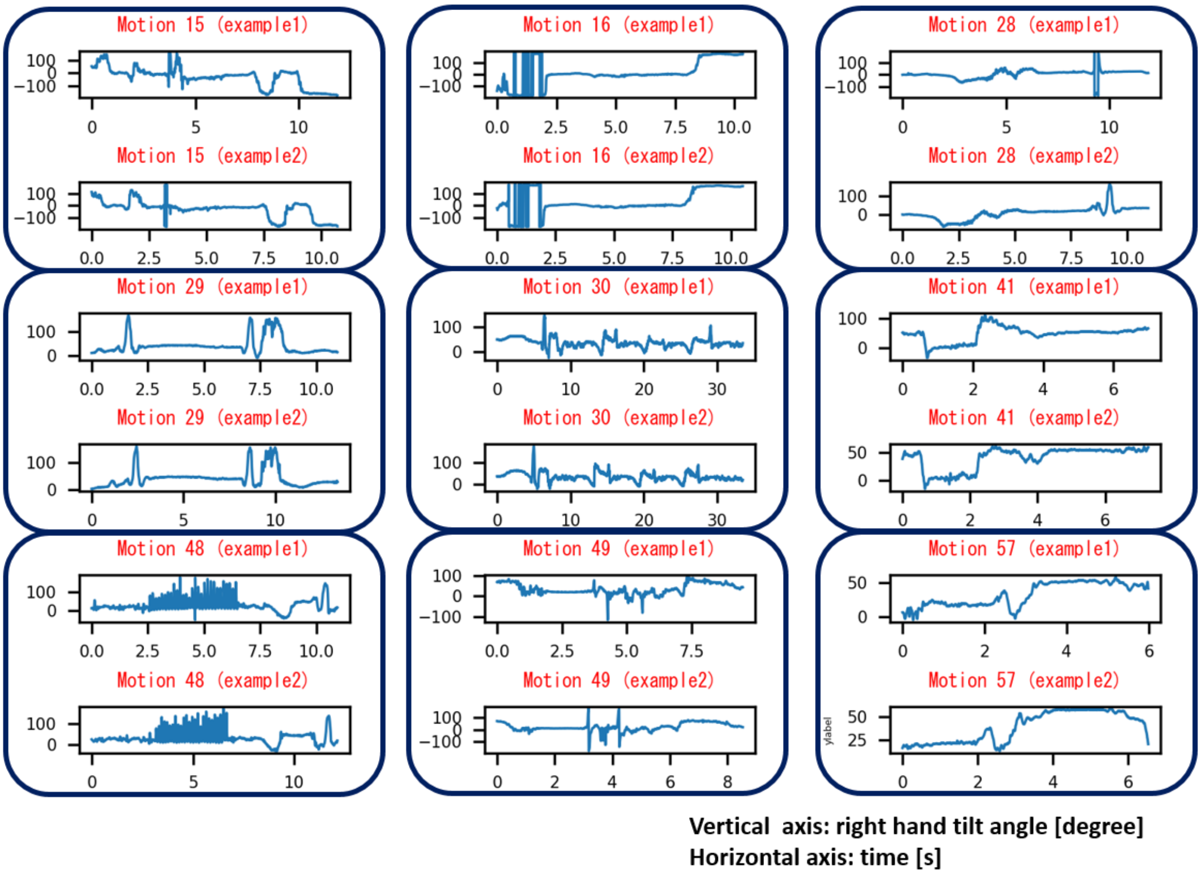

Figure 3. Examples of the 9 motions' right-hand tilt angle waveforms

3.3 Classification model for the 12 motion classes of the tea-making procedure

As a classifier model, random forest was adopted because this model has often been used for acceleration-based motion recognition [7-10] and has yielded results with high accuracy. Here, random forest was implemented by scikit-learn 0.24.2 in python 3.9.7, and default parameters were used.

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Explanatory variables were 138 features as stated in Section 3.2, and target variables were the labels of the 12 motion classes mentioned in Section 3.1. Additionally, 60% data were used to learn the random forest model, and the remaining 40% were used for validation using by the train_test_split function in python.

4. EVALUATION AND RESULT

As evaluation metrics, this research adopted accuracy ($= \mathrm{TP} + \mathrm{TN}/(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})$), precision ($= \mathrm{TP}/(\mathrm{TP} + \mathrm{FP})$), recall ($= \mathrm{TP}/(\mathrm{TP} + \mathrm{FN})$), and F1-score ($= 2 \times \mathrm{recall} \times \mathrm{precision}/(\mathrm{recall} + \mathrm{precision})$). TP, TN, FN, and FP mean true positive, true negative, false negative, and false positive, respectively. These four evaluation metrics were computed for every class of motion ofthetea-making procedure, and finally, performance of random forest-based motion recognition model was evaluated by averaging values of the 12 motion classes, also known as macro-averaging. Macro-averaged evaluation results are shown in Table 5. Fig. 4 illustrates the confusion matrix of the 12 motion classes. Additionally, the top 10 of 138 random forest feature importance scores are shown in Table. 6.

Table 5. Evaluation results

Evaluation index	Score
Accuracy	0.981
Precision	0.982
Recall	0.981
F1-score	0.981

Figure4: Confusion matrix of the 12 classes of motion of the tea-making procedure

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Table 6.Top 10 of the random forest feature importance scores

Importance rank	Feature	Importance score
1	MEAN (z-axis of right-hand tilt angle)	0.038
2	TEF (z-axis of right-hand tilt angle)	0.027
3	MED (y-axis of right-hand tilt angle)	0.024
4	STD (y-axis of acceleration)	0.024
5	RMS (z-axis of right-hand tilt angle)	0.023
6	MED (z-axis of acceleration)	0.021
7	CL (z-axis of angular velocity)	0.021
8	MP (z-axis of acceleration)	0.020
9	MED (x-axis of angular velocity)	0.020
10	MED (x-axis of acceleration)	0.020

5. DISCUSSION

As shown in Fig. 3, signal waveforms were similar to each other if same motions of the tea-making procedure were measured. All four evaluation metrics: accuracy, precision, recall, and F1-score exceeded 0.98.

Table 6 shows that features of each axis of acceleration and right-hand tilt angle signals computed from acceleration account for eight in top 10 of important features importance scores of VN features were lower. From these results, it can be concluded that motion characteristics of the tea-making procedure appear in respective axes of acceleration and disappear in VN. Additionally, Table 6 shows that MEAN, TEP, MED, and RMS computed from each acceleration axis were selected as important features. This result indicates that amplitudes and variances of acceleration are different for each motion of the tea-making procedure.

Regarding recognition errors, Fig. 4 indicates that motion 15 was misrecognized once as motion 16; motion 57 was misrecognized twice as motion 47; and motion 41 was misrecognized thrice as motion 15, 16, and 303. In motions 15, 16, 303, and 41, utensils were used above the level of the plexus, and motion 57 is similar to motion 49 in that the subject moved the position of the utensil over a wide range. Thus, it can be concluded that similarities of position and moving distance of utensils causes misrecognitions.

Here, the proposed method achieved high recognition accuracy. However, this method is not practical yet. In a general motion recognition method, objective motions have to be recognized from a series of continuous motion using a moving window. In the tea-making procedure, we have to recognize when and what motion is performed from a continuous series of 98 motions of the tea-making procedure. However, in this study, the motion recognition was performed for segments previously separated into objective motions of the tea-making procedure as discussed in Sections 3.2 and 3.3. In general motion recognition, it is difficult to accurately recognize a motion when the moving window is located in a transition period from one motion to other motion; this aspect was not incorporated here. Additionally, variability of statistics in the same motion class may have been small because only one subject conducted the tea-making procedure. These two elements could facilitate recognition of the 12 motion classes of tea-

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making procedure. However, the purpose of this study was only to demonstrate the feasibility of motion recognition of the tea-making procedure, in which, it proved successful.

In future works, this method will be improved so as to recognize objective motion from a continuous series of 98 motions of the tea-making procedure with more subjects. Furthermore, a support system to analyze communication during tea ceremony by automatic motion recognition of the tea-making procedure will be developed.

6. CONCLUSION

The goal of this study was to recognize 9 motions (12 motion classes) of CHA-NO-YU, traditional Japanese tea-making procedure, using acceleration, angular velocity, and right-hand tilt angle data. In the experiment, 99-sensor dataset were obtained for every motion class, thus amounting to $99 \times 12 = 1188$ data. For the motion recognition, random forest classifier was adopted, and the 12 motion classes were recognized with approximately 0.98 accuracy, precision, recall, and F1-score. However, as the proposed method did not recognize 12 motions from a series of continuous motion of tea-making procedure using a moving window, it will be improved in a future work.

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