2016 Joint 8th International Conference on Soft Computing and Intelligent Systems and 2016 17th International Symposium on Advanced Intelligent Systems

An Analysis for Switching of Feedback and Feedforward Mechanism in Motor Internal Model

Isao Hayashi
Kansai University
Takatsuki, Osaka 569–1095, Japan
Email: ihaya@cbii.kutc.kansai-u.ac.jp

Sayaka Kita
Ushio Consultants Co.
Kashiba, Nara 639–0225, Japan
Email: saya1990k@gmail.com

Masaki Ogino
Kansai University
Takatsuki, Osaka 569–1095, Japan
Email: ogino@res.kutc.kansai-u.ac.jp

Jasmin Leveille
Wheatsone Techonologies LLC
Washington, DC, USA
Email: jasminl@cns.bu.edu

***Abstract*—The internal model was proposed by Kawato [3], in order to express physical motion by associativity of feedback and feedforward control processes. In this paper, we test the internal model in an experiment in which participants push a button on an equipment to match a number displayed on a computer screen. The experimental results can be interpreted as a change in the relative contributions of feedback and feedforward control processes in the internal model.**

***Index Terms*—Motion Analysis, Motor internal model, Control Process**

I. Introduction

Among models that analyze motion trajectories in terms of the structure different functional processes [1], [2], the motion internal model [3]–[5] and MOSAIC model [6]–[8] are particularly useful. The internal model is based on the model of Allen-Tsukahara and is able to express physical motion by associativity of feedback and feedforward control processes. In this model, movement is controlled well gradually, because the inverse model reduces the error between the desired trajectory and the trajectory realized by a feedforward function. MOSAIC(Module Selection and Identication for Control) model is a computational model that structured a mechanism of switching internal models. Because the priority of internal model is determined by the responsibility predictor and the likelihood module, we can select the appropriate internal model even though the external environment changes. As a result, the control for flexible movement is possible.

In this paper, we discuss feedback and feedforward processes in relation to the internal model and MOSAIC model when a repetition task involving vision and motion is given to participants. In the experiment introduced here, subjects watch “a number” displayed on the computer screen and simply push a button on the equipment corresponding to the same number. As the experiment is repeated over several trials, the feedforward control representation is strengthened in the internal model, and the ratio of the feedforward control to the feedback control rises. Based on an analysis of Response Times, the motion trajectories and the electroencephalographic (EEG) signals, we discuss the weighting of feedback and feedforward processes in the internal model.

II. Motion internal model

Figure 1 shows the concept of internal model. When a nonzero difference is present between the desired trajectory and the realized trajectory of the movement, the difference signal is transmitted to Purkinje cells in the cerebellum and controls both motion output and initiation time. The cerebellum structures forward model and inverse model for voluntary movement. We call the model internal model. In the forward component of the internal model, the output is controlled by motion so that the actual movement trajectory converges onto the target position as much as possible. In the inverse model, low-level learning is slow, but learning is performed so that the error between the position of the motion signal and the position of the actual trajectory of the movement decreases, so as to adjust the position of the actual movement using signals from the forward model. At a start of the movement, the feedback model is not able to control the trajectory movement smoothly. Gradually, the movement is controlled well, because the inverse model reduces the error

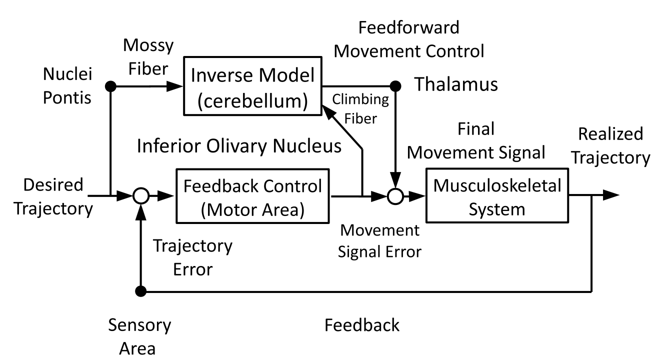

Fig. 1. Structure of the internal model

On the other hand, There is a MOSAIC(Module Selection and Identication for Control) model, which is a computational

978-1-5090-2678-4/16 $31.00 © 2016 IEEE
DOI 10.1109/SCIS&ISIS.2016.44

model that structured a mechanism of switching internal models. Figure 2 shows the concept of MOSAIC model. In the architecture of MOSAIC model, a switching mechanism is consisting of the responsibility predictor and the likelihood module. Because the priority of internal model is determined by the responsibility predictor and the likelihood module, we can select the appropriate internal model even though the external environment changes. As a result, the control for flexible movement is possible.

The responsibility predictor selects a forward model among all forward models, which adapts to environmental information most. The likelihood module increases the output of an inverse model pairing the forward model by a difference with the target position and the actual movement trajectory. To choose a forward model by the responsibility predictor is a top-down signal selecting by outside environmental information. In addition, to choose an inverse model by a likelihood module is a bottom-up signal to estimate the output of the internal model. By the likelihood module and the forward model, the most precise pair of models can be selected. Therefore, a timing to select the internal model pairing the forward model is late if outside environmental information is not provided because MOSAIC model refers to only the feedback of sensory and motor function. As a result, the model selection by the likelihood module cannot follow a sudden environmental change, and the learning gradually is activated in accord with motion.

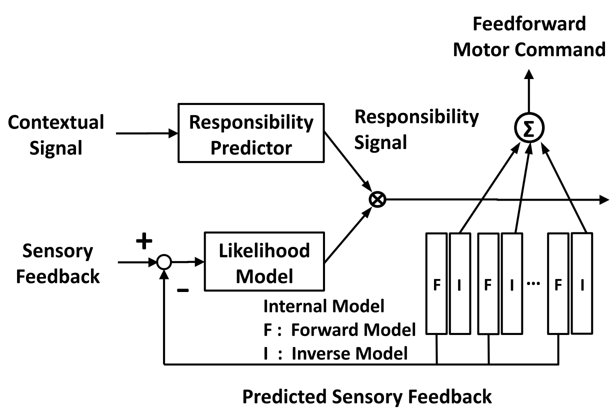

Fig. 2. Structure of MOSAIC Model

III. Experiment

Figure 3 shows the experimental setup. A participant's head is held against a chin support device, and the computer screen is set to be $61cm$ in the front of the subject. A set of buttons (1, 2, 3) is placed at a distance of $46cm$ - $54cm$ in the front of the participant. After a 2-seconds resting time, the participant fixates a cross mark at the center of the computer screen followed by a number, also presented for 2 seconds. The participant is instructed to push the button whose number matches the number shown on the screen. Figure 4 shows the experimental procedure. The number displayed on the screen is repeatedly shown five times and is therefore referred to as a repetition pattern. Another pattern, called a non-repetition pattern, is displayed only three times. The set of presentations consisting of the five iterations of the repetition pattern and the three iterations of the non-repetition pattern is referred to as a presentation pattern. One trial consists in three repetitions of a presentation pattern, and the experiment is repeated over 7 trials. We selected five participants, including two men (early 20s, all right-handed) and three women (early 20s, all right-handed). Overall, we measured the motion trajectories of subjects as they pushed the buttons a total of 504 times, corresponding to 168 pattern presentations. The time required for each subject was approximately 40 minutes. In particular, we measured the motion trajectories of subject H to analyze his characteristic of movements between feedback and feed-forward.

Fig. 3. Experiment

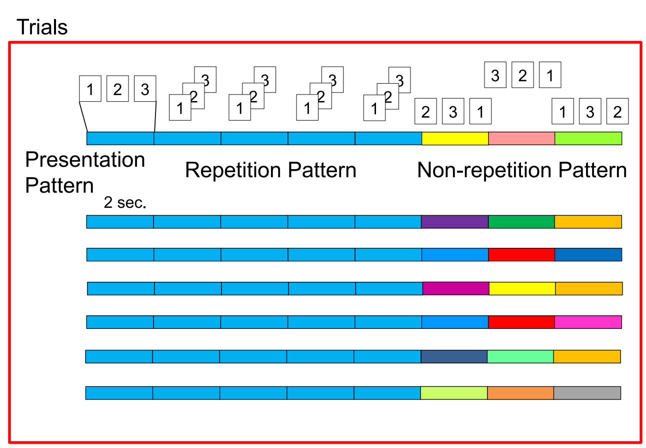

Fig. 4. Experimental Procedure

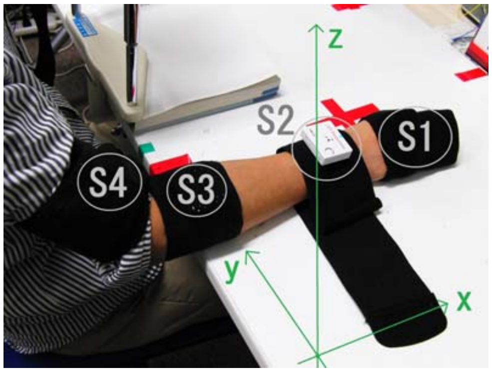

Fig. 5. Motion Sensors

We recorded subjects' Response Time and motion trajectory during each button push following the presentation of a number on the screen, and also simultaneously recorded electroencephalographic (EEG) activity. Figure 5 shows the positions of sensors used to measure acceleration and angular velocity (TSND121, ATR-Promotions Co. Ltd., sampling frequency: $100Hz$). In this experiment, the feedforward signal is activated by inverse model of the internal model, when several times of repetition patterns were shown. In addition, switching time of the internal model of the MOSAIC model is observed as response time when the first non-repetition pattern was shown.

The EEG signal was recorded at the following eight electrode locations: F_{p1}, F_{p2}, C_1, C_2, C_z, P_z, O_1, and O_2. Electrodes were placed according to the international 10-20 system using the EEG measurement device (AP216 Polymate-II, TEAC Corporation, sampling frequency: $200Hz$). In addition, we used Java Processing Program and Arduino for switching control of buttons, and displaying a number on the screen. In addition, we used softwares of AP Moniter and Sensor Controller for control of AP216 and TSND121, respectively.

The procedure of the experiment is shown as follows;

Step 1 The experimenter distributes the certificate of consent of experiment to a subject, and the subject understands the contents and fills in the certification.

Step 2 A participant's head is held against a chin support device, and we place electrodes at the eight locations of his/her head. In addition, we place sensors at the four locations of his/her right arm to measure acceleration and angular velocity.

Step 3 We record subjects' response time, acceleration and angular velocity during 3 trials, and also simultaneously record electroencephalographic (EEG) activity.

Step 4 After having a ten-minute break, we record subjects' response time, acceleration and angular velocity, and electroencephalographic (EEG) activity for 4 trials test.

Step 5 We distribute a questionnaire to participants and we collect them. We finish the experiment.

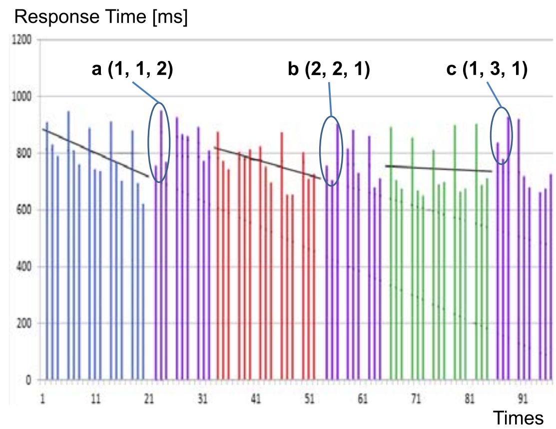

Fig. 6. Response Time of the First Trial

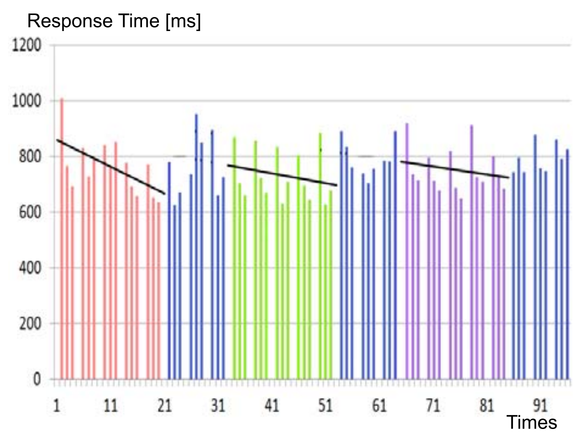

Fig. 7. Response Time of the Second Trial

IV. Measurement Result

Figure 6 to 12 show the result of the first trial of subject H. The vertical axis shows the Response Time (ms) for a subject to push a button following presentation of a number. We estimated a regression line for the Response Time using regression analysis. In Figure 6 to 12, the gradient of the regression line for the first presentation pattern is steeper than the gradient for the second and third presentation patterns, and the gradient becomes more shallow with the number of presentation patterns. We suggest that the phenomenon can be explained with the internal model as a switching from feedback to feedforward process occuring over multiple trial repetitions. In Figure 6, the average Response Time of the fifth repetition pattern (1, 2, 3) of the first presentation pattern is $731ms$, but the average Response Time of the non-repetition pattern a(1, 1, 2) continuing after the first repetition pattern is

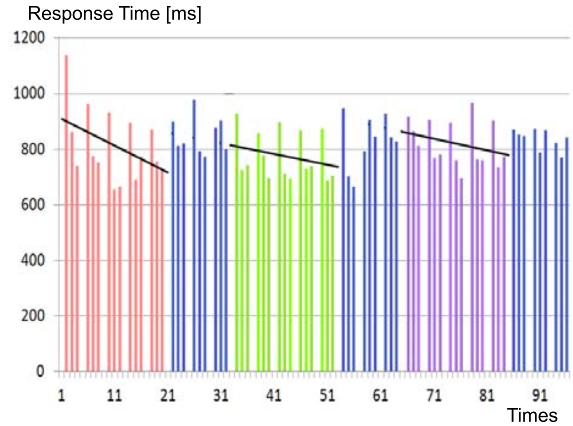

Fig. 8. Response Time of the third Trial

$824ms$. In addition, the average Response Time of the non-repetition pattern is $789ms$ and $848ms$ for the second and third presentation patterns. respectively. These average Response Times are larger than the corresponding averages of the fifth repetition pattern of the second and the third presentation patterns, which are $745ms$ and $767ms$, respectively. In particular, the Response Time of the second number (number "1") of the non-repetition pattern is extremely large, approximating $950ms$. In Figure 7, the Response Time of the first number (number "1") of the repetition pattern becomes smaller with the number of repetitions. The average Response Time of the fifth repetition pattern of the first presentation pattern (1, 2, 3) is $688ms$, but the average Response Time of the non-repetition pattern (1, 3, 3) continuing after the first repetition pattern is $693ms$. In addition, the average Response Times of the non-repetition pattern is $829ms$ and $763ms$ for the second and third presentation patterns. respectively. The Response Times are larger than the corresponding averages of the fifth repetition pattern of the second and the third presentation patterns, which are $731ms$ and $740ms$, respectively. In Figure 8 of the third trial, the gradient of the regression line for the first presentation pattern is steeper than the gradient for the second and third presentation patterns, and the gradient becomes more shallow with the number of presentation patterns. In the fourth to seventh trials, the gradient of the regression line for the first presentation pattern is steeper than the gradient for the second and third presentation patterns, and the gradient becomes more shallow with the number of trials.

Table I shows the iterations of the average Response Time of the repetition pattern and the non-repetition pattern for the presentation patterns. The Response Time of the repetition pattern becomes smaller with the number of repetitions. In particular, the Response Time is smaller for the second and third repetition patterns after the fourth trial. On the other hand, the Response Time is the nearly same for the non-repetition pattern. We suggest that this phenomenon can be explained in terms of a delay incurred during switching among

TABLE I
RESPONSE TIME OF PRESENTAION PATTERNS

	Repetition Pattern				Non-Reptition Pattern			
Trial	1	2	3	Average	1	2	3	Average
1	800.1	765.9	746.0	770.7	844.7	782.9	770.1	799.2
2	765.1	734.2	752.9	750.7	767.3	795.7	795.0	786.0
3	813.5	776.1	820.4	803.3	850.8	829.1	837.3	839.1
4	820.3	763.2	772.1	785.2	771.9	792.1	806.1	790.0
5	740.3	790.1	777.4	769.3	781.7	817.0	834.0	810.9
6	791.5	754.4	714.5	753.5	805.6	771.6	840.1	805.7
7	777.7	753.5	747.1	759.4	815.4	785.4	779.9	793.6
Average	786.9	762.5	761.5	770.3	805.3	796.3	808.9	803.5

feedback and feedforward processes in the MOSAIC Model.

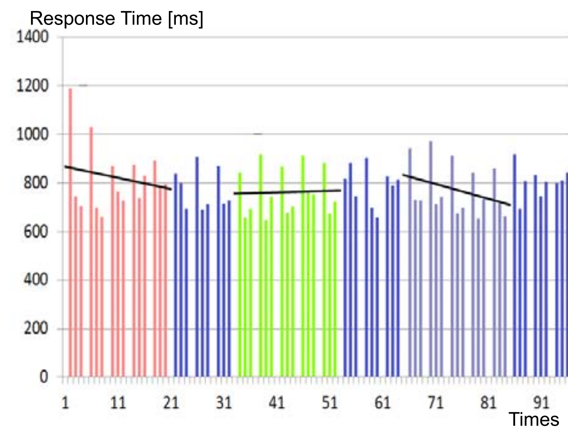

Fig. 9. Response Time of the Fourth Trial

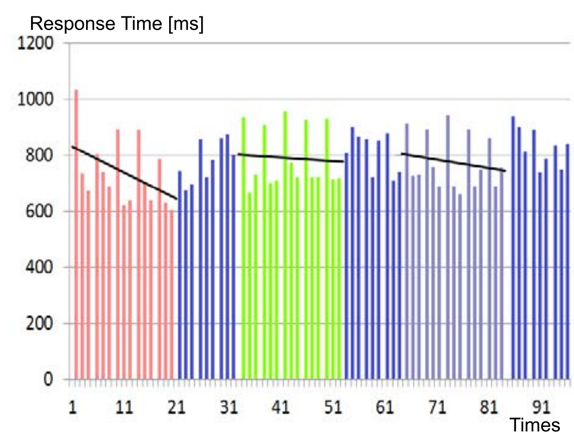

Fig. 10. Response Time of the Fifth Trial

The vertical axis in Figure 13 to 15 show the angular velocity (dps) of finger (S_1) along the Z axial dimension for the first pattern of subject H. Measurements corresponding to the repetition pattern are shown to the left of the vertical

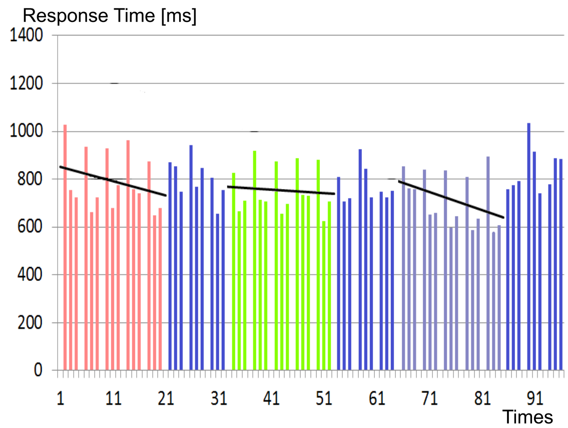

Fig. 11. Response Time of the Sixth Trial

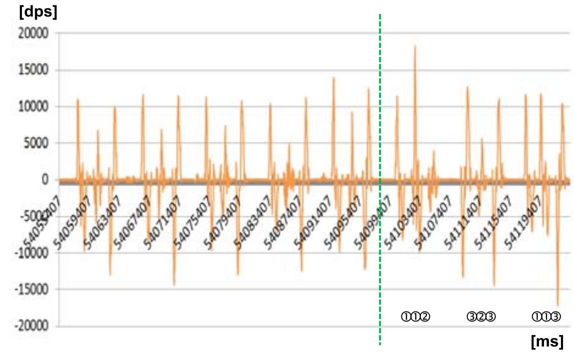

Fig. 13. Angular Velocity of the First Pattern

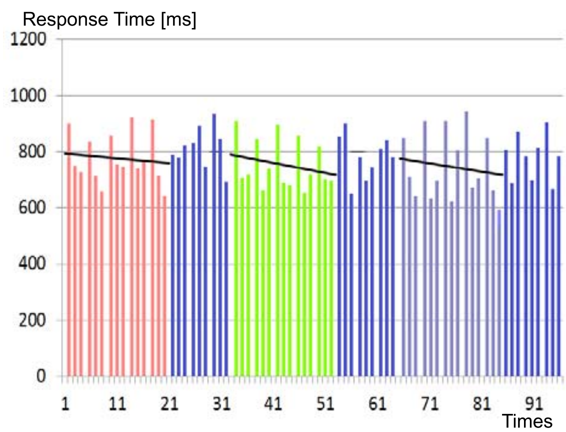

Fig. 12. Response Time of the Seventh Trial

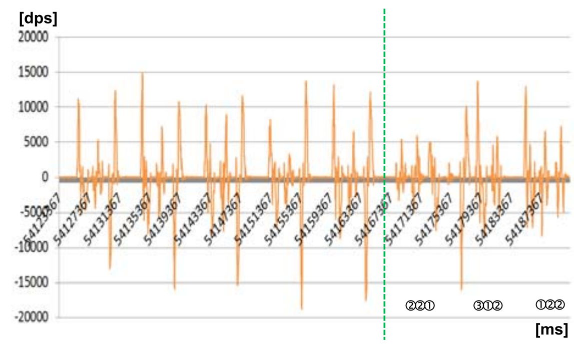

Fig. 14. Angular Velocity of the Second Pattern

dashed line, whereas measurements for the non-repetition pattern are shown to the right of the dashed line. The negative and positive regions of the vertical axis correspond to clockwise and counterclockwise motion, respectively. At the second presentation of the non-repetition pattern, the movement recorded is first clockwise, which is similar to "2", but suddenly becomes counterclockwise. We suggest that this reflects switching processes in the internal model. This confusion is seen at the second presentation pattern of Figure 14, but it is not seen at the third presentation pattern of Figure 15. In other words, we assumed that the subject modified a misunderstanding by iterative learning. We interpreted it as a switching of the internal model in the MOSAIC model.

Finally, we show an EEG result for subject H in Figure 16. It shows an addition value of the repetition pattern of 21 times for 7 trials. The averages values of EEG are 0.16, 0.06, 0.11, -0.06, and 0.11 for each repetition pattern, and the variance values are 40.5, 49.8, 34.5, 22.4, and 32.9. The variances are relatively large for the first and second repetition pattern, but it can be seen that the variance is smaller for the third and fourth repetition patterns because of repetition response. However, the variance of the fifth repetition pattern is large because of preparing the non-repetition pattern continuing after the fifth repetition pattern. Learning thus occurs immediately over the course of a few repetitions of the pattern. We assumed that the learning was activated by inverse model by several times of repetition patterns in the internal model.

V. Discussion

We discuss the results measured by experiment. We concluded the following results from the Response Time measured by experiment.

1) Because the Response Time is nearly same at the start of the repetition pattern, the initial learning by the feedback control in the internal model is constant.
2) Because the gradient of the regression line for the repetition pattern becomes more shallow with the number of presentation patterns, a switching function from the feedback process to the feedforward process is carried out smoothly.

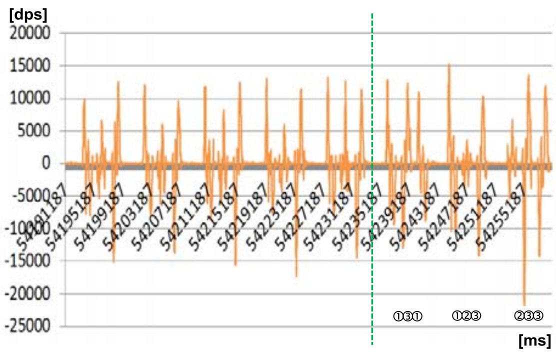

Fig. 15. Angular Velocity of the Third Pattern

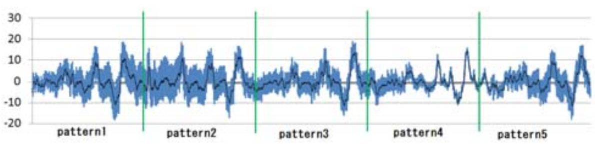

Fig. 16. EEG of Repetition Pattern at FP1

3) Because the gradient of the regression line for the repetition pattern of the seventh trial becomes nearly zero, the feedforward process of the internal model works stably.
4) Because the change of the Response Time is nearly zero even though the non-repetition patterns are iterative, the MOSAIC model works stably. In addition, a switching timing of the repetition pattern to non-repetition pattern is slow, and so we assume that a switching of the internal models in the MOSAIC is slow.

Next, we concluded the following results from the angular velocity measured by experiment.

5) The internal model works stably when the subject's movement is iterative for the repetition pattern.
6) If the repetition pattern is similar to the non-repetition pattern, we assume that a switching of the internal models in the MOSAIC is late.

Finally, we concluded the following results from the EEG measured by experiment.

7) Because the variance becomes smaller with the number of the repetition response, a switching process of the inverse model from the forward model in the internal model works effectively.

From these results, we concluded that the initial learning by the feedback control in the internal model is constant, and the internal model becomes quickly stable. In addition, the feedforward process of the internal model works stably, and a switching function from the feedback process to the feedforward process is carried out smoothly. On the other hand, the MOSAIC model works stably, but the switching of the internal models in the MOSAIC is slow.

VI. Conclusions

In this paper, we discussed feedback and feedforward processes in relation to the internal model and MOSAIC model when a repetition task involving vision and motion is given to participants. In addition, we discussed characteristics of the internal model and MOSAIC model from the results measured by experiments.

In the near future, we should discuss the relationship between Response Time and EEG through more specific experiments.

References

[1] T.B.Moeslund, A.Hilton, and V.Kruger, "A Survey of Advances in Vision-based Human Motion Capture," *Journal of Computer Vision and Image Understanding*, No.104, pp.90-126, 2006.
[2] C.M.Lu and N.J.Ferrier, "Repetitive Motion Analysis: Segmentation and Event Classification," *Journal of IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol.26, No.2, pp.258-263, 2004.
[3] M.Kawato and H.Gomi, "A Computational Model of Four Regions of the Cerebellum Based on Feedback-error Learning," *Journal of Biological Cybernetics*, Vol.68, No.2, pp.95-103, 1992.
[4] H.Imamizu and M.Kawato, "Cerebellar Internal Models: Implications for the Dexterous Use of Tools," *Journal of the Cerebellum*, Vol.11, No.2, pp.325-35. DOI:10.1007/s12311-010-0241-2, 2010.
[5] A.M.Green and D.E.Angelaki, "Internal Models and Neural Computation in the Vestibular System," *Journal of Experimental Brain Research*, No.200, pp.197-222. DOI:10.1007/s00221-009-2054-4, 2010.
[6] D.M.Wolpert and M.Kawato, "Multiple Paired Forward and Inverse Models for Motor Control," *Journal of Neural Networks*, Vol.11, pp.1317-1329, 1998.
[7] M.Haruno, D.M.Wolpert, and M.Kawato, "MOSAIC Model for Sensorimotor Learning and Control," *Journal of Neural Computation*, Vol.13, No.10, pp.2201-2220, 2001.
[8] H.Imamizu, T.Kuroda, T.Yoshioka, and M.Kawato, "Functional Magnetic Resonance Imaging Examination of Two Modular Architectures for Switching Multiple Internal Models," *Journal of Neuroscience*, Vol.24, No.5, pp.1173-1181, 2004.