Segmentation of Human Body Movement using Inertial Measurement Unit

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***Abstract*—This paper proposes an approach for the temporal segmentation of human body movements using IMU (Inertial Measurement Unit). The approach is based on online HMM-based segmentation of continuous time series data. In previous studies, the real-time segmentation of human body movement using joint angles acquired by optical motion capture has been realized, using stochastic motion modeling. The approach is now adapted for angular velocity data. The segmented motions are recognized via HMM models. The segmentation and recognition results of the proposed algorithm are demonstrated with experiments. Auto segmentation of each motion and recognition of motion patterns are verified using angular velocity data obtained by IMU sensors and the Wii remote. The success rate of auto segmentation using the data obtained by Wii remote was more than 80% on average.**

***Index Terms*—HMM; Inertial Measurement Unit; Wii Remote; Segmentation; Recognition; Arm motion.**

I. Introduction

The analysis of human body motion is useful in many fields such as sports, medical diagnosis and rehabilitation. Optical motion capture is commonly used for observing human movement data [1][2][3], however, optical motion capture may not be suitable for many applications such as sports or rehabilitation, where low-cost, ambulatory sensors would be preferred. Human motion observation is also used intensively for Human Robot Interaction. Recently, cleaning, home-care and security robots are beginning to be widely used in human environments such as at home and in the office [4][5]. Nursing care robots are also being deployed as a response to the issue of aging [6]. Human motion analysis using joint angles and joint angular velocities obtained by optical motion capture has been reported previously [7][8][9]. However optical motion capture systems need large space and several cameras, and the use of markers. Therefore, optical motion capture is not suitable for daily life use.

In this paper we propose a segmentation method using data obtained by Inertial Measurement Units (IMUs). Segmentation is an important issue for analysis of human motions. When human watch the motions of others, they recognize them as segmented motion patterns. The analysis of human motions is affected by the accuracy of segmentation, as motion patterns are generated from the segmented data.

In this paper, we acquire the angular velocities and accelerations directly from the IMUs. When calculating the joint angles from angular velocities and accelerations, integration error and drift are often significant concerns [6]. By not modeling the human body, we avoid the need to know the body dimensions, the exact placement of the sensors and the errors caused by joint state estimation. Therefore, for accurate pattern recognition of human body motion from IMU data, we use the angular velocity data directly. We need not use kinematics for modeling.

We conducted two types of experiments: in the first one a Japanese traditional drumming performance is demonstrated using portable IMUs, in the second experiment, we used the Wii remote game controller as the IMU sensor and drumsticks [10]. The Wii remote has a three-axis acceleration sensor and gyro sensor, and is inexpensive and easily accessible, making it a promising platform for home rehabilitation applications.

The paper is structured as follows: in section II the proposed segmentation method is introduced. In section III the two experiment methods are explained. In section IV, the results of auto segmentation and recognition using IMU data are given. Section V provides the results of auto segmentation and recognition using Wii remote data. Conclusions and directions for future work are outlined in Section V.

II. Unsupervised Probabilistic Segmentation

When humans observe the behavior of others, human motion is recognized as a sequence of motion primitives. To segment continuous time-series data into discrete motion segments, we apply the Kohlmorgen and Lemm segmentation algorithm [11] adapted for human movement.

This section introduces the unsupervised probabilistic segmentation algorithm proposed in [8]. The algorithm considers $\boldsymbol{y}_1, \boldsymbol{y}_2, \boldsymbol{y}_3, \cdots$ to be an incoming data stream to be analyzed. The data is embedded into a higher dimensional vector

$$\boldsymbol{x}_t = (\boldsymbol{y}_t, \boldsymbol{y}_{t-1}, \cdots, \boldsymbol{y}_{t-(m-1)\tau}), \tag{1}$$

where m is the embedding dimension and τ is the delay parameter. We want to track the density distribution of the embedded data and therefore estimate the probability density function over a sliding window of length L. We use a standard density estimator with multivariate Gaussian kernels, centered on the data points in the window $\{\boldsymbol{x}_{t-i}\}_{i=0}^{L-1}$,

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$$p_t(\mathbf{x}) = \frac{1}{\mathrm{L}} \sum_{\mathrm{i}=0}^{\mathrm{L}-1} \frac{1}{(2\pi\sigma^2)} \exp\left(-\frac{(\mathbf{x}-\boldsymbol{x}_{\mathrm{t-i}})^2}{2\sigma^2}\right) \tag{2}$$

The kernel width σ is a smoothing parameter. The value of σ is important to obtain a good representation of the underlying distribution. σ is chosen proportional to the mean distance of each $\boldsymbol{x}_t$ to its first k nearest neighbors, averaged over a sample set $\{\boldsymbol{x}_t\}$. Given two neighboring windows t1 and t2, the distance between them can be computed as the distance between their associated Gaussians as follows;

$$\begin{aligned} d(p_{t1}(\mathbf{x}), p_{t2}(\mathbf{x})) \quad = \quad & \frac{1}{L^2(4\pi\sigma^2)^{d/2}} \\ & \sum_{i,j=0}^{L-1} \Bigg[\exp\left(-\frac{(\boldsymbol{x}_{t1-i} - \boldsymbol{x}_{t1-j})^2}{4\sigma^2}\right) \\ & -2\exp\left(\frac{(\boldsymbol{x}_{t1-i} - \boldsymbol{x}_{t2-j})^2}{4\sigma^2}\right) \\ & +\exp\left(-\frac{(\boldsymbol{x}_{t2-i} - \boldsymbol{x}_{t2-j})^2}{4\sigma^2}\right) \Bigg] \end{aligned} \tag{3}$$

The segmentation analysis is carried out by defining a Hidden Markov Model [12] over a set S of sliding windows. Each window corresponds to a state of the HMM. For each state, the observation probability distribution is defined as;

$$p(p_t(\mathbf{x}|\mathrm{s}) = \frac{1}{\sqrt{2\pi}\zeta} \exp\left(\frac{d\big(p_s(\mathbf{x}), p_t(\mathbf{x})\big)}{2\zeta^2}\right) \tag{4}$$

where $p(p_t(\mathbf{x})|s)$ is the probability of observing the window represented by $p_t(\mathbf{x})$ in state s. The HMM transition matrix, $A = (a_{ij})_{i,j \in S}$, determines the probability to switch from state s_i to state s_j. The initial state distribution is the uniform distribution. The state transition matrix is designed so that transitions to the same state are k times more likely than transitions to any of the other states.

$$a_{ij} = \begin{cases} \frac{k}{k+N-1} & \text{if} \quad i = j \\ \frac{1}{k+N-1} & \text{if} \quad i \neq j \end{cases} \tag{5}$$

where N is the number of states of the HMM. The Viterbi algorithm [12] can then be used to find the optimum state sequence given the current set of observations. An on-line variant of the Viterbi algorithm is applied to enable on-line segmentation [8] [11].

This segmentation approach proposed for joint angle data by Kulić and Nakamura [8][9] is here applied to angular velocity data obtained from the IMU. We use the angular velocity data obtained using the IMU sensor instead of each joint angle. Following segmentation, to identify each motion we use HMM modeling as proposed in [7][13], and illustrated in Figure 1. An HMM model is generated for each movement type. In this study, we adopt the left-to-right type. In the left-to-right type, each state can only transition to itself or to the adjacent state. HMM λ is defined as shown in (6).

$$\lambda = \{\mathbf{Q}, \mathbf{A}, \mathbf{B}, \mathbf{\Pi}\} \tag{6}$$

- $\mathbf{Q}$ = $\{q_1, \cdots, q_n\}$: the set of states
- $\mathbf{A}$ = $\{a_{ij}\}$: the state transition probability matrix which is the transition probability from state q_i to q_j
- $\mathbf{B}$ = $\{b_1, \cdots, b_n\}$: the probability density functions
- $\mathbf{\Pi}$ = $\{\pi_i\}$: the set of the prior distribution of the initial state

where the prior distribution of the initial state is set to [1,0,0,$\cdots$] for a left to right HMM. The observation function for each state is defined by the Gaussian distribution as follows;

$$b_i = \frac{1}{\sqrt{(2\pi)^m|\Sigma_i|}} \exp\{-\frac{1}{2}(\hat{\mathbf{o}} - \boldsymbol{\mu}_i)^T \Sigma_i^{-1} (\hat{\mathbf{o}} - \boldsymbol{\mu}_i)\} \tag{7}$$

where $\boldsymbol{\mu}_i$, $\sum_i$, m represent the mean vector, covariance matrix and dimension of the motion data, respectively [12]. We generate sets of N_U HMMs Λ_k ($k = 1, 2, \cdots, N_U$), where N_U is the number of motion primitives. HMMs Λ_k have 6 to 12 states. The number of states is selected empirically through cross-validation. To recognize each segment, the likelihood $P(O_{segment}(i)|\Lambda_k)$ of the segmented motion pattern $O_{segment}(i)$ against each HMM Λ_k is calculated. The HMM Λ_{k0} with the largest likelihood is selected.

$$\Lambda_{k0} = \arg\max_{\Lambda_k} P(O_{segment}(i)|\Lambda_k) \tag{8}$$

In an off-line training step, the segmented $O_{segment}(i)$ are provided to the HMM Λ_{k0} as training data. The HMM is optimized using the Baum-Welch algorithm [12].

III. Experiments

A. Measurement device

In this study, both IMU sensor and Wii Remote controller (Nintendo Co., Ltd.) are used as measurement devices. Wii Remote has comparable sensors to the IMU. Figure 2 shows the direction of the axes of both sensors. We consider that the Wii Remote will be easy to use in daily life because the Wii Remote is popular and inexpensive, and does not require any user expertise. Therefore, we have performed two types

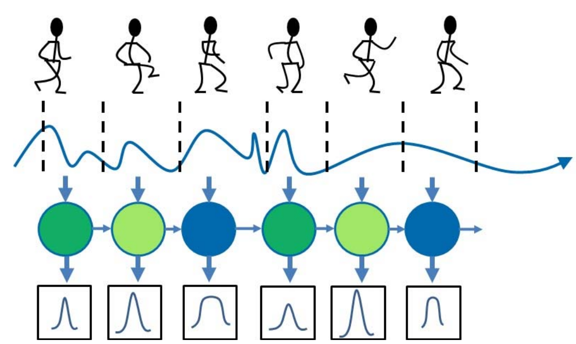

Fig. 1. Conceptual diagram of HMM motion modeling.

of experiments. Experiment I used the IMU for exploring the possibility of pattern recognition using angular velocities. The photos of the experiment I are shown in Figure 3. After confirmation, we have performed experiment Ⅱ using the Wii Remote.

B. Experiment I using IMU

In this experiment the angular velocity data of the right arm is measured when the subject beats the drum. The subject wears an IMU as shown in Figure 3. The subject repeats the same motion ten times for generating the HMMs. There are three beating types as shown in table I. Both "Strongly" and "Weakly" are vertical arm movements, starting from the maximum height and moving downwards. Another type of movement is the "Sideways" movement, where the arms move towards the drum from the side. One set of the movements is collected for HMM training, and a second set of movements is recorded for testing the segmentation. The subject beats the drum using vertical arm movements, with three action types up to down by varying the strength. First, the subject beats the drum strongly for four repetitions; next, the subject uses intermediate strength for four beats, and finally, the subject beats the drum weakly four times. This measurement data is segmented into each motion pattern. Each motion pattern is recognized and compared with the prepared models. This data sequence is called "Mixed".

C. Experiment using Wii Remote

In this experiment, the angular velocity of the right arm is now measured when the subject shakes his hand. The subject holds the Wii Remote as shown in Figure 4. The subject repeats the same motion ten times for generating each motion. Both "Widely" and "Small" are vertical arm movements, moving the arm from up and down. "Sideways" is from left to right.

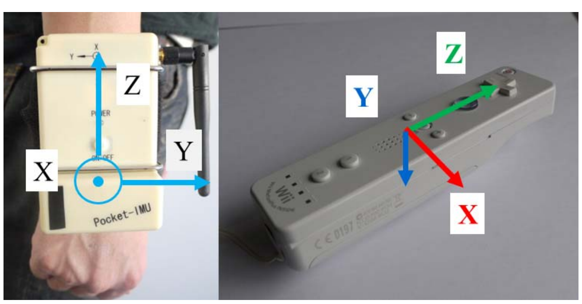

Fig. 2. IMU and Wii Remote axial directions.

TABLE I
MODEL TYPES

Name	Type	Name	Type
IMU Model 1	Strongly	Wii Model 1	Widely
IMU Model 2	Weakly	Wii Model 2	Small
IMU Model 3	Sideways	Wii Model 3	Sideways

Fig. 3. Photos of Experiment I (Taiko drumming).

Fig. 4. Photos of Experiment Ⅱ (Wii Remote holding).

IV. SEGMENTATION RESULTS USING IMU DATA

A. Auto segmentation and models generation

To validate the possibility of segmentation and recognition we use the data of Experiment I. To analyze the performance of the automated segmentation algorithm, manual segmentation results are generated as ground truth. The manual segmentation represents the frame number at which there is a change in the motion pattern. The manual segmentation is decided using recorded video during experiments and observing the waveform corresponding to the experiments. From the video, we define a motion segment each time that the subject beats the drum once. Based on this definition, the segment point is identified at the start of each drum beating motion. When we look at the graph of the angular velocity in Figure 5, we observe that the same wave form is repeated 10 times. The manual segmentation points are determined from the wave form of the angular velocity data, using the video as confirmation.

The automated and manual segmentation results are compared in Figure 5. The algorithm can use all 6 sensor elements but we use angular velocities of ϖ_x and ϖ_y. Because other elements are small magnitude and affected by the gravitational acceleration. The auto segmentation performs well in these results. However, the algorithm does not perform well at the start and end of a data sequence, as the algorithm does not have a full set of windows for performing the distance evaluation. This can be observed in Figure 5, where all the segment results correspond to the manual segmentation, except for the first and the last segment points. The algorithm performance is also poorer if there is a difference in the magnitude of the motion. This can be observed in Figure 9, where motion 10 is not segmented as the magnitude of the motion is very small compared to the previous motions, resulting in low distance values.

Figure 6, 7 and 8 show the data for each learning model. The wave forms of strongly and weakly are similar in wave

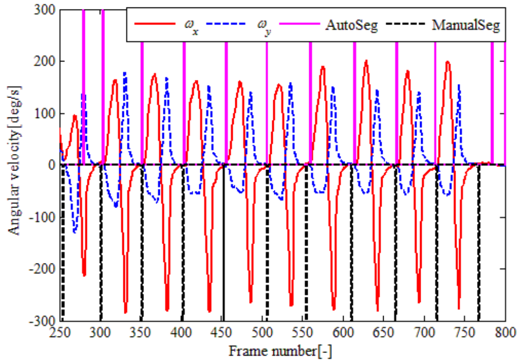

Fig. 5. Segmentation results of Experiment I ”Strongly”.

TABLE II
RECOGNITION RESULTS USING IMU SENSOR MIXED.

	IMU model 1 Strongly	IMU model 2 Weakly	IMU model 3 Sideways
Strongly	100%	0%	0%
Middle	50%	50%	0%
Weakly	0%	100%	0%

shape. The difference is that the magnitude of the ”strongly” motion is three times larger than ”weakly” motion. The wave forms of sideways look qualitatively different.

B. Recognition results of motion patterns

To test the motion recognition, we generate HMMs for each motion pattern as shown in table Ⅲ. The number of HMM states is 6 for the IMU models. After segmentation, the data is compared with those models. From the data sequence shown in Figure 5, the motion patterns from segment 1 to segment 4 are similar to IMU model 1. The subject hits strongly 4 times, medium 4 times and weakly 4 times in this series. Therefore, motion patterns from segment 5 to segment 8 are between IMU model 1 to IMU model 2. The motion patterns of segment 9 and segment 11 are similar to IMU model 2. The motion pattern 10 is not segmented because this motion is too small in amplitude compared to the other segments, so we cannot perform recognition of the motion pattern 10. Motion patterns from 1 to 6 are recognized as IMU model 1, from 7 to 9 and 11 as IMU model 2. All motion patterns are never recognized as IMU model 3 because IMU model 3 is not included in the test data.

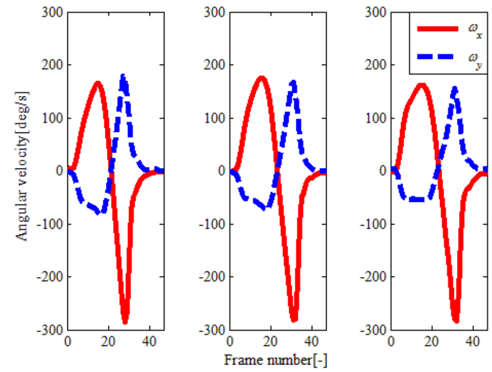

Fig. 6. IMU Model 1 ”Strongly”.

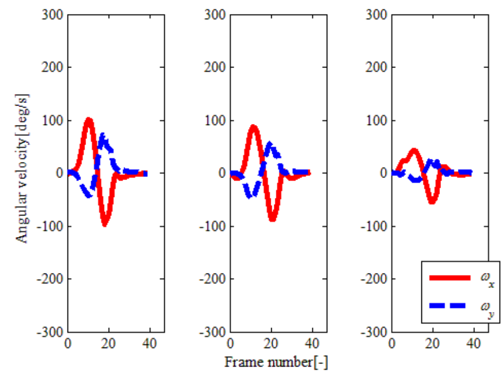

Fig. 7. IMU Model 2 ”Weakly”.

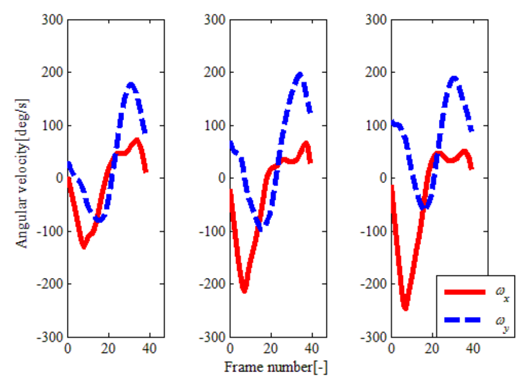

Fig. 8. IMU Model 3 ”Sideways”.

V. SEGMENTATION RESULTS USING WII DATA

A. Auto segmentation and models generation

Figures 10, 11, 12 and 14 show the segmentation results from the Wii Remote data. For this dataset, a quantitative measure of segmentation error was also generated. A segmentation error was considered if the automated algorithm fails to identify a segment point, or if manual and automatic points differ, by more than 5 frames. Figure 12 and 14 show perfect segmentation. Figure 10 and 11 show some segmentation errors. There are missing segmentation points following the fifth and sixth motion primitives in figure 11. Table Ⅱ shows the success probability of auto segmentation for each motion type. Overall, for the widely motion, the success probability of auto segmentation is 88.9%. The success probability of auto segmentation is 63.0% for small motion, due to the small amplitude of the small motion. The auto segmentation is 100% accurate for the sideways motion. This is because the wave forms of sideways motion have the clear boundaries of each

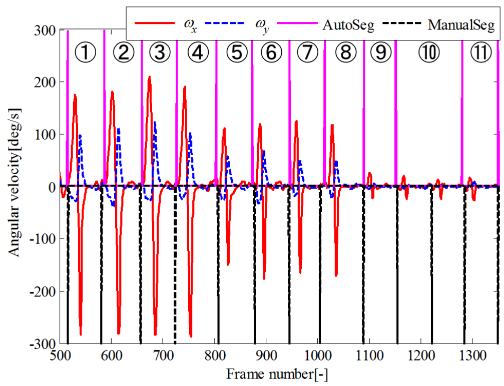

Fig. 9. Recognition results of IMU data "Mixed".

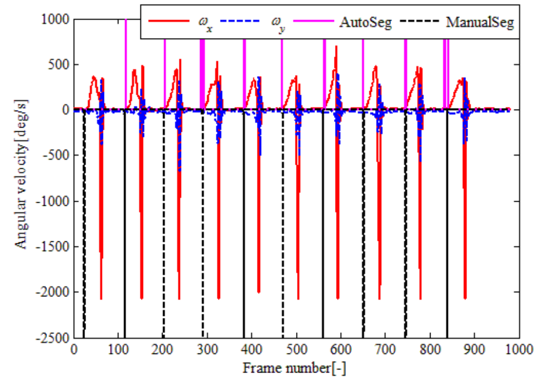

Fig. 10. Segmentation results of Experiment II "Strongly".

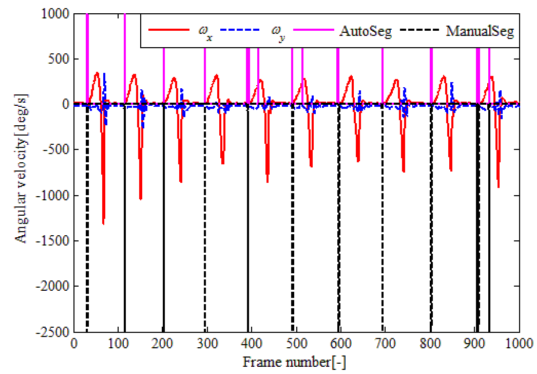

Fig. 11. Segmentation results of Experiment II "Weakly".

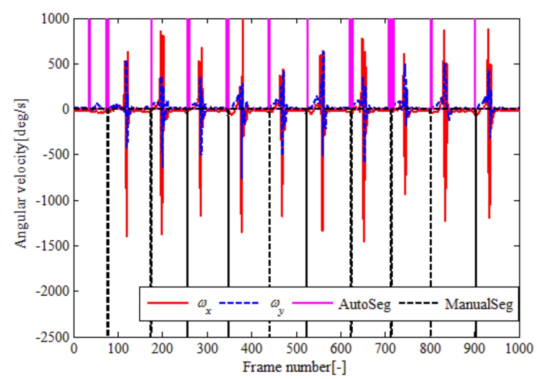

Fig. 12. Segmentation results of Experiment II "Sideways".

motion pattern.

Figure 13 shows the data for each learning model. This figure shows that the three types of wave form are different.

TABLE III
THE SUCCESS OF PROBABILITY OF SEGMENTATION

	Widely	Small	Sideways
Success probability of segmentation	88.9%	63.0%	100%

B. Recognition of motion patterns

The number of HMM states is 12 for the Wii models. Figure 13 shows each of the models for the Wii Remote motions. Table I shows which motion types correspond to each model. The wide motion is Wii model 1, the small motion is Wii model 2 and the sideways motion is Wii model 3. The wave forms of the wide motion are similar to the wave forms of the small motion. The angular velocity ϖ_x is the direction of shaking the Wii Remote. So the strength of the shaking is observed in the angular velocity ϖ_x. The angular velocity ϖ_x of the sideways motion is larger than ϖ_y. Table IV shows the results of the recognition for the Wii models for the data sequence in Figure 14. From the results of this experiment, we verified that recognition can be performed by the data obtained by Wii Remote.

TABLE IV
RECOGNITION RESULTS USING WII REMOTE DATA "STRONGLY"

	Wii model 1	Wii model 2	Wii model 3
Widely motion	90%	0%	10%

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we propose an unsupervised probabilistic segmentation algorithm suitable for on-line segmentation using angular velocity data from IMU sensor and Wii remote. We also demonstrated motion recognition using HMMs based on angular velocities rather than joint angles.

For future work, we aim to extend the proposed approach to improve the segmentation accuracy of small amplitude motions and motions at the start and end of a movement sequence. We will reconsider the evaluation method of accuracy segmentation [15]. We aim to improve the success rate of the auto segmentation and the recognition, by considering other segmentation algorithms and factorial HMMs [16].

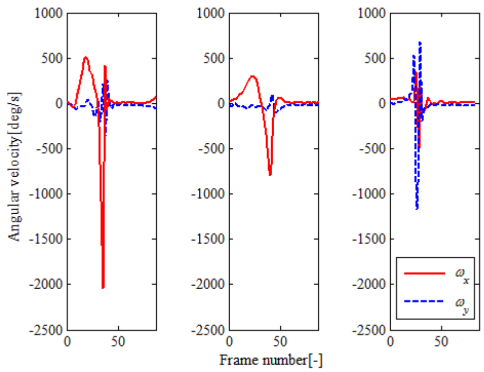

Fig. 13. Wii Models.

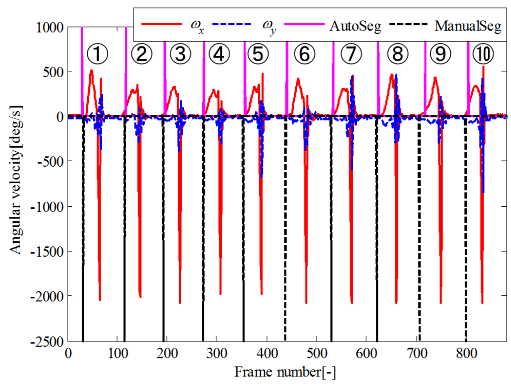

Fig. 14. Recognition results of Wii Remote.

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