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Prediction of Basketball Free Throw Shooting by OpenPose

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Abstract. OpenPose, which was developed by Carnegie Mellon University (CMU) presented at CVPR 2017 last summer, takes in real-time motion images via a simple web camera and is capable of recognizing skeletons of multiple persons in these images. It also generates recognized skeleton point coordinates to files. OpenPose is featured by CMU's original top-down method for real-time recognition and it is open online especially for research purposes. Thus we aimed to build a posture analysis model using OpenPose skeletal recognition data and verifying the practicality of OpenPose by verifying the accuracy of the model. As a posture analysis model, we adopted a logistic regression model that predicts the shooting probability of the basketball free throw with skeleton posture data as explanatory variables and the shooting or not as a target variable. As the result, high prediction accuracy was obtained. Therefore, posture analysis using OpenPose has been verified to be practical with our model. We consider that with many skeleton data which are easily provided by a simple web camera, OpenPose make statistical diagnostic approach possible. We also consider it could lower costs (in both financial and time-wise) of such analysis which has previously required more equipments and more time for preparation regarding motion capture analysis systems.

Keywords: OpenPose, Logistic regression, Basketball shooting prediction, Posture diagnosis

1 Introduction

We consider that a large amount and variety of human posture data with high precision are required to improve performance in statistical posture analysis. However we found that there are little available posture data because of complexity for acquiring posture data. In order to acquire the whole posture data as a time-series, there are major two methods. One is video motion analysis(manual marking) and the other is motion capture analysis. Video motion analysis, which divides into photographs and marks annotations on the pose images, is very laborious. Motion capture analysis is necessary to attach so many sensors on human limbs that acquisition of data is complicated in operation. At CVPR 2017 conference, Carnegie Mellon University (CMU) presented OpenPose[1][1] which can recognize skeletons of multiple players in real-time, using a simple web camera, as shown in Fig. 1. OpenPose adopted the unique top-down position recognition using Deap Learning and also the unique algorithm as affiliation recognition of body parts by PAF (Part Affinity Fields)[2]. As a result, in the moving skeletal pictures generated by OpenPose, the skeleton marks are shown and overlapped well with the figure of people, and it seems that recognition accuracy is very high even for various people in various environments. OpenPose can be expected as a convenient generation model of available and accurate posture data. In oder to evaluate performance of OpenPose, we built a basketball shooting prediction model as a prototype using real-time skeletal data generated by OpenPose. As the result, we found that the shooting prediction model showed sufficient high accuracy. Thus, we found that OpenPose is a convenient and practical generator of posture data. The rest of this paper is structured as follows. In Section 2, we briefly review of previous posture analysis method. In Section 3, we define the experimental methods. In Section 4, we show experimental results. In Section 5,we conclude this paper. In Section 6, we present future work.

Fig. 1. OpenPose

2 Previous research for posture analysis

As a previous analysis of sports motion, there was a method called video motion analysis which divides video into photographs and marks points on the pose image for annotation[3]. As a direct sampling posture data, motion capture was used to collect data from sensors on body and limbs[4]. However, these methods are so expensive to collect data that statistical models such as regression could not be applied. Thus, these method were often used for argument about the difference of posture between beginners and experts. On the other hand MicroSoft

[1] OpenPose realizes three-dimensional acquisition by stereo (compound eye) camera in March 2017, but in this research, OpenPose of 2D position recognition version using monocular Web camera is used because of easy operation and sufficient use frequency.

KINECT, which is not sold now, can easily take 3D posture data, but the sensing range is very narrow and recognition accuracy of skeletal point is low[5].

As a statistical approach, it is realized that winning prediction of basketball game was modeled by logistic regression using records which include the winning / losing result and the frequency of shooting and robbing ball in the game[6].

As a time-series analysis for motions, there was a research that tried to transfer abstracted motions from a human to a robot with hidden variables estimated by Hidden Markov and reversely predict the next action of the robot from estimated hidden variables [7]. However our shooting prediction of basketball free throw is not a general time-series model that predicts the next action from the last time-series of motions because our model predicts a result whether to shoot in the basket or not rather than an aciton. The number of persons monitored in this experiment was limited to 51. We adopted a logistic regression[8] using the features which are composed with the position of start and end or the difference, velocity and acceleration between start and end position extracted from a time-series of the free throw motions.

3 Method

3.1 Subject of Experiment

In order to construct the shooting prediction model of basketball free throw, we took movies about basketball free throw motion with web camera. The subject of Experiment covered various skill levels of 51 people. We generated their skeletal data by OpenPose from the movies. In the experiment, twenty of 51 people succeeded in free throw.

3.2 Output of OpenPose

The version of OpenPose[1] adopted in this paper is for 2 dimensional skeleton recognition, and the skeletal coordinates of 18 points shown in Fig. 2 are outputted to files by about 10 to 20 frames per second depending on a computer performance[2] and connected as shown in Fig. 3 to make time-series data. A skeletal coordinate is composed of 3 values which are x as horizontal, y as vertical and p as confidence probability. We ignored low confident coordinates with less than 0.7 confidence probability.

[2] Our experimental machine is CPU: AMD Ryzen 7 1800X, MEMORY: 16GB, GPU: NVidia GeForce GTX 1080ti,OS: Ubuntu 14.04 LTS,CUDA version: 8.0, cuDNN version: 5.1 for CUDA8.0

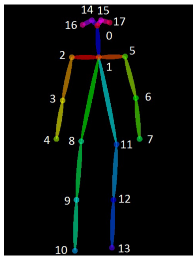

Fig. 2. Skeleton points of OpenPose referred from [2]

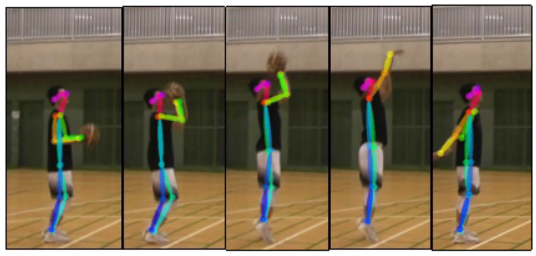

Fig. 3. Connection of frames

Though we used only skeletal data for prediction of shooting model, OpenPose can recognize also hands and faces as shown in Fig. 4 and outputs each recognized data to each file.

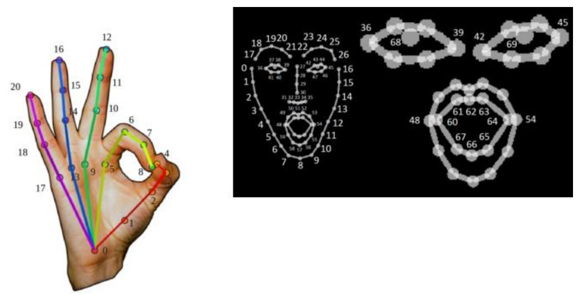

Fig. 4. Recognized finger and face points of OpenPose (cited from [2])

3.3 Statistic model

The shooting prediction model is a binary prediction as to whether to enter a basket or not. As major binary prediction models there are logistic regression[8], SVM[9] and Xgboost[10]. The SVM using the kernel method is a nonlinear model which may make high accuracy but cannot calculate the shooting probability. Xgboost using the stochastic gradient method that has a high reputation for accuracy and robustness is not adequate for a diagnostic model because this model cannot indicate explicitly the degree of importance of explanatory variables. So we adopted a logistic regression model as shown in Fig. 5 that is one of most used in data analysis.

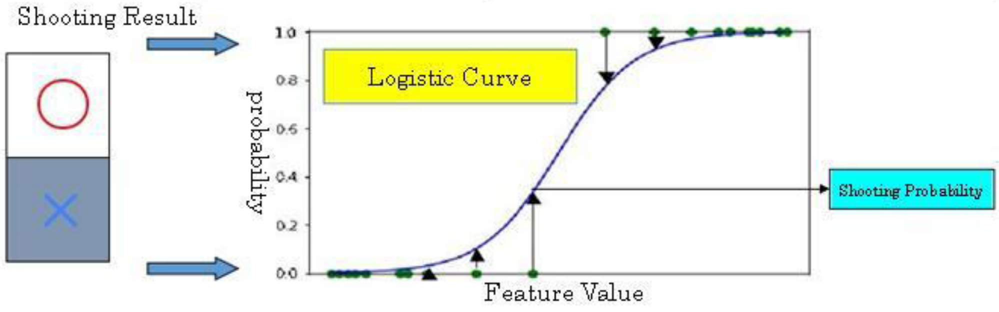

Fig. 5. Logistic regression

Probability of logistic regression is as follows using multiple regression coefficients β and features.

$$\mathcal{Z} = \sum_{i=1}^{n} \beta_i \cdot feature_i \tag{1}$$

$$probability = \frac{1}{1 + \exp(-\mathcal{Z})} \tag{2}$$

3.4 Valuable of Logistic regression

The explanatory variables of the logistic regression model were features calculated from the time-series data. Features include the positions of skeletal points, moving speed, acceleration, etc. The target variable is the fact whether a shooting ball entered into the basket or not. In the time-series data, as shown in Fig. 6, everyone bent knees at the start of the throw and lifted hands to the highest level upon completion of the throw. So we decided to define the interval of a free throw between the time point when the knees were bent the most as its start and the time point when the hands were lifted to the highest physical point as its end. All the coordinate positions were relative from the neck point.

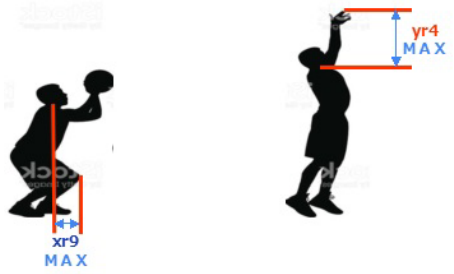

Fig. 6. Posture of start and end

4 Result

4.1 Accuracy of Logistic Regression

In general, the precision of the logistic regression model is expressed in the pareto diagram in Fig. 7. In this diagram, the horizontal axis shows the composition rate of all the members in descending order of shooting probability, and the vertical axis shows the composition rate of the number of people who succeeded in shooting into the basket. Red dots in Fig. 7 indicate number of accumulated people who shot in basket. About 40% people succeeded in shooting into the basket at this experiment. If the model was perfect, it would be represented by the line of the perfect model with descending order of shooting probability, and if the shooting probability of the model was uncorrelated with the actual shooting in basket, it would be the line of the uncorrelated model. The accuracy of logistic regression model is indicated by the ratio of the area A of the cumulative curve shown in Fig. 8. This figure shows that high accuracy AR = 41% was obtained.

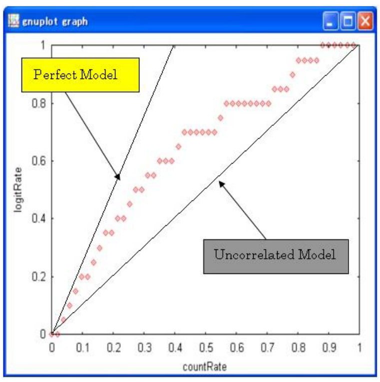

Fig. 7. Parete figure

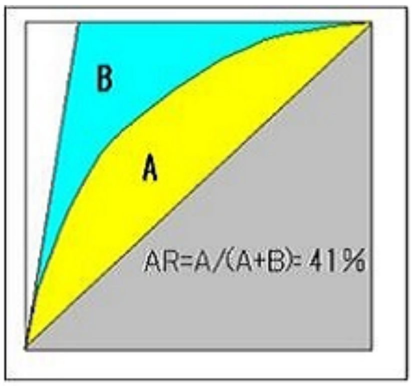

Fig. 8. Area of AR value

4.2 Interpretation of significant features in Logistic Regression

As a result, significant features that make the high shooting probability in the logistic regression were shown in Fig. 9. The shooting probability becomes higher when the blue color features are larger. The shooting probability also becomes higher when the red color features get smaller. From this result, the following was found out. It shows that the shooting probability is higher if the bend of the knee is increased and knees are pulled quickly and at the same time the ball is pulled and thrown over head. This motion uses the force of the knee extension and the centrifugal force created when throwing the ball overhead.

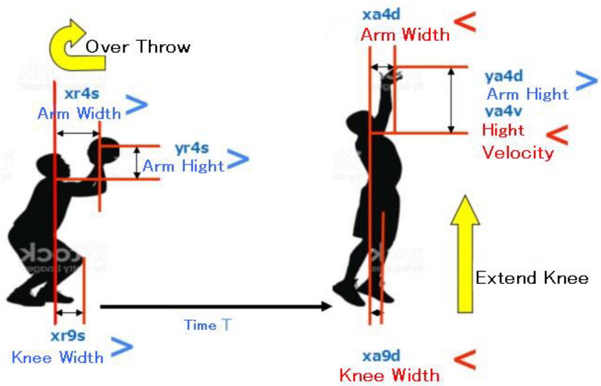

Fig. 9. Relation for shooting probability and features

4.3 Real time Diagnosis

The diagnostic system using OpenPose can display the shooting probability in real-time as shown in Fig. 10. and even if there are not any basket and ball, it becomes possible to judge the skill level directly just by gesture.

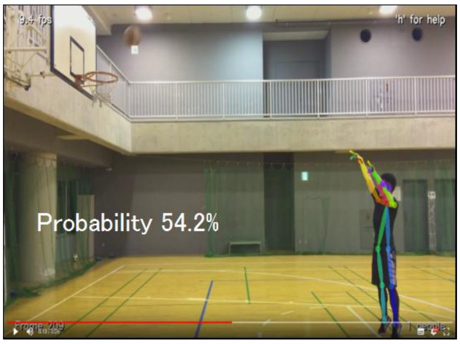

Fig. 10. Real time diagnosis by OpenPose

4.4 Posture diagnosis

By comparing feature quantities between beginners (people with low shooting probability) and experts (people with high shooting probability), it is possible to diagnose the amount of correction for beginner postures. In the example of Fig. 11, one of the remarkable differences between beginners and experts is the position of the arm at the start. The beginners pushed the ball from the chest but the experts put the ball in front of the head and threw the ball over head. In this case, it is necessary to teach the beginners the form of overhead throwing.

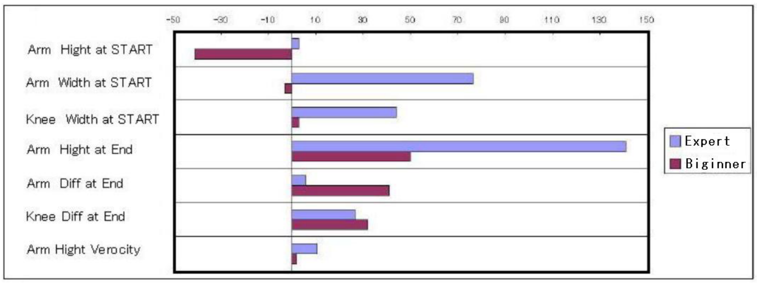

Fig. 11. Comparison of features between beginner and senior

5 Conclusion

As a result, high accuracy was obtained in logistic regression model, the following was found out.

1. The skeletal data recognized by OpenPose were found to be highly applicable with sufficient accuracy.

2. In the previous posture diagnosis, data were generated by marking on a picture frame from a video stream or collected sensor signals by motion capture on the human parts. These methods were so expensive for data collection that statistical models could not be introduced. On the other hand, OpenPose can easily collect data by using a simple web camera, it became possible to obtain more accurate posture diagnosis by collecting more data.

6 Future work

The data of basketball free throw in this experiment were taken from one side only by a web camera, so it was suitable to analyze with 2 dimensional data provided by OpenPose. However analysis of general sports motion requires 3 dimensional data like a tennis or ballet dance, so it is necessary to use 3 dimensional OpenPose or expand 2D data generated by 2D OpenPose to 3D data[11].

Acknowledgment

We would like to thank Basketball Club Team of Tokyo Metropolitan College of Technology for taking movie of basketball free throw. We would like to special thank to Dr. Atushi Shibata of AIIT for provision of experimental computation environment.

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Detecting Freezing-of-Gait Symptom in Parkinson's Disease by Analyzing Vertical Motion from Force Plate

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Abstract. Introduction: Freezing of Gait (FoG) is a common symptom in Parkinson's Disease (PD), which has impact on the gait pattern and relevant to risk of falls. Data-driven approach to FoG detection would allow systematic assessment of patient's condition and objective evaluation of the clinical effects on treatments. Many researchers recently studied FoG in PD by analyzing patient's center of pressure dynamics in term of various features such as path-length. **Objective**: In this research, we attempt to automatically separate two groups of PD patients that with and without FoG by considering standing balance ability during cognitive loading tasks. **Methods**: The dataset consists of sixty PD patients (Hoehn and Yahr stages 1-3) were collected from Thammasat University Hospital, Thailand. The participants were categorized either to be FoG or non-FoG according to the Freezing of Gait-Questionnaire (FoG-Q) scores. Their postural balance ability was measured with Nintendo Balance board which produces a time-series of center of pressure along with the value of changing weight. We turn to a new kind of feature named "FVA" which informs us the acceleration due to the body's up-down motion, and employ Wilcoxon signed-rank statistic to compare the changing of postural control between one with the cognitive loading state (Reading or Counting Backward) and the other in the rest state (Before I or Before II). We also use Student's t-test statistic to analyze the difference of the changing of postural control between two groups, FoG and non-FoG. **Results**: Significant increases of FVA were observed for all cases (for all data, for each group) with cognitive loading ($p<0.001$). The FVA also increases between the rest state and the other rest state after a cognitive loading ($p<0.001$). The changing of FVA between Reading (RE) and Counting Backward (CB) is significant for all data ($p<0.001$) and it is more sensitive in FoG group than in non-FoG group (p 0.03 and 0.21 respectively). To compare two groups, the increase of FVA from the rest state to other with cognitive loading is larger in FoG than in non-FoG ($p<0.01$). The significance is for most cases greater than or equal to features extracted from trajectory of center of pressure (such as path-length). **Conclusions**: The new feature FVA seems to well reflex postural control in people with PD. It informs us the postural instability in PD, which is more informative than other indices when the subject are under cognitive loading. It is also monotonous with level of complexity of cognitive loading, and is sensitive with FoG group.

Keywords: Parkinson's disease, Postural control, Cognitive loading, Freezing of gait

1 Introduction

Freezing-of-gait (FoG) is a common clinical symptom in Parkinson's disease[2] (PD), observed as inability to start doing a motion and shaking/shuffling gait in a motion [13, 9]. FoG is usually found in PD patients in the advanced stages, but recently FoG has been reported in the early stages as well. Approximately 44–53% of PD patients have the symptom of FoG [6, 12] and the percentage increases up to 80% of PD patients in the advanced stages [17, 10]. PD patients with FoG often have significant changes in their gait progression, decreased foot length, and tremors in FoG attacks [13]. Due to these changes, a basic risk for PD patients with FoG is falling over [15, 1, 14] and so PD patients with FoG are exposed to high risk of fatal accidents, such as fractures or immobility [3]. Therefore, early detection of FoG symptom among PD patients is helpful to prevent them from such accidents, as well as to improve their quality of life.

The mechanism of FoG is yet not entirely understood up to now. Currently, with or without FoG is classified by clinical assessment but often detected after accidents. Recent researches have attempted to elucidate procedures of FoG assessments by incorporating recent findings on the relationship between FoG and other factors. In bio-mechanical approach, Pelykh et al. [16] and Buated et al. [4] characterized the postural control ability of PD patients during cognitive loading tasks by analyzing their center-of-pressure time series. Both studies showed reduced postural control during cognitive loading tasks in both FoG and non-FoG groups; however, no significant difference between groups was reported. In clinical approach, Duncan et al. [8] invented the sub-clinical screening test, called the BESTest, to examine some difference between FoG and non-FoG and obtained high reliability ($p < 0.001$). However, a shortcoming of this test is taking longer than 30 minutes, and expert factors will be cause of limitations in clinical application to a large number of patients.

In this study, our objective is to defect the freezing-of-gait (FoG) symptom in Parkinson's disease (PD) patients based on physical or bio-mechanical data. For this objective, we develop a new feature statistic (or factor) for automatically detecting the FoG symptom of PD patients, easily applicable in clinical assessments. To test our proposed feature, including the standard path length, we analyzed the center-of-pressure time series under cognitive loading tasks.

2 Methodology

2.1 Participants

We briefly describe our data, originally collected by our colleagues [4]. See Buated et al. [4] for details.

60 patients (24 males and 36 females) with Parkinson's disease (PD) were recruited and their center-of-pressure time series were collected in Thammasat Hospital, Thailand. Their clinical stages of Parkinson's disease were classified according to the modified Hoehn & Yahr scale [11]. Patients who can stand alone for 3 minutes were included to this study. Patients with other problems (e.g., atypical parkinsonism, unable to stand without support, partial or complete blindness, etc.) were excluded. All participants with Parkinson's disease were examined during the on-time medication without presenting excessive rigidity, bradykinesia, or tremor.

2.2 Apparatus and Procedures

Center-of-pressure (CoP) time series were recorded using a force place, called Nintendo Wii Balance Board [5], which is a platform for measuring distribution of weight bearing of the subject on it. A recorded data consists of the relative positions of the center-of-pressure (CoP) along the medial-lateral (x) and anterior-posterior (y) dimensions, on the two dimensional surface of the Wii Balance Board. Plus, as a force plate, this Wii Balance Board can record the additional dimension, we call it, 'weight' acting on the balance board surface, due to the motion of the subject. This 'weight' is measured in units of kilogram [kg], unlike the units in physics [kg $\times$ g] with gravitational acceleration $g = 9.8(m/s^2)$.

Each patient was instructed first to stand upright on the balance board, looking horizontally to a marker on the wall at 3 meter apart, and then to follow the four instructions: (1) Before I: Keep standing for 30 seconds; (2) Reading (RE): Keep standing with reading a material for 30 seconds; (3) Before II: Keep standing for 30 seconds; and (4) Counting Backward (CB): Keep standing with counting numbers backward for 30 seconds.

3 Features for Postural Instability

In this section, we described the newly proposed feature statistic, called Fluctuation of Vertical Acceleration (FVA), as well as the clinical standard, known as path length.

3.1 Path Length

Path length is simply the total length of a CoP path. Given time series of CoP $(x(t), y(t))$ at time frame t, it was calculated by summing up the distances between consecutive data points [7], i.e.,

$$\text{PathLength} := \sum_t \sqrt{[x(t+1) - x(t)]^2 + [y(t+1) - y(t)]^2} \qquad (1)$$

3.2 Fluctuation of Vertical Acceleration (FVA)

We derive a new feature statistic, we name it, Fluctuation of Vertical Acceleration (FVA). As we have described, the Wii Balance Board can record the 'weight', divided by $9.8(m/s^2)$ (unit equivalent to kg) of the subject for each time. This 'weight' has not been incorporated for characterizing the balance dynamics of PD patients. You may think that it is strange if the 'weight' of the subject changes over time. Then, we have to clarify the difference of 'weight' and 'mass' in physics terminology. In physics, 'weight' is simply the mass $\times$ 9.8, in units of kg $\times$ 9.8, where 9.8 is the gravitational acceleration on Earth. If the subject has exactly no motion on the balance board (or force place), then the 'mass' of the subject and 'weight' divided by 9.8 can take the same or close value. However, if the subject has in motion on it, then the force (or kinetic acceleration) acted on the surface of the balance board can be detected and included in part of the 'weight' measured by the balance board. And so, the 'weight' of the subject measured can vary over time. In other words, the 3rd dimension of recorded data, 'weight' divided by 9.8, contains information due to vertical acceleration. In this paper, we proposed to incorporate this feature, vertical acceleration, to characterize the postural stability of subjects.

According to the Newton's second law, the weight $\bar{w}$ on Earth at the rest state is the body mass m times gravitational constant g: $\bar{w} = mg$. In addition to this, the weight $w(t)$ measured by the balance board at time t can include the additional factor due to the acceleration (or force) approximately along the vertical $a_z(t)$: $w(t) = mg + ma_z(t)$. Then, from recorded time series $w(t)$, we can extract the vertical acceleration at time t by

$$a_z(t) = \frac{w(t) - \bar{w}}{m} \quad . \qquad (2)$$

Taking the ratio gives a quantity independent of the body mass m as

$$\frac{a_z(t)}{g} = \frac{w(t)}{\bar{w}} - 1 \quad . \qquad (3)$$

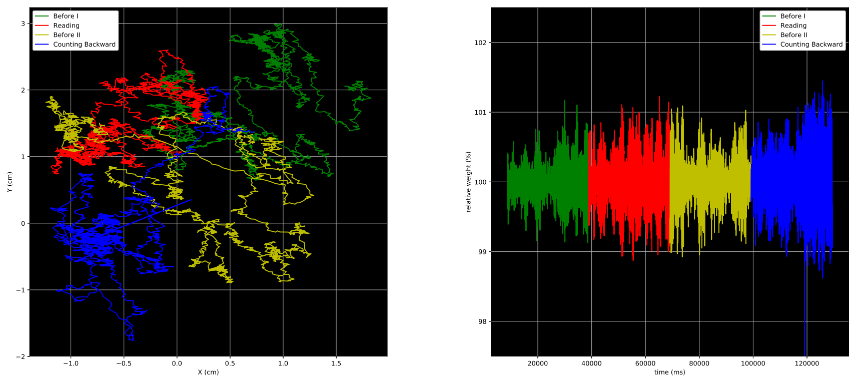
which is in units of percent [%]. The value of $\bar{w}$, the weight at no motion, can be measured by a weight scale at home or estimated by the average over time $\bar{w} = (1/T)\sum_t w(t)$. Finally, our new feature, Fluctuation of Vertical Acceleration (FVA), is defined as its deviation from the mean

$$\text{FVA} = \text{std}\left(\frac{a_z(t)}{g}\right) \times 100 \quad , \qquad (4)$$

where the std$(\cdot)$ operator calculates the standard deviation.

3.3 Visualization of Features

Figure 1(a) visualized a CoP path of a patient. Four colors, green, red, yellow, and blue, were used for the four conditions, i.e., Before I, Reading, Before II, Counting Backward, respectively. In Figure 1(b), we showed the time series of Vertical Acceleration (VA), calculated by using Equation (3). Our new feature, Fluctuation of Vertical Acceleration (FVA), Equation (4), characterizes the variation of Vertical Acceleration in Figure 1(b).



(a) Center-of-Pressure path (b) Vertical Acceleration (VA)

Fig. 1: (a) A visualization of a patient's center-of-pressure data. The green, red, yellow, and blue colors corresponds to the four conditions: Before I, Reading, Before II, Counting Backward. (b) Part of the new feature, Vertical Acceleration, in Equation (3).

4 Results

4.1 Data Processing

In our data analyses, for each PD patient's CoP path, we calculated two feature statistics, Path Length (PL) and Fluctuation of Vertical Acceleration (FVA), for four data segments corresponding to the four conditions of our data recording: i.e., Before I, Reading, Before II, and Counting Backward. In some analyses, we also used two combined features, difference in the values of each feature (FVA or PL) between Before I and Reading and between Before II and Counting Backward. Resulting, we obtained $4 \times 2 = 8$ features, or $4 \times 2 + 4$ features for each PD patients.

PD patients were classified into two groups, FoG and non-FoG, based on FoG-Q scores, FoG-Q ≥ 6 for FoG (n = 39) and the rest for non-FoG (n = 21).

Table 1 is the summary of two kinds of feature statistics for all combinations of the four conditions times three subsets of data. Each cell of Table 1 contains $\mu \pm \sigma$ as the mean μ and the standard deviation σ. In most cases, the mean values increase from non-FoG to FoG and from Before I, Before II, RE, to CB, orderly.

Feature	FVA			Path length		
Task	All data	FoG	non-FoG	All data	FoG	non-FoG
Before I	0.23 ± 0.18	0.25 ± 0.21	0.19 ± 0.08	81 ± 33	85 ± 39	73 ± 14
RE	0.32 ± 0.32	0.36 ± 0.39	0.23 ± 0.07	93 ± 58	100 ± 70	79 ± 16
Before II	0.27 ± 0.28	0.32 ± 0.34	0.20 ± 0.06	89 ± 47	95 ± 56	77 ± 17
CB	0.41 ± 0.54	0.48 ± 0.65	0.28 ± 0.12	109 ± 82	121 ± 98	87 ± 24

Table 1: The average and standard deviation of FVA and path length in the dataset. RE = Reading; CB = Counting Backward; FVA: unit in percent; Path length: unit in centimeter

4.2 Goals and Procedures of Statistical Analysis

In this study, we set two goals for analysis. Firstly, we analyze the effects of the cognitive loading tasks (Reading and Counting Backward) on postural control by comparing them from the preceding rest conditions (Before I and Before II), within the groups. Secondly, to demonstrate the power of the new feature for detection of FoG in PD patients, we compared the effects on postural control between the groups, the FoG and non-FoG group. To evaluate the influence of cognitive loading to postural control within the groups, we used the Wilcoxon signed-rank test with the null hypothesis of no difference between the tasks. To evaluate differences between the groups, we used the Student's t-test with the null hypothesis of no difference between the groups.

4.3 Impact of Cognitive Loading on Postural Control

The results of empirical data analysis showed in Table 2. Each cell contains the p-values of Wilcoxon signed-rank statistics in comparison between the conditions. We observed that both FVA and PL produced the significant influence (mostly $p \leq 0.01$) of cognitive loading on posture control. Generally, using FVA tends to be more significant. The results suggest that both features, FVA and PL, can work for defecting FoG in comparing the CoP paths within the groups or between the conditions.

We observed the influence of the cognitive loading tasks, within the groups, also in Figure 2. Figure 2 shows the FVA's of all patients, their ID $= 0, 1, 2, \ldots, 59$, separately, along the horizontal axis of each figure. The bottom figure includes all four conditions, i.e., Before I (green), Reading (red), Before II (yellow), and Counting Backward (blue). The top-left includes only Before I (green) and Reading (red) and the top-right includes only Before II (yellow) and Counting Backward (blue). We also observed the increases in FVA's clearly from Before I (green) to Reading (red), and from Before II (yellow) to Counting Backward (blue).

Task		FVA			Path Length		
A	B	All data	FoG	non-FoG	All data	FoG	non-FoG
Before I	RE	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Before II	CB	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Before II	RE	< 0.001	0.002	< 0.001	0.010	0.044	0.120
RE	CB	< 0.001	0.035	0.021	0.002	0.008	0.010
Before I	Before II	< 0.001	0.001	0.01	0.003	0.01	0.006

Table 2: Results (p-values) of Wilcoxon signed-rank test between the experimental conditions. RE = Reading, CB = Counting Backward

4.4 Comparison between the FoG and non-FoG group

Next, we examined differences between the FoG and non-FoG group. In this analysis, we used the combined features, described in the section of data processing, denoted by Δ(Before I, RE) for the difference in a feature between the Before I and Reading condition, and Δ(Before II, CB) between the Before II and Counting Backward condition. The results showed in Table 3 with p-values of the Student's t-test. We observed the significant difference between the non-FoG and FoG group, in using both features, FVA and PL. In some cases, using FVA tends to be more significant.

We can also confirm visually the results of statistical tests in Figure 3. Figure 3, the left two figures compare the impacts of the Reading task and the right two figures compare the impacts of the Counting Backward task. The bottom two figures contain the FVA's of PD patients with non-FoG and the top two figures contain the FVA's of PD patients with FoG. From these figures, we observed that the patients with FoG tend to show larger individual variation in FVA, in both the cognitive loading tasks.

5 Discussion

In this paper, we tried to defect the freezing-of-gait (FoG) symptom in Parkinson's disease (PD) patients based on physical or bio-mechanical data. In our data analysis, in addition to the standard Path Length (PL), we evaluated our newly proposed feature, called Fluctuation of Vertical Acceleration (FVA). Our results

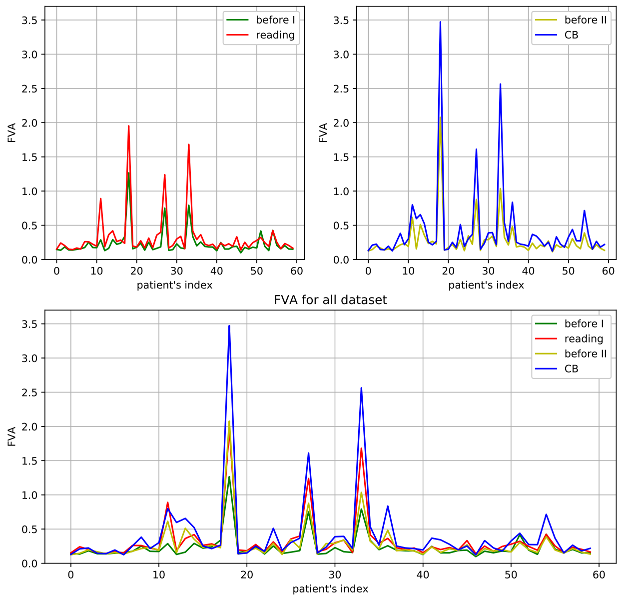


Fig. 2: Comparison of FVA between the experimental conditions. Before I (green), Reading (red), Before II (yellow), and Counting Backward (blue).

Task	FVA	Path length
Before I	0.073	0.054
RE	0.018	0.035
Before II	0.017	0.042
CB	0.034	0.023
$\varDelta$(Before I, RE)	0.010	0.040
$\varDelta$(Before II, CB)	0.085	0.022

Table 3: Results (p-values) of Student's t-test between the FoG and non-FoG group. RE = Reading and CB = Counting Backward. $\varDelta$(Before I, RE) = change from Before I to Reading. $\varDelta$(Before II, CB) = change from Before II to Counting Backward.

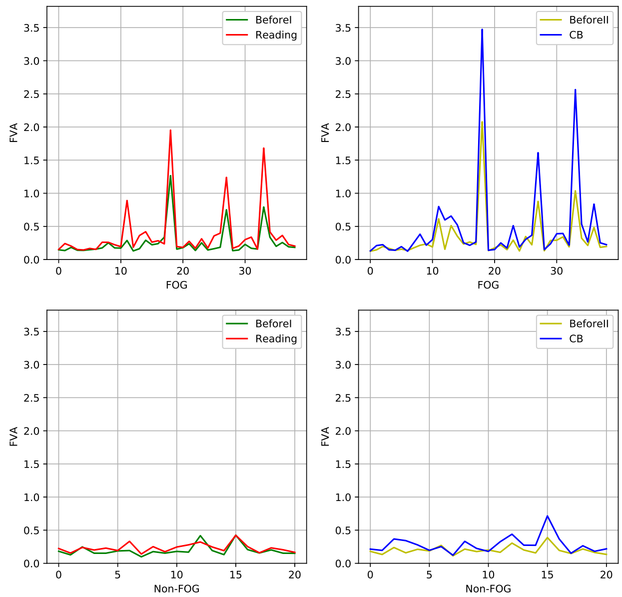


Fig. 3: Comparison of FVA between the FoG and non-FoG group. Before I (green), Reading (red), Before II (yellow), and Counting Backward (blue).

suggest that both PL and FVA can work for defecting the FoG symptom. Thus, our new feature, FVA, can be as good as the clinical standard, PL. In our results, we observed that, in some experimental conditions, our new feature, FVA, can be better than PL. This suggest that we can develop some experimental schemes suitable for FVA, which can be helpful for earlier defection of the FoG symptom. One of our future works is to develop such experimental schemes, toward data-driven clinical assessments, to help people with the freezing-of-gait symptom in Parkinson's disease patients.

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Relationship between degrees of freedom and adaptability or flexibility in human postural standing

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Abstract. This study aimed to investigate the direct relationship between the joint degrees of freedom (DoF) of human movement system and its postural dynamics in terms of adaptability/flexibility. In our pilot experiment we fixed the join DoF (knee and ankle) to constrain the functional DoFs (one for knee, two for ankle). Young healthy participants were required to maintain single-leg standing task with their dominant leg fixed. The center of pressure (COP) trajectory data were measured and analyzed by linear and nonlinear methods to assess static and dynamic property of their postural dynamics. As a result of comparing across conditions (normal no-fixation, ankle and knee fixation condition), static measure (COP trajectory length) did not significantly differ across conditions. However, dynamic measures (the fractal scaling exponent and sample entropy) significantly differed. The ankle joint fixation affected the scaling behavior (weakening the under-diffusive postural control process), and sample entropy decline (losing efficiency of postural control) in the ML direction. These results seemed to agree with the notion of the loss of complexity framework.

Keywords: loss of complexity, freezing degrees of freedom, single-leg standing, fractal analysis, entropy analysis

1 Introduction

1.1 Adaptability/flexibility as an embodied skill

Adaptability and flexibility can be considered unique abilities of human beings or living organisms in contrast to traditional robots or artificial intelligence (AI). These abilities enable living systems to adapt flexibly to their environment which can vary dynamically. In the AI research field, such a dynamic ability to respond to dynamic situations and behave flexibly is considered an essential feature of *intelligence* (Suwa, 2013). It is also related to another important concept *embodiment*. The living body consists of perception and action systems that have dynamic real-time interactions with their environment (Gibson, 1966). Authors have called such an embodied skill *dynamic embodied adaptability* and it is supposed to be a characteristic property of living systems, which differ from traditional robots or AI (Kodama, Kikuchi, & Yamagiwa, 2017). Although these artificial systems are good at repeating the same movement or process in the same way, living systems are not; however, they perform the same task in a variety of the different ways. Such variability is an important feature of human skilled performance particularly in terms of adaptable/flexible behavior (Bernstein, 1967; Kudo & Ohtsuki, 2008).

For example, Nonaka (2013) investigated skilled coordinated behavior of an exceptional tetraplegic individual who has practiced Japanese calligraphy with a mouth-held brush (Nonaka, 2013). The author showed evidence that joint configuration variances at different phases of writing were structured so as to maintain some important task variables across different realizations of the writing task; moreover compensatory coupling between joint variables contributed to the observed structure of joint configuration variance (Nonaka, 2013). In another study, he and his colleague compared flexible bead-making behavior of bead craftsmen with different skill levels (Nonaka & Bril, 2014). As a result, they found that the highly skilled craftsman had rich flexibility and exquisite context sensitivity as well as the largest interstroke variability in the coordination of movement (Nonaka & Bril, 2012, 2014). Ito and her colleagues examined the role of postural control in a skilled task that requires perceptual-motor coordination of expert *Kendama* players (Ito, Mishima, & Sasaki, 2011). They revealed the importance of flexibility of knee movement to support dynamical coordination between body movement and the moving ball and the stability of the strong coupling of the head and the ball (Ito et al., 2011). Then how can adaptability/flexibility be realized and how can variability of observed data be explained?

1.2 Degree of freedom and complex systems

In human movement science and skill science research fields, it is said that the functional degrees of freedom (DoF) can provide the human movement system with the foundation of adaptive/flexible or skilled behavior. The human body has many multifarious DoFs, from the microscopic cell level to macroscopic joint level (Bernstein, 1967; Turvey, 1990). The DoF problem suggested that the large number of controllable DoFs poses a computational burden to the central nervous system, if we assume a computational model (Turvey, 1990). This indicates the difficulty of the unidirectional top-down motor control model using computer metaphor. Bernstein, who proposed the DoF problem, supposed that each component (DoF) is coordinated and coupled with other components to organize a functional unit (*synergy*) rather than being controlled separately (Bernstein, 1967). Bernstein attempted to solve the DoF problem with the idea of synergy. Such coupled components are not organized in non-directional or random ways, but in sensitive and flexible way to achieve a specific task in a specific situation/environment (Bernstein, 1996).

Although the DoF problem is actually a problem from the viewpoint of the computational model (top-down motor control model), it is also possible to consider redundant DoFs as a benefit to enable movement systems to behave adaptably/flexibly. The human body has an intrinsic fluctuation derived from a physiological mechanism and is exposed to external perturbation from its environment or own body movement. However, if the system has redundant DoFs and an ability to freeze and release them quickly, it might realize stable behavior in an adaptive/flexible way against intrinsic fluctuation or external perturbation (Kodama & Aoyama, 2017).

After Bernstein’s proposal of the DoF problem and the idea of synergy, the self-organization theory (Haken, 1978; Nicolis & Prigogine, 1977) was applied to human movement studies to understand emergent properties of a human movement system. It is called the *dynamical systems approach* (DSA) and has been widely applied to human movement science areas. Compared to the traditional approach to motor behavior assuming internal computation, DSA focuses more on interactions between the body (including brain), environment, and task (Davids, Glazier, Araújo, & Bartlett, 2003). While the traditional top-down motor control model supposes a dominant central system (i.e., brain) and focuses on its component, DSA focuses on the interaction among system’s component (Van Orden, Holden, & Turvey, 2003). Complex systems consist of a large number of interacting components (DoF); the emergent behavior of the system is self-organized and can be difficult to anticipate from dynamics of the individual components (Boccara, 2003). Their emergent behavior does not result from the existence of a central controller like brain (Boccara, 2003).

1.3 Loss of complexity hypothesis

The perspective of the self-organizing theory provides new insight and a useful framework for not only human movement science and skill science, but also the clinical and therapeutic research fields. The *loss of complexity hypothesis* is a broad theoretical perspective applied widely to physiological and behavioral processes (Lipsitz & Goldberger, 1992). According to the hypothesis, the age- and/or disease-related changing process can be defined by a progressive loss of complexity within the dynamics of physiologic outputs (e.g., physiological and behavioral data) (Manor & Lipsitz, 2013). In other words, loss of complexity leads to an impaired ability to adapt to stressors or perturbation (Lipsitz & Goldberger, 1992). It is supposed to be due to a loss or impairment of functional components, and/or altered nonlinear coupling between these components (Lipsitz & Goldberger, 1992). Thus, the hypothesis assumes that a system’s adaptive/flexible function relates to its complexity and is observed in the dynamics of the system’s output behavior (e.g., physiological and behavioral times series data). Moreover, these dynamics are characterized by the presence of fractal scaling or the amount of regularity/predictability in the dynamics (Lipsitz & Goldberger, 1992; Stergiou, 2016).

For postural balance studies, the loss of complexity hypothesis has been applied and the center of pressure (COP) fluctuation is supposed to relate to the adaptive/flexible function of the postural system. For example, the postural dynamics of healthy young and healthy elderly people have high complexity than that of elderly people who have a history of falls (Costa et al., 2007). Parkinson’s disease patients also show lower flexibility in terms of deterministic structure of the COP dynamics than healthy participants (Schmit et al., 2006). Sensory impairments contributed to a decreased COP complexity, which reflected a reduced adaptive capacity of the postural control system (Manor et al., 2010).

Those postural balance studies applied nonlinear analysis methods like *fractal analysis* and *entropy analysis* to COP time series data. Fractal analysis is a time series analysis that obtains a dynamic measure. It can evaluate the temporal correlation of a time series (Brown & Liebovitch, 2010). Such a property is called a fractal property or $1/f$ noise and indicates that fluctuations in the time series extend across many time scales (Eke, Herman, Kocsis, & Kozak, 2002). Such relative independence of the underlying processes at different time scales suggests that $1/f$ noise renders the system more stable and more adaptive to internal and external perturbations (Delignières, Torre, & Lemoine, 2005). Thus, fractal property is considered a dynamic measure and is associated with health/pathology (Lipsitz & Goldberger, 1992) and flexibility/adaptability (Hausdorff, 2009). To assess the complexity of the system, dynamic measure based the idea of *entropy* derived from information theory has been also applied to biological and physiological data. Entropy refers to the rate of information generation by a system. While repeating systems generate less new information, systems with varying complexly generate new (non-redundant) information when the system visits new states. Generally, high entropy means relatively irregular and complex variability. In contrast, low entropy means regular and predictable behavior. According to the loss of complexity hypothesis, healthy systems are characterized by an irregular and complex variability, whereas disease or aging is associated with regularity/predictability and less complexity (Goldberger et al., 2002; Pincus, 1991).

It is supposed that the loss of complexity relates to a decline in the capability to reorganize the interactions between its components (its functional DoF) to adjust the degree of unpredictability of behavioral fluctuations to meet task demands (Sleimen-malkoun, Temprado, & Hong, 2014). Aging and/or disease are involved in change in coupling between components (DoFs) and the decrease in interaction between them. In other words, systems with less interaction between their components and few functional DoFs tend to behave regularly and their dynamics lose dimensionality or complexity (Sleimen-malkoun et al., 2014). However, most previous studies have investigated the relationship between DoF and system dynamics by comparing particular populations such as elderly/impaired people with healthy young people. In these cases, it is difficult to reveal the direct relationship between the DoF and system dynamics because other factors derived from aging and/or disease cannot be ignored.

1.4 Our research aims

As an exploratory investigation, our pilot study manipulated the DoF of a human movement system (i.e., joint) as an independent variable, and compared different DoF conditions within subjects. We fixed and constrained the ankle joint (two DoFs) and knee joint (one DoF) of the dominant leg and required young healthy participants to perform single-leg standing task by their dominant legs; this was compared to the no-fixation normal condition. The COP trajectory data were measured and analyzed by linear and nonlinear methods to assess a static and dynamic properties of the postural dynamics. Then, the direct relationship between the DoF and COP dynamics was investigated. Such an investigation may lead to deeper understanding of their relationship and provide an experimental evidence of the loss of complexity hypothesis.

2 Method

2.1 Participants

Six healthy male participants (average = 23.50 (SD=4.68) years, all right-handed) were recruited to join the experiment. The experimental procedures were approved by the research ethics committee of Kanagawa University, where the experiment was conducted. Each participant provided informed consent for participation in this study.

2.2

Joint fixation equipment (REAQER ankle supporter, REAQER knee supporter, **Fig.1**) were used to fix the ankle and knee joints. The center of pressure (COP) trajectories were measured using a force plate (Leptrino CFP600YA302US, sample rate = 200 Hz). To process and analyze COP data, MATLAB (R2017b, MathWorks) and RStudio (Version 1.1.423) were used to process and analyze the COP data.

2.3 Procedure

In the current pilot experiment, three conditions were compared, namely, the normal condition (no joint fixation), ankle condition (ankle joint fixation), and knee condition (knee joint fixation) as shown in **Fig.1**. Under the joint fixation conditions, each joint of the dominant leg (i.e., right leg) of each participant was fixed using the equipment. Each participant was asked to maintain single-leg standing with their dominant leg for 35-s. After conducting the normal condition task first as a baseline condition, the ankle and knee condition tasks were counterbalanced between the participants. Under each condition, they were required to repeat a 35-s trial four times with 30-s interval between trials, and with 3-min rest between conditions.

Fig. 1. Experimental conditions and joint fixation equipment (Left: Normal condition, Middle: Ankle condition, Right: Knee condition).

2.4 Data Analysis

After measuring the COP trajectory data, we removed the initial 5-s data and analyzed the remaining 30-s of time series data of the COP in the mediolateral (ML) and anteroposterior (AP) directions. Before performing the following time series analyses, all COP data were smoothed by a 10-Hz low-pass filter (4^{th} order Butterworth filter).

To assess postural stability, the COP trajectory length was calculated and regarded as a static measure (Horak, 1989; Shumway-Cook & Woollacott, 2013). This measure defines shorter trajectory length as less movement (less postural sway) and it means more stable posture. In this sense, we interpret this as a static measure.

By contrast, to evaluate dynamic postural stability, we also applied nonlinear time series analyses, *detrended fluctuation analysis* (DFA; Peng et al., 1994) and *sample entropy* (SampEn; Richman, R., & Moorman, 2000). DFA is a fractal analysis for nonlinear time series data, and has been used to assess a system's adaptability/flexibility (Hausdorff, 2009) in terms of temporal correlation in time series data (Brown & Liebovitch, 2010). DFA calculates the scaling exponent α as the slope of the log-log plot of fluctuation vs. time scale. A linear relationship on a log-log plot indicates the presence of scaling. The DFA scaling exponent α is interpreted as an estimation of the Hurst exponent H, and is related to H as follows (Delignières, Torre, & Bernard, 2011): if $0 < \alpha < 1$, then H=α; if $1 < \alpha < 2$, then H=α-1. H can be interpreted for the time series as follows: if $0 < H < 0.5$, the time series is anti-persistent/under-diffusive; if $H = 0.5$, it is uncorrelated (*white noise*); if $0.5 < H < 1$, it is persistent/over-diffusive; if $H = 1$, it is considered 1/*f noise* (Marmelat, Torre, & Delignières, 2012). *Sample entropy* analysis is a method with which to quantify the complexity or irregularity of a time series (Richman et al., 2000). Sample entropy (SampEn) indexes the (ir)regularity of a time series and is used to analyze the dynamics of complex systems. While a smaller sample entropy means greater regularity, a larger sample entropy indicates relatively irregular or complex dynamics. For a given embedding dimension m, tolerance r, and number of data points N, SampEn is the negative logarithm of the probability that if two sets of simultaneous data points of length m have distance $< r$ then two sets of simultaneous data points of length m+1 also have distance $<r$ (Stergiou, 2016). DFA was performed using the R package '*nonlinearTseries*' (Constantinoet al., 2015). SampEn was performed using the R package '*pracma*' (Borchers, 2018) with input parameters, embedding dimension m=3 and a ratio of standard deviation of the data of r=0.2.

3 Result and Discussion

3.1 COP Trajectory Length

Fig. 2 shows the mean COP trajectory length for each condition (left: normal condition; center: ankle condition; right: the knee condition; error bar: standard deviation). The mean value was 1393.61 (SD=228.82) [mm] in the normal condition, 1507.60 (SD=210.93) [mm] in the ankle condition, and 1471.48 (SD=350.43) [mm] in the knee condition. The results seem to indicate that postural sway is the smallest in the normal condition, which is the largest DoF condition. However, the result of one-way ANOVA revealed no significant differences between the conditions (F(2, 10)=0.995, p=0.404, *N.S.*). This implies that the joint fixation did not affect the static measure, which is the COP trajectory length (i.e., how much posture fluctuate) in the case of our pilot study (N=6).

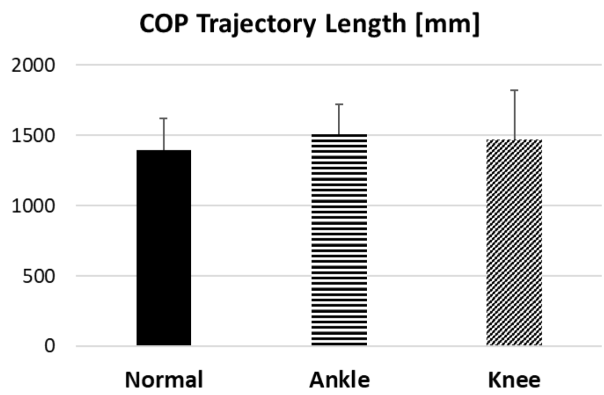

Fig. 2 COP trajectory length [mm] (Left: Normal condition; Center: Ankle condition; Right: Knee condition).

3.2 DFA Scaling Exponent α

Fig. 3 displays the mean DFA scaling exponent for each condition in the ML and AP directions, respectively (left: normal condition; center: ankle condition; right: the knee condition; error bar: standard deviation). In the ML direction, the mean value was 1.17 (SD=0.07) in the normal condition, 1.25 (SD=0.05) in the ankle condition, and 1.18 (SD=0.06) in the knee condition. In the AP direction, the mean value was 1.30 (SD=0.09) in the normal condition, 1.31 (SD=0.09) in the ankle condition, and 1.30 (SD=0.10) in the knee condition. To compare these values statistically, one-way ANOVA was conducted for each scaling exponent α of both the ML and AP directions. The results show that we found the significant main effect on the scaling exponent α only in the ML direction (F(2, 10)=0.011, p<0. 05). Because of multiple comparisons (Ryan's method), significant differences were found between the ankle and normal conditions (t(5)=2.833, p<0.05), and between the ankle and knee conditions (t(5)=2.415, p<0.05). These results indicate that the scaling exponent α was larger in the ankle condition than in the other conditions in the ML direction. In contrast, there was no significant main effect in the AP direction (F(2, 10)=0.081, p=0.922, *N.S.*).

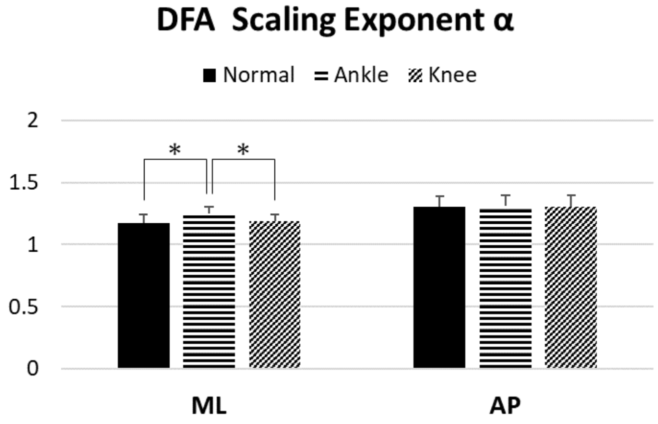

Fig. 2 DFA scaling exponent α (Left side *x*-axis ML direction, Right side: *y*-axis AP direction, in each side, Left: Normal condition, Middle: Ankle condition, Right: Knee condition).

The DFA scaling exponent is interpreted as follows: if $\alpha=1$, then the time series has persistent long-range correlations (i.e., $1/f$ pink noise); if $\alpha=1.5$, indicates Brownian motion. For $1<\alpha<1.5$, the time series has correlation, but lose fractality and ceases to be a power-law relation (Peng, Havlin, Stanley, & Goldberger, 1995). In the current data, the DFA scaling exponents were ranged between 1 and 1.5. Within this range, the scaling exponent α is related to the Hurst exponent H as $H=\alpha-1$. This implies that an increasing trend in the past is likely to be followed by a decreasing trend, and an anti-persistent correlation/under-diffusive process (Marmelat et al., 2012). In terms of fractality, if $0.75<\alpha<1.25$, then the time series has long-range correlation and indicates $1/f$ pink noise (Marmelat et al., 2012). Comparing our results across conditions, α was higher in the ankle condition than other two conditions in the ML direction. This means that the under-diffusive process that regulates single-leg standing posture in the ML direction weakened when the ankle joint was fixed. In other words, adaptability/flexibility was higher in the normal and knee conditions than in the ankle condition because the scaling exponent in the normal and knee conditions were ranged between $0.75<\alpha<1.25$. If so, the ankle joint fixation might cause loss of adaptability/flexibility.

3.3 Sample Entropy

Fig. 4 represents the mean SampEn for each condition in the ML and AP directions respectively (left: normal condition; center: ankle condition; right: the knee condition; error bar: standard deviation). In the ML direction, the mean value was 0.117 (SD=0.023) in the normal condition, 0.095 (SD=0.018) in the ankle condition, and 0.116 (SD=0.025) in the knee condition. In the AP direction, the mean value was 0.073 (SD=0.026) in the normal condition, 0.076 (SD=0.026) in the ankle condition, and 0.074 (SD=0.026) in the knee condition. To compare these values statistically, one-way ANOVA was conducted for each SampEn of both the ML and AP directions. The results show that we found the significant main effect on SampEn only in the ML direction ($F(2, 10)=4.295$, $p<0.05$). Because of multiple comparisons (Ryan's method), significant differences were found between the ankle and normal conditions ($t(5)=2.616$, $p<0.05$), and between the ankle and knee conditions ($t(5)=2.453$, $p<0.05$). These results indicate that SampEn was larger in the ankle condition than in the other conditions in the ML direction. In contrast, there was no significant main effect in the AP direction ($F(2, 10)=0.071$, $p=0.931$, *N.S.*).

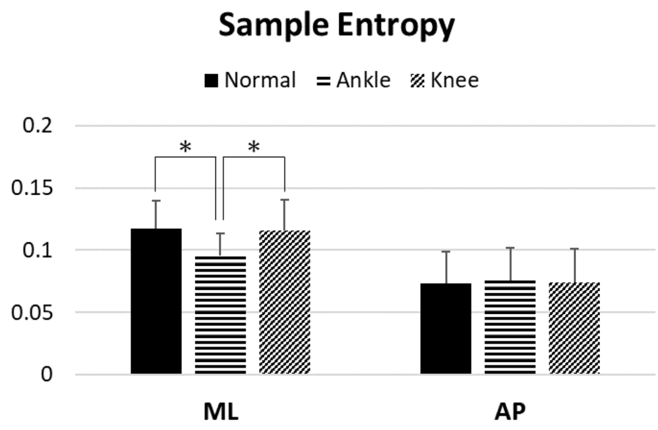

Fig. 3 Sample Entropy (Left side *x*-axis ML direction, Right side: *y*-axis AP direction, in each side, Left: Normal condition, Middle: Ankle condition, Right: Knee condition).

A high SampEn indicates relatively low regularity or complexity, while low SampEn means relatively high regularity or predictability. In the current data, postural sway was more regular in the ML direction in the ankle condition than the other two conditions. The result suggests that low SampEn (more regular postural sway) in the ankle condition was interpreted as an increase in the effectiveness of postural control in the ML direction in terms of amount of attention or cognitive involvement (Donker, Roerdink, Greven, & Beek, 2007). Some previous studies argued that postural sway regularity is positively correlated with the degree of cognitive involvement in postural control (Donker et al., 2007; Roerdink et al., 2006). Actually, some participants reported that it was more difficult to perform the single-leg standing task in the ankle condition than in other two conditions. We guess that such a difficulty leaded to more attention to postural control and more regular postural sway in the ankle condition.

3.4 General Discussion

COP trajectory length can be interpreted as a static measure because it indicates how much postural sway is observed and it is defined as less movement or more stable sway. In the current pilot experiment, we could not find any significant differences between the conditions in terms of the quantity of postural sway. This means that joint fixation did not affect the static balancing ability of single-leg standing. In contrast, the DFA scaling exponent α and SampEn can be considered dynamic measures because they quantify how the posture fluctuated in terms of temporal correlation or temporal pattern complexity of the time series data. Our results suggest that postural sway during the single-leg standing task had a weaker under-diffusive process and less irregular/complex fluctuation in the ML direction in the ankle condition than in the other two conditions.

The single-leg standing task requires postural control based on foot function using ankle joint movement (King & Zatsiorsky, 2002). The ankle joint fixation seemed to constrain the mobility of the foot movement and postural control in the ML direction, whereas the knee joint fixation did not affect the postural dynamics because the knee joint has only one DoF (flexion-extension) and is not involved in postural control in the ML direction. In terms of functional DoF, the knee joint has one DoF and the ankle joint has two DoFs, therefore the results of fractal analysis show that the ankle joint fixation might cause less adaptability/flexibility. This notion is reasonable from the viewpoint of the loss of complexity hypothesis (Sleimen-malkoun et al., 2014). On the other hand, the results of entropy analysis suggest that the ankle joint fixation might cause relatively regular postural sway (low sample entropy); in other words, it might evoke a loss of complexity in the postural dynamics in the ML direction. This notion also seems to agree with the loss of complexity hypothesis (Sleimen-malkoun et al., 2014).

3.5 Future directions

The present article reports only the results of the pilot experiment (N=6). We should collect more data and confirm whether a similar tendency can be found in the future. In addition, we also plan to investigate not only single-leg standing with the dominant leg, but also other balancing tasks. In terms of data analysis, other methods should be conducted to quantify adaptability/flexibility, complexity, and dimensionality (Bravi, Longtin, Seely, & Ca, 2011; Cavanaugh, Guskiewicz, & Stergiou, 2005; Hidaka & Kashyap, 2013), and associate them with empirical data of previous studies.

As discussed, our results should be explained from kinematic or biomechanical perspective in more detail to understand the relationship between the functional DoF (and its fixation) and the system dynamics in terms of complexity and adaptability/flexibility. Further experimental studies regarding the effects of the freeze and release of DoF on the static and dynamic properties of system dynamics may lead to a deeper understanding the direct relationship between them and to obtaining empirical evidence on the loss of complexity hypothesis. We also expect that such experimental strategies can provide more applied research on not only the clinical assessment of the fall risk of elderly/impaired people, but also practical evaluation of sports skills or dexterous performances of athletes with further validity of quantification and evaluation using various data analytical methods.

4 Conclusion

This article reported the results of our pilot experiment to investigate the direct relationship between the joint DoF of the human movement system and its postural dynamics in terms of adaptability/flexibility. In the experiment we manipulated the join DoFs (knee and ankle) with joint fixation equipment. Young healthy participants were required to maintain single-leg standing with their dominant leg fixed. The COP time series data were measured and analyzed by linear and nonlinear methods to assess the static and dynamic properties of their postural dynamics. The results of comparing across conditions (normal no-fixation, and ankle and knee fixation condition) show that the static measure (COP trajectory length) did not significantly differ across conditions; however, the dynamic measures (DFA scaling exponent and sample entropy) differed significantly. The ankle joint fixation (two DoFs constrained condition) affected the scaling behavior leading to weakening of the under-diffusive postural control process, and a sample entropy decline which indicated the losing efficiency of postural control requiring an amount of attention (cognitive involvement). These results of dynamic measures seem to agree with the previous studies' insight within the loss of complexity framework that suggests that less functional DoF might lead to loss of complexity or adaptability/flexibility of the system behavior.

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Visualization of Cognition and Action in the Shooting Skill Acquisition Process in Ice Hockey

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Abstract. To support the process of skill acquisition, a system that visualizes both cognition and action is required. This study aims to build such a system. To this end, this study conducted experiments on slap shot in ice hockey and attempted to visualize cognition and action in the process of acquiring shooting skills. Slap shot is a type of shot performed when a player swings his stick back and then down to strike the puck with maximum force toward the goal. It is the strongest shot in ice hockey. This study conducted 9 identical experiments in about two months. Each experiment consisted of a pre-test, practice, and post-test. The research participant made 15 slap shots in each test. Practice lasted for 10 minutes. The 21-year-old research participant had eight years of experience in ice hockey. The experiments of shooting training were conducted on acrylic boards, rather than on ice, in an experimental laboratory. The research participant wore gloves and used sticks but did not wear skates in the experiments. The experiments were conducted with shooter tutors for ice hockey goals. The research participant was instructed to make a strong shot at the upper right of the goal area by slap shooting. The research participant described his cognition data in the report after the post-test. In the report, the research participant was guided to answer four questions; an example is: To which aspects did you pay attention when you made a strong and accurate slap shot in today's practice? Please describe them in detail as much as possible. This study created a network analysis on the report using "KBDex," which visualizes the process of discussions. Action data were measured and converted into variables using video cameras and motion capturing systems. Then such variables, which described the positions and velocities of body parts, were analyzed. FWDpowershot, an acceleration sensor and ice hockey stick center, presumed and recorded the shooting speeds in the pre- and post-tests. The number of shots that came into the upper right zone was also recorded in the pre- and post-tests. We aimed to clarify further the process of acquiring shooting skills in ice hockey, thereby enabling the building of a visualizing system based on adequate analyses.

keywords: Expertise, Conceptual Change, Visualization, Ice Hockey Shooting

1 Introduction

It is essential to evaluate and support the learning process. The new (2018) version of Japan's curriculum course guidelines (Ministry of Education, Culture, Sports, Science and Technology[1]) stipulates that teachers should focus on the process of learning when evaluating their teaching and designing future lessons. But this presents frontline teachers with a challenge: what methodology should they employ to this end? Educators have for years stressed the importance of evaluating and visually modeling the learning process. However, there is now a plethora of learning applications in use thanks to the rise of information and communications technologies, and it is essential to evaluate how these applications should be used in practical settings. In many learning settings, and in sports skill learning in particular, complex knowledge and skills acquisition occurs tacitly. Accordingly, it is important in such learning settings to visualize the relationship between these two aspects of learning.

To support the process of sport skills acquisition, it is necessary to visualize two processes in the learner—a tacit cognitive change process and a motor skill acquisition process—and then share this information with learners and coaches. Therefore, we sought to visually model the cognitive and biomechanical aspects of sport skills acquisition.

1.1 Visualizing the Learning Process

Strom et al. (2001)[2] developed a graph for visually modeling mathematical argumentation in a second-grade classroom. The graph presents the children's conversation in 10-minute sections, allowing one to see how conceptual knowledge changes over time in the class as a whole. Such a visual model can help educators evaluate the learning process and provide support accordingly. However, this model presents a burden to teachers: they have to transcribe every conversational exchange and manually compose a network chart.

In another study, Zhang et al. (2009)[3]visually modelled students' learning interactions. In a three-year experiment, they analyzed network structures in three classes of fourth graders (taught by the same teacher) and derived teaching strategies from these analyses. Thus, new technology is dramatically changing researchers' analytical techniques and visual modeling.

1.2 Network Analysis

As we see in the works by Barabási (2005)[4] and Strogatz (2001) [5], network analysis is garnering increasing scholarly attention because it allows researchers to analyze and visualize complex social networks. A basic analytical index used in network analysis is "degree centrality," which describes the number of connections in a network (Nieminen, 1973)[6]. Using the principles of network analysis, Matsuzawa (2011)[7] developed a computer application called Knowledge Building Discourse eXplorer (KBDeX). KBDeX analyzes inter-word connections (collocations) in learning discourses. It has already been used in learning settings to analyze learners' discourses. Oshima et al. (2012)[8] used KBDeX to analyze learners' physics group work and found that the assistant teacher's utterances heavily influenced the quality of learners' discourses. Studies such as this demonstrate that KBDeX compares favorably against traditional discourse protocol analysis, and that it is therefore valid as a tool for analyzing discourses.

1.3 Visualizing Motion in Sports

Up to this point, we have cited examples of visually modeling discourse data (such as network analysis). When it comes to supporting sport skills acquisition, however, it is also important to measure and visually model the motions of learners' athletic maneuvers. If educators could visualize learners' key biomechanical actions and then compare them with their past biomechanical actions, they might be better able to support the skill acquisition process. There have been attempts to visualize learners' biomechanics and provide support accordingly. Nishiyama and Suwa (2010)[9], for example, quantitatively measured the biomechanics of learners' baseball swings. They then visualized this biomechanical aspect by, among other things, paring color tones with swing speeds. Accumulating a body of such video data and sharing it with the learner and his/her coach will make both parties aware of the key biomechanics and how they are changing; they can then use this information to guide their learning/coaching. A number of studies have explored the process of motor skill acquisition and highlighted qualitative changes that arise in this process, including slumps (e.g., Suzuki & Ohnishi, 2007) [10] and changes in coordination/regulation of different body parts (freezing/freeing degrees of freedom; e.g., Bernstein, 1967[11]; Higuchi et al., 2002 [12]; Konczak et al., 2009[13]; Vereijken et al., 1992[14], 1997[15]). Using numeric values or graphs to visually model these qualitative changes (or indications that such changes will arise) will make the learner and his/her coach aware of the level of attainment of the target skill as well as the change thereof; they can then use this information to guide their learning/coaching. Thus, in addition to visually modelling the cognitive aspects of learning (as represented in learning discourses, for instance), visually modelling learners' motions and accumulating a body of such data may prove an effective strategy for supporting skill acquisition.

1.4 Ice Hockey as a Subject of Study

We chose ice hockey as the sport in which we would explore the potential for supporting skill acquisition by visually modelling cognitive and biomechanical aspects. The literature on ice hockey is limited when it comes to empirically verifying performance changes and coaching support; nonetheless, we regarded ice hockey as an appropriate subject to study in view of the findings of several studies on the sport. The literature has shown, for example, that cognitive skills, in addition to physical skills, are an important element among ice hockey players (e.g., Holt & Beilock, 2006 [17]; Thiffault, 1974 [18]). Thiffault (1974) [18]analyzed decision-making skills among ice hockey players of differing skill levels (elite and novice) by making them watch videos that simulated an ice hockey match situation. The study reported, among other things, that skill level influences decision speed. In a study by Hove et al. (2006)[19], participants used dynamic touch to infer the affordances of different hockey sticks. The study reported that ice hockey experience (novice vs. expert) affected how well they could perceive the affordances. Thus, the studies assert that physical and cognitive aspects are closely linked. In view of these findings, we assumed that ice hockey learners will, in the course of the learning process, experience changes in their motor and cognitive performances as well as changes in the relationship between motor and cognitive aspects. Ice hockey is appropriate for examining ways of visually modeling cognitive and athletic aspects and providing support accordingly. Therefore, we decided to focus on the skill acquisition process in ice hockey.

1.5 The Purpose

In this study, we sought to visually model the cognitive and biomechanical aspects of the process of acquiring ice hockey shooting skills. We did so with a view to deriving hints on how to support the process of shooting skill acquisition.

2 The Experiment

We conducted an experiment in which the participant performed a "slap shot," the most powerful shot in ice hockey. To perform a slap shot, the player winds up (raises the stick in the air behind the puck) and then aggressively swings the stick down so that the blade brushes the ice just behind the puck (see Figure 1). We focused on the slap shot because, of all the hockey shots, it requires the most extensive maneuvering, and it would therefore make for a relatively easy shot in which to visually model the player's changes in the skill acquisition process.

2.1 The Participant

The experiment was conducted on a single participant: a 21-year-old male with 8 years' experience in playing ice hockey. We selected this relatively experienced adult participant because the slap shot requires muscular strength. It is also too complicated a shot for novices to perform. The participant was a member of a university ice hockey club, so he may have had opportunities to practice the slap shot outside of this experiment (such as in team practice sessions). Nonetheless, we recruited this participant believing that being an active member of an ice hockey team, he would have all the more motivation to master the slap shot.

2.2 Experimental Setting

Rather than conducting the experiment on an actual ice hockey rink, we conducted it in an experimental setting—specifically, a hitting practice site with a

Fig. 1. Slap shot

plastic (rather than ice) surface. The participant did not wear skates during the experiment; his equipment was restricted to a hockey stick and a pair of gloves. To simulate an ice hockey goal, we used a "shooter tutor" (see Figure 2). The player took his shots from a distance of five meters from the goal. Figure 3 shows the experimental setting.

Fig. 2. shooter tutors

2.3 Experimental Design

The experiment consisted of nine sessions over a roughly two-month period. Each session consisted of a pre-training test, training, post-training test, and report.

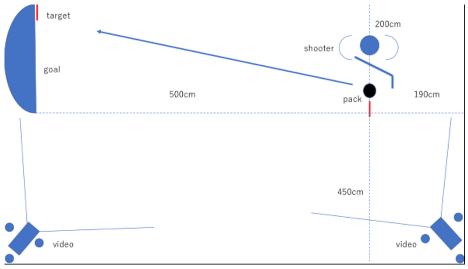

Fig. 3. experimental setting

For each test, the participant had to attempt 15 slap shots. The training segment lasted for 10 minutes.

After the first and ninth sessions' post-training tests, we obtained motion capture data at three time-points (pre-hit, hit, and post-hit). Figure 4 describes the flow of each experimental session.

Fig. 4. experiment

2.4 Instructions

For each test, the participant was instructed to slap shoot the puck as powerfully as possible into the upper right corner of the goal. For each training segment, he was instructed to practice this task for 10 minutes.

For the report segment, the participant had to respond to the following questions: "During today's training, what aspect(s) did you focus on in an attempt to master powerful and accurate slap shots? Please be as detailed as possible." "Why did you focus on this/these aspect(s)?" "For the next training session, what aspect(s) do you intend to focus on?" and "Why do you intend to focus on this/these aspect(s)?" The participant inputted his responses using a PC.

3 Analysis

3.1 Performance

To measure the speed of the participant's shots, we used FWD Powershot, a sensor that slides into the hollow shaft of a hockey stick. To measure shot accuracy, we counted the number of shots on target (shots that went into the upper right corner of the goal). We used the participant's post-training test performance as a measure of his advancement. Regarding performance feedback, the participant would have been aware of his shot accuracy (he could count the number of shots on target himself), but he was not informed about his shot speed.

3.2 Motion Analysis

After the first and final post-training tests, we recorded five motion capture data sets tracking the participant's knees and toes during his five shot maneuvers. We used two OptiTrack motion capture systems (OptiTrack V120: Trio; NaturalPoint) sampling rate=120 Hz. To record the data, we operated the systems synchronously with two video cameras (Handycam HDR-PJ390; Sony) running at 30 FPS.

When analyzing the video data, we identified three maneuver points in each video: swing-initiation, hit, and shot-end. "Swing-initiation" refers to the point when the participant commenced the downward swing. "Hit" refers to the moment the hockey stick hit the puck. "Shot-end" refers to the point when the participant commenced the downward swing after hitting the puck. We also identified pre-hit and post-hit maneuver phases. We defined the pre-hit phase as time from swing-initiation to hit, and the post-hit phase as time from hit to shot-end. We defined the overall shot maneuver time as the time from start to end. For each shot maneuver, we noted the total shot maneuver time as well as the time for each maneuver phase. We then compared the average times for the five shot maneuvers in the first session with those for the five shot maneuvers in the last session.

To eliminate noise from the motion capture data, we used data processing software (Motive 2.0.1, NaturalPoint; cutoff point: 10 Hz). Once we had eliminated the noise, we analyzed the height of the participant's knees and toes at each of the three maneuver points. We then compared the average positions for the five shot maneuvers in the first session with those for the five shot maneuvers in the last session. We did the same for the inter-knee and inter-foot distances.

3.3 Visualization of Action

Although analysis based on motion capture data is highly accurate, the issue is that experiments and analysis are time consuming. In this study, we aimed to establish a visualization system for practical applications and we considered visualization based on motion analysis with a monocular camera.

Cao et al. (2016) [16]released a library called OpenPose, which uses deep learning to estimate the 2D pose of individuals appearing in monocular camera images. Japanese company DeNA took OpenPose's algorithm and applied it to a deep learning framework called Chainer to create the application "Chainer-Realtime Multi-Person Pose Estimation." We used this application in our study after refining it. The application can detect 18 key points of the human body. We refined the application so that it could generate a CSV file with XY coordinates for the key points it detected. We then created a program that selects three of the detected key points and estimates a pose angle.

To consider visualization in this study, we conducted the following analysis using motion images taken using the camera at the back of the laboratory. We used motion images for one slap shot in the first and the last sessions, and the data for two seconds, or 60 frames, before and after the impact were subject to analysis. The angles between the shoulders, elbows, knees, and feet were subject to visualization. As skeletons are sometimes accidentally detected in the analysis, we calculated the moving average of nine sections.

3.4 Report Analysis

To analyze the participant' s reports, we used KBDeX (the application for visually modeling learning discourses that we mentioned in 1.2). We separately analyzed the participant' s responses to the four question items and plotted a network of the collocations in each sentence. We then analyzed this network focusing on collocations between collocating words associated with slap shot mastery—specifically, words describing maneuvers and words describing body-part positions. For each experimental session, we plotted a network and calculated its degree centrality.

We used the sum of the network' s node values as a measure of its degree centrality. Nodes that are connected to many other nodes will have a higher value. For example, take the network shown in Figure 5. There are five nodes: A, B, C, D, and E. Node A has three edges (it is connected to three other nodes), Nodes E, D, and C each have two edges, and Node A has one edge. Accordingly, Node A, being connected to 3/4 of the other nodes, has a value of 0.75. Nodes C, D, and E have a value of 0.5 (each is connected to half of the other nodes), and Node B has a value of 0.25 (it is connected to 1/4 of the other nodes). The sum of these values is 2.5. Therefore, this network' s degree centrality is 2.5.

An increase in node edges would result in higher degree centrality if the number of nodes did not increase. A decrease in node edges would result in lower degree centrality even if the number of nodes did not decrease (such an event never occurs). If edges and nodes both increased, the degree centrality would rise commensurate with the increase in edges. If nodes increased but edges did not, the degree centrality would fall. Thus, the network' s degree centrality will increase if a newly occurring word connects with the network, and will decrease if the new word does not.

4 Results

4.1 Performance

Figure 6 shows the post-training test results for each experimental session. The left vertical axis indicates shot accuracy and the right vertical axis indicates shot speed estimates.

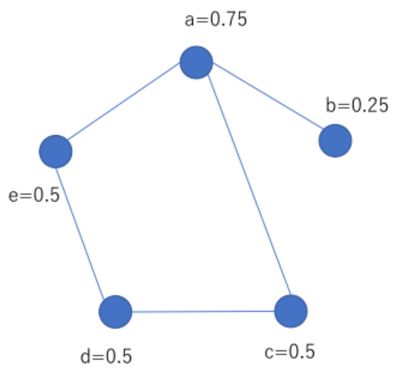

Fig. 5. centrality

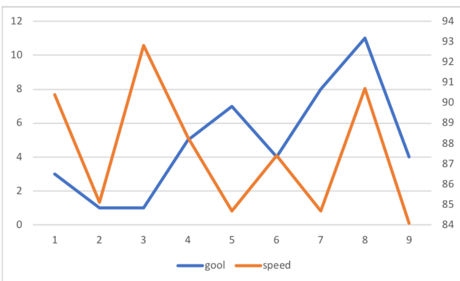

Fig. 6. gool and speed

We defined the first three sessions as "first sessions," the middle three as "second sessions," and the final three as "third sessions." Table 1 shows the average number of accurate shots and average shot speed for 1st, 2nd, and 3rd sessions. Figure 6 and Table 1 indicate that the participant's shooting accuracy improved with successive experimental sessions. On the other hand, shot speed appears to have declined over the sessions. Looking at Figure 6, from the third to seventh sessions, accuracy and speed rise and fall contrastively (when one rises, the other falls, and vice-versa). Across the eighth and ninth sessions, they rise and fall together. This phenomenon suggests that the participant was at one stage sacrificing either accuracy or speed for the other, but that he subsequently acquired the form and cognition to achieve accuracy and speed at the same time. As we mentioned earlier, the participant could know his shot accuracy (by counting his successful shots), but he was unaware of his shot speed (we did not give him this information). Given this, we surmised that providing feedback on shot speed might be necessary to help learners master fast shots.

Table 1. gool and speed

	first	second	third
gool	1.67	5.33	7.67
speed	89.4	86.8	86.5

4.2 Motion Results

Time Required for Shot Maneuver Figure 7 presents the average total maneuver time for the five shots executed in the first session (black bar) and that for the five shots executed in the last session (gray bar). The error bar indicates the standard deviation. In the first experimental session, the participant's average maneuver time was 586.67 ms (SD = 38.01 ms). In the final session, it was 533.33 ms (SD = 23.57 ms). This result suggests that the participant reduced his maneuver time slightly as a consequence of training.

Figure 8 compares the average maneuver phase time (pre-hit and post-hit) for the five shots executed in the first session (black bar) with that for the five shots executed in the last session (gray bar). In the first experimental session, the participant took on average 333.33 ms (SD = 40.82 ms) for the pre-hit phase and 253.33 ms (SD = 29.81 ms) for the post-hit phase. In the final session, he took on average 253.33 ms (SD = 38.01 ms) for the pre-hit and 280.00 ms (SD = 18.26 ms) for the post-hit phase. These results indicate that, as a consequence of training, the participant's pre-hit maneuver time reduced while his post-hit maneuver time increased.

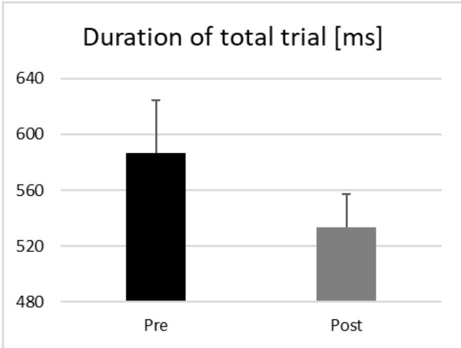

Fig. 7. duration of total trial

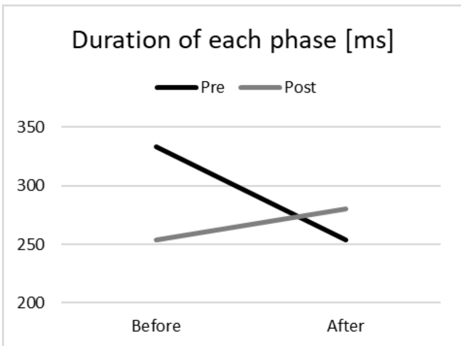

Fig. 8. duration of each phase

Knee/Toe Spatial Data Figure 9 shows the average knee heights at the three maneuver points (swing-initiation, hit, and shot-end) for the five shots executed in the first session (black bar), and the same for the five shots executed in the last session (gray bar). In the first experimental session, the average swing-initiation knee height was 53.12 cm (SD = 0.29 cm), the average hit knee height was 50.97 cm (SD = 5.34 cm), and the average shot-end knee height was 51.21 cm (SD = 4.59 cm). In the final session, the average swing-initiation knee height was 49.51 cm (SD = 0.74 cm), the average hit knee height was 49.27 cm (SD = 0.54 cm), and the average shot-end knee height was 50.67 cm (SD = 0.46 cm). These results indicate that, as a consequence of training, the participant lowered his left knee slightly during the pre-hit phase, thus lowering his center of gravity.

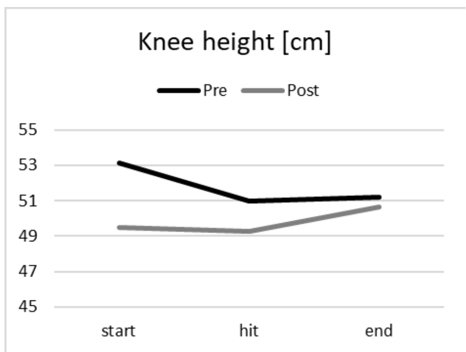

Fig. 9. knee height

Figure 10 shows the toe heights at three points (swing-initiation, hit, and shot-end) for the five shots executed in the first session (black bar), and the same for the five shots executed in the last session (gray bar). In the first experimental session, the average swing-initiation toe height was 5.52 cm (SD = 0.45 cm), the average hit toe height was 5.98 cm (SD = 0.96 cm), and the average shot-end toe height was 5.21 cm (SD = 0.47 cm). In the final session, the average swing-initiation toe height was 5.67 cm (SD = 0.27 cm), the average hit toe height was 5.48 cm (SD = 0.11 cm), and the average shot-end toe height was 5.39 cm (SD = 0.15 cm). These results indicate that the participant' s toe height changed little throughout the experimental sessions.

Figure 11 shows the inter-knee distances at three points (swing-initiation, hit, and shot-end) for the five shots executed in the first session (black bar), and the same for the five shots executed in the last session (gray bar). In the first experimental session, the average swing-initiation inter-knee distance was 30.30 cm (SD = 5.12 cm), the average hit inter-knee distance was 30.00 cm (SD = 1.96 cm), and the average shot-end inter-knee distance was 35.45 cm (SD = 2.11 cm). In the final session, the average swing-initiation inter-knee distance was 36.99

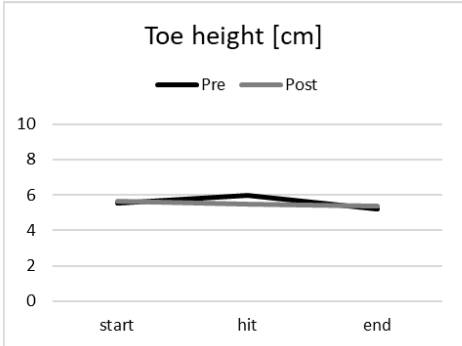

Fig. 10. toe height

cm (SD = 2.07 cm), the average hit inter-knee distance was 38.05 cm (SD = 2.36 cm), and the average shot-end inter-knee distance was 41.18 cm (SD = 2.10 cm). These results indicate that, as a consequence of training, the participant's inter-knee distance increased with successive sessions. The increased inter-knee distance meant that the participant could manipulate his body more fully during the shot.

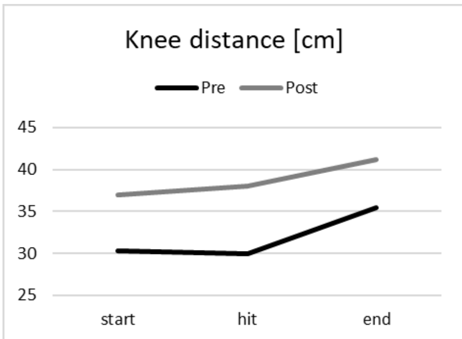

Fig. 11. knee distance

Figure 12 shows the inter-foot distances at three points (swing-initiation, hit, and shot-end) for the five shots executed in the first session (black bar), and the same for the five shots executed in the last session (gray bar). In the first experimental session, the average swing-initiation inter-knee distance was 48.92 cm (SD = 9.56 cm), the average hit inter-knee distance was 52.38 cm (SD = 15 cm), and the average shot-end inter-knee distance was 63.98 cm (SD = 11.1 cm). In the final session, the average swing-initiation inter-knee distance was 56.18

cm (SD = 2.87 cm), the average hit inter-knee distance was 57.10 cm (SD = 4.24 cm), and the average shot-end inter-knee distance was 61.21 cm (SD = 2.54 cm). These results indicate that, as a consequence of training, the participant's inter-foot distance from swing-initiation to hit increased with successive sessions. The increased inter-foot distance meant that the participant could manipulate his body more fully during the shot.

Fig. 12. toe distance

4.3 Visualization of Action

Figure 13 shows the program utilizing the skeleton detection function of the monocular camera extracting the skeleton from the motion images.

Fig. 13. uses deep learning to estimate

Figure 13 shows the skeleton being extracted from the images before and after the moment of the shot. Figure 14 shows the results of the analysis of the first and the last sessions of the experiment.

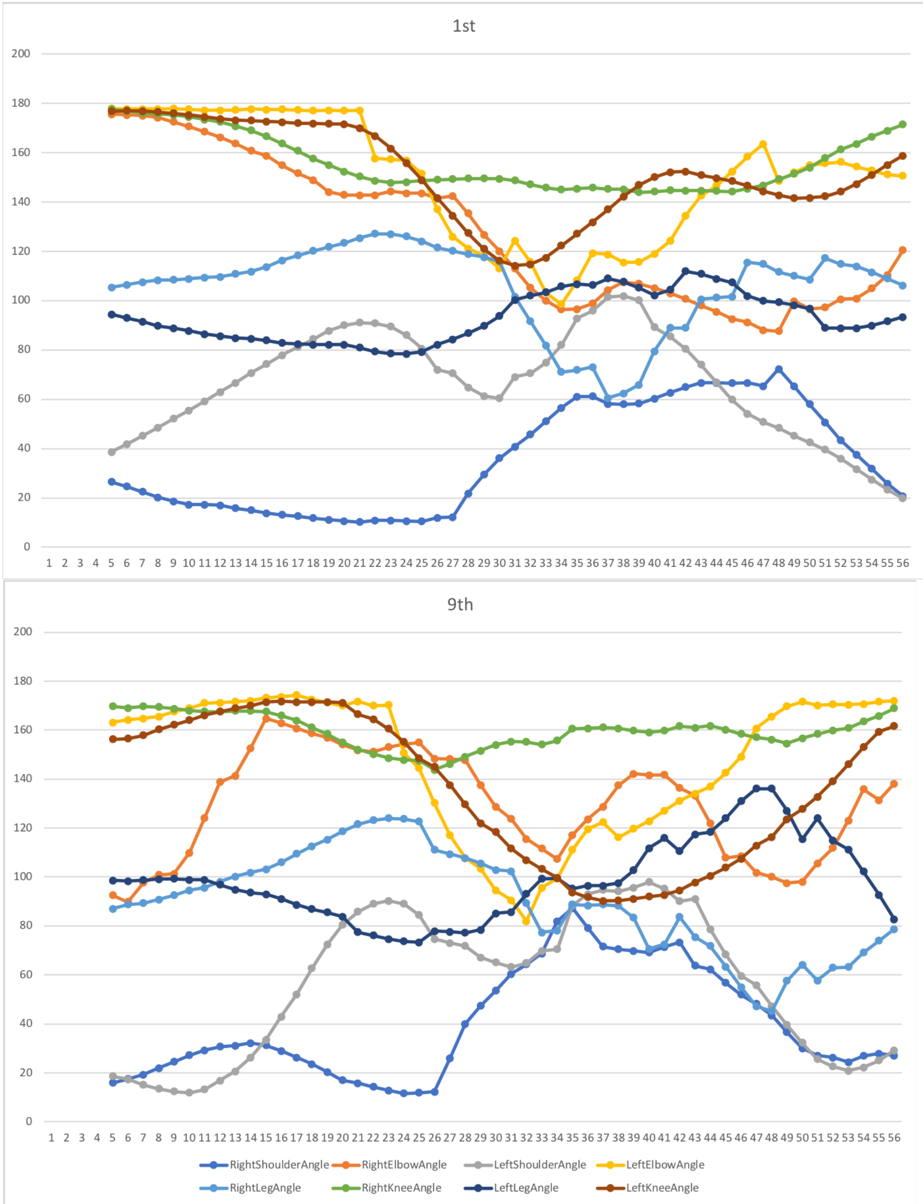

Fig. 14. Visualization of action

Figure 14 indicates that changes in the motion are seen, especially in the second half of the last session, compared with that of the first. The results are in agreement with the motion analysis based on motion capture data. The results of this study suggest that it is possible to extract skeletons and visualize motions by using images taken by a commonly available monocular camera.

4.4 Report Results

The following is an example of a phrase that the participant wrote in his report: "During the shots, I tried to avoid tensing up my body during wind-up." Such a phrase appeared at an average rate of 8.1 times per day. Focusing on such phrases, we analyzed 25 words related to slap shot mastery. Examples include "puck," "hands," "tried," and other words describing maneuvers or body parts.

Figure 15 shows the degree centrality across the nine experimental sessions. The horizontal axis indicates the number of sentences and the vertical axis indicates the degree centrality. The degree centrality fluctuated wildly in the early part of the experiment, but became more stable in the latter half.

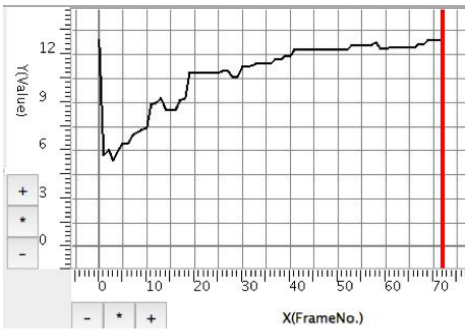

Fig. 15. centrality

Figure 16 shows the networks of the nine experimental sessions. Numerous nodes appeared in the networks of the first 5 sessions, but the 6th, 7th, and 8th sessions' networks had fewer than 10 each. In the ninth session, the nodes recovered to a high level and presented a complex structure. Given the instability of the degree centrality during the first half of the experiment, the participant may have been figuring out slap shot strategies during this time. If the participant had figured the strategies out by the end of the fifth session, it would explain why we saw more stable networks for the sixth, seventh, and eighth sessions. The return to a complex network structure in the ninth session might reflect the fact that the participant performed less well in this session.

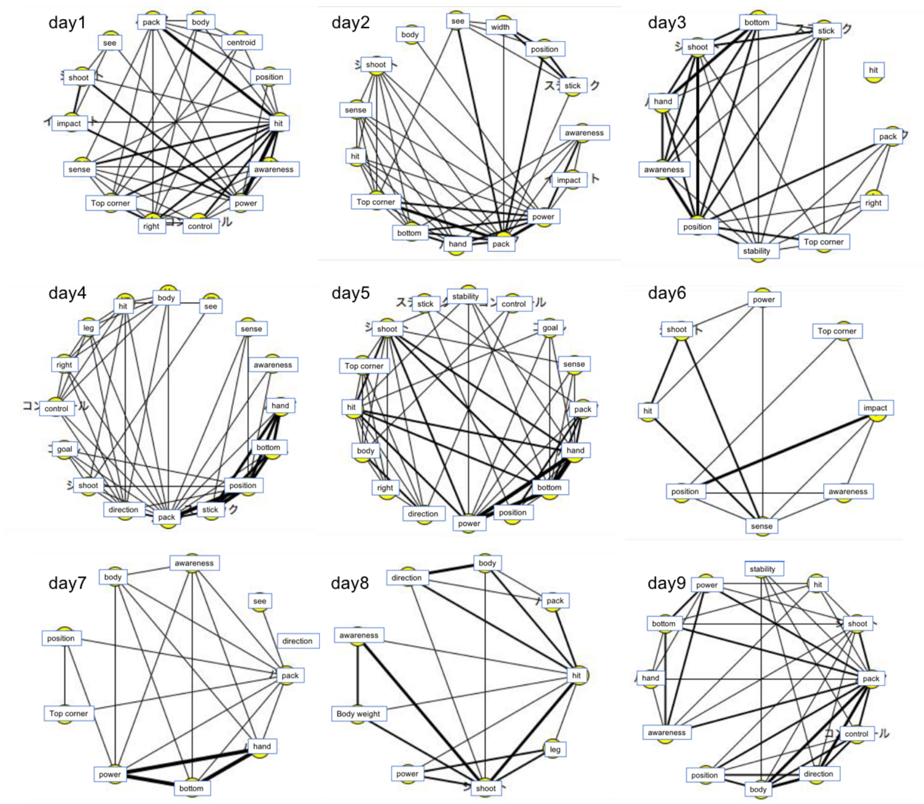

Fig. 16. network

5 Summary

In this study, we sought to visually model the cognitive and biomechanical aspects of the process of acquiring ice hockey shooting skills. We did so with a view to derive hints for how to support the process of shooting skill acquisition.

Judging from the test results, the participant's shooting accuracy improved over the course of the experiment. However, we did not observe any such improvement in his shooting speed.

The biomechanical analysis revealed that the following changes occurred over the course of the experiment: the participant's overall shot maneuver time decreased slightly; his pre-hit maneuver time decreased while his post-hit maneuver time increased; his knee height, and thus his center of gravity, decreased; furthermore, his inter-knee and inter-foot distances widened. These results imply that the participant's movements became more extensive, particularly during the post-hit phase.

We conclude that the approach we adopted in our study—conducting a network analysis (of the player's reports) combined with a biomechanical analysis —is capable of visualizing the cognitive and biomechanical aspects of a player's progress in respect to the performance indicators of shot speed and shot accuracy.

6 Future Outlook

Our findings have limited applicability because we conducted the study on only a single participant; moreover, we analyzed only a single ice hockey shot. Future studies should explore more cases. We did not inform the participant of the speed of his shots. However, to ensure that the research can be applied in coaching practice, it is necessary to obtain data on the learning effects of communicating such visualized information to the participant, and to ascertain how such data could help coaches support players. Finally, we conducted our experiment at an experimental site. Future studies should conduct experiments on a larger scale so that they are more applicable to ice hockey practice.

Acknowledgement

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A Research about Rhythm and Phrase Recognition of Classical Music Performer Learning Jazz Ad-lib Solo Phrases based on Score

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Abstract. The author has conducted a survey that rhythm and phrase recognition when classical music performers score based sight-read about jazz ad-lib solo. Classical music performer generally takes the 1st and 3rd quarter as accented beat when they perform 4/4 beat phrases. However the jazz performer generates their ad-lib phrases, taking the 2nd and 4th quarter as accented beat. Thus for the classical music performers, sight-reading the generated jazz phrase is difficult.
In this paper, the author reports the survey that records the processes that the classical music performers sight-reading jazz blues ad-lib phrases, changing the accented beat. The targeted ad-lib phrase is Charlie Parker's blues solo which given by musical notated score. At first time, the performers sight-reading the target ad-lib phrase counting off beat (2nd and 4th quarter) as accented beat, jazz style. At second time, the performers do the same sight-reading counting on beat (1st and 3rd quarter) as accented beat, normal classical style. Final time, the performers do the same sight-reading counting all quarter. The performers records their stumbling phrases for the each different counting tried. As a result, most performers recorded different the stumbling phrases between the jazz style counting and the classical style counting. These results indicate that difference of their beat counting and accented beat, between classic style and jazz style, effect their recognition of the ad-lib phrases.

Keywords: Musical Recognition · Jazz Ad-lib Performance

1 Introduction

It is very difficult for the audience to observe not only the expression of music as expressing music but also the recognition of the performance expression of the performer. In this paper, we discuss the recognition of the phrase and its rhythm by the difference of position of accented beat between jazz style and classical music style, based on interviews conducted by classical music performers playing Ad-lib solo of jazz.

Butterfield disscused about a typical element of the jazz rhythm, "Swing"[1, 2]. However, Swing alone is not the typical rhythm of jazz compared to classical music. The author thinks that it is important that jazz learners become sensitive to the difference of accented beat with classical music in order to acquire the jazz improvisation likelihood. The author expects that the problem of internalization of rhythm due to differences in the accented beat may be referred to as "Groove" in researche field on music cognition and perseption. Stupacher et al. did general discussions based on quantitative experiments from the viewpoint of brain cognitive science about "Groove"[4]. However, it is difficult to say that these experiments and discussions are not from music, musical theory and music educational perspective, thus the author thinks that they are out of the sense of actual jazz learners.

Figure 1 shows Chalie Parker's own ad-lib solo in *Now's the Time*[3]. The author predicts that classical music performers cannot internalize this ad lib phrase easily from the rhythmic point of view compared to regular classical music. Figure 2 shows several red square frames which means "stuck places" when the author, classical music singer in music academy major in old days, himself actually practiced this ad-lib phrase. The author analized that a type of phrases confused the author's rhythm recognition. The typcal phrases is which it begins with anacrusis then has a certain length non code tone at the head of bar. The cause is the differecnt position of accented beat between jazz style and classical music style.

In classical music style, we feel accented beat in 1st and 3rd quarter. On the other hand, in jazz style, we feel accented beat in 2nd and 4th quarter. The author predicts that the differences of accented beats will affect the internalization of the phrase ryhthm. The Charlie Parker's ad-lib solo has a lot of phrases with a rhythm deviated from anacrusis and beat which is difficult to understand in the context of classical music. If those phrases are attributed to the jazz style accented beat, it makes it very difficult for classical music performers to internalize their phrases.

Therefore, the authors investigated the influence of differences in accented beat when classical musicians copied jazz ad-lib solo phrases on a score basis.

2 Experimantal Detail and Result

The purpose of this experiment, to observe clear emergence of differences of rhythm recognition between jazz style accented beat and classical style accented beat in practice of jazz ad-lib solo copy based on score.

There were 4 subjects, classical saxophone performers. 2 subjects finished graduate master's degrees and 2 other finished undergraduate degrees in music college. Experimental instruction was sended to subjects by e-mail with the score which shows as figure 1. The experimental instruction as follows:

> Please sight-read this score. You can use or not use your instruments.The instruction sets limits to count beats of the sight-reading. Please do not use the metronome while you beat yourself.
>
> 1. 2 counts for a bar (2nd and 4th quarter)

Fig. 1. Charlie Parker *Now's the Time* Ad-lib Solo in *Charlie Parker Bee Boppers*(1945)

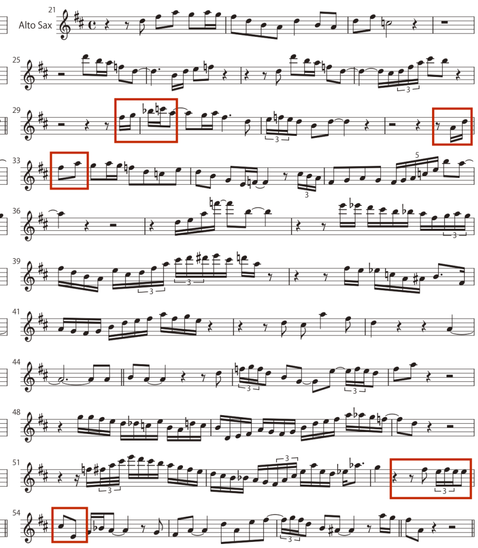

Fig. 2. Mistake point of the author

2. 2 counts for a bar (1st and 3rd quarter)
3. 4 counts for a bar (every quarter)

At first, please sight-read while taking the count, indicated by 1. (2nd and 4th quarter). Please write down where you stucked places. The sight-read is done once or twice.

Secondly, please sight-read while taking the count, indicated by 2. (1st and 3rd quarter). Please write down where you stucked places, similarly.

Finally, please sight-read while taking the count, indicated by 3. (every quarter). Please write down where you stucked places, similarly.

Figures 3, 4, 5, 6 are result of subject 1, 2, 3, 4. Gray squares mean stucked places in the count style 1. (2nd and 4th quarters, jazz style), blue squares mean stucked places in the count style 2. (1st and 3rd quarters), and red squares mean stucked places in the count style 3. (every quarter).

Only the test subject 1 (figure 3), her stucked places in the count style 1. (2nd and 4th quarter) is improved by the count style 2. (1st and 3rd quarter) and the count style 3. (every quarter). On the other hand, subjects 2 (figure 4), 3 (figure 5), and 4 (figure 6 had different stucked places for the count style 1. (2nd and 4th quarters) and the count style 2. (1st and third quarters), respectively.

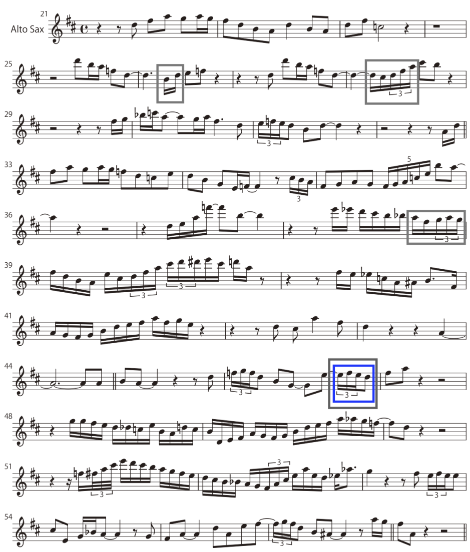

Fig. 3. Subject1

Fig. 4. Subject2

Fig. 5. Subject1

Fig. 6. Subject2

3 Discussion

3.1 Defferences depends on Accented Beat

The result that, in subjects 2, 3, and 4, the stucked place was different depending on the difference in position between the jazz style and the classical music style of accented beat is observed. This result suggests that the internalization of the phrase's rhythm may be affected by the location of the accented beat.

3.2 Triplet with Anacrusis in Loose Rhythm Fluctuation

The 3 out of 4 subjects answered that they stucked at 28th and 51st bar measure. At the 28th bar measure, the subject 1 and 3 stucked with the count style 1. (2nd and 4th quarter), the subject 2 stucked with the count style 2. (1st and 3rd quarter). At the 51st bar measure, the subject 3 and 4 stuked with both count style 1. and 2. Note that both notes shape of the 28th and 51st bar measure, the bar's start is not note-on, then a phrase which begins at eigth off beat in 2nd quarter includes triplets and 16th notes. In jazz style 2nd quarter is accented beat, in classical music style 2nd quarter is up beat. Also Charlie Parker himslef perfomed this phrase's rhythm not in just time, accompanied by a rather loose rhythm fluctuation at his CD[3]. The author predicts that the rather loose rhythm fluctuation is due to the difference in accented beat, and hence the difference between jazz and classical performers' rhythm cognition, thus this phrase arises from the sense of jazz style rhythm and it is difficult for classical music players to easily grasp this.

4 Conclusion

In this paper, the author predicted that the difference between jazz and accented beat of classical music might have influence on cognition of phrase, then had experiment to let actual classical music performer to sight-read the jazz ad-lib solo phrases changing accented beat. The result suggesting that the difference of accented beat has an influence on cognition of jazz phrases. In addition, the author speculated from classical experiments that classical musicians are hard to grasp the phrases in which the rhythm fluctuation is severely brought about in actual performance.

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Effects of Casual Computer Game on Cognitive performance through Hemodynamic Signals

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Abstract. Intervention of the cognitve declines process is essential. Computer game has been assumped to give effects on activation of brain activity. However, there are many types of computer games. At the same time, the brain activation can be understood through the brain signals. In this study, we present the changes of cognitve performances through the scores of neuropsychological testing after the entertainment of casual puzzle game. Our controlled experiment was done with seven paticipants. The evidence showed the better performance in spatial imaginary and perceptual speed ability, yet unstable performance in working memory and attention through the task of finding different items after the computer game entertainment. Moreover, we then illustrated the changes in hemodynamics signals derived by using a wearable functional-Infrared repectroscopy (fNIRs). Median of max-min normalized oxy-Hb and the power spectral density indicated the small viariation of brain activation after involving into the casual puzzle game playing.

Keywords: Cognitive performance, fNIRs, oxygenrated hemoglobin signals, stroop task, mental rotation task, power spectral density, normalization.

1 Introduction

Declining of cognitive performance does not always happen to the elderly but sometimes to younger adults [1]. Enhancing the cogntive capacity is essential in order to intervene the process of cognitive decline.

Affectivity is likely to have association with changes in cognitive performance. For example, the previous study indicates that the negative affectivity such as perceived stress and depression have influences on the rapid process in cognitive decline among eldery [2], [3]. On the other hand, involving into activities that stimulate postive arousal has been suggested to enhance cogntive ability through working memory [4]. Computer game provides fun and entertainment that lead to positive arousal and was claimed to be beneficial on cognitive abiities [5]. However, each type of computer game might have different effects on the different domians in cogntive performance. Previous studies conducted the experiment with action game and claimed that the vedio action game can enhance cogntive performance[6]. However, investigating other types of games and cognitive abilities are still remained for futher studies. Thus, investigation of computer games to fulfill the applicable knowledge to support the early intevention and therapetics of cognitve decline is needed.

The phenomena relating to affections and cognitions in neuronscience studies are understood through activities of brain signal such as electroencephalogram (EEG), functional magnetic resonance imaging (fMRI), and near-Infrared spectroscopy (NIRs). Emotion status was understood regarding the EEG signal patterns[7], while cognitive abilities among Alzheimer patients can be observed through MRI [8], [9]. Moreover, hemodynamic oxygenation changes via NIRs were also investigated during brain acitivities in patients [10]. Brain signals now provide promissing sources. It is believed to be an effective tool for monitoring brain activities during various mental tasks, entertainment actitvities and social events.

In this paper, we focus on the brain oxygenated hemoglobin signal during the mental tasks before and after playing a computer-based casual puzzle game. The computer-based puzzle game is addicitve and easy to play, at the same time, it provides dimensions for a player to activate more on his brain function. We hypothsize that the effects of playing computer games can be reflected through oxygenate hemodynamic of brain. Additionally, the casual puzzle game might improve performance of cognitve function. The cognitve domains investigated in this paper include cognitive flexibility via stroop task, visuo-spatial ability via mental rotation task, memory capacity via pair association task, and attention ability via finding difference task.

2 Method

2.1 Subject

The study initially recruited seven subjects. The subjects are students atJapan Advanced Institute of Science and Technology. They are considered as healthy subjects due to the non- clinical history related to brain, and neurological, psychiatric and cardiovascular disorders. The mean age of subjects is 27 $\pm$ 3.8 and three of all subjects are male.

2.2 Neuropsychological testing

Neuropsychological testing is one of performance-based methods to assess a wide range of cognitive functioning and ability. For neuropsycholoical test in this study, stroop task and mental rotation are used.

Stroop task was originally developed since 1993 [11]. It was used widely in various research purposes under cogntive psychology domain [14], [13]. The study recruits the stroop task to measure the perceptual processing speed ability. We use PsyToolkit "psytoolkit.org/" [15], [16] as a tool to demonstrate a computer-based stroop task experiement. Aside, mental rotation task, whose concept was first introduced in 1971 by Shepard and Metzler [17], was used to examinne the visuo-spatial ability of each subject before and after the puzzle game. Mental rotation task in this study is to rotate a mental representative of two dimentional objects.

Moreover, some additional tests of attention and memory were also taken. The additional memory test is an associated pair matching game. This game allows subjects five seconds to remember 9 position of 3 pairs of pictures. Then, the subject was asked to match each picture with its pair on a correct position. Another game for testing attention is finding different item among the group. The subject was given sets of pictures. The subject was required to pick a different picture among each set.

2.3 Optical topography fNIRs device

To observe changes of hemodynamic signal in the prefrontal cortex, we used fNIRs wearable optimal topography WOT 220, manufactored by HITACHI. The fNIRs allows us to observe both oxygenated heboglobin (Oxy-Hb), and deoxygenate hemoglobin (deoxy-Hb) blood flow in the cerebral prefrontal cortex. The mesurement consists of 22 chanals to capture the signals on the cortex. The fNIRs optical WOT 220 is non-invasive device, which is light weight and easy to wear on subject's head. The device supports the real-time monitoring on an event in which the subject can freely move his body during the experiement.

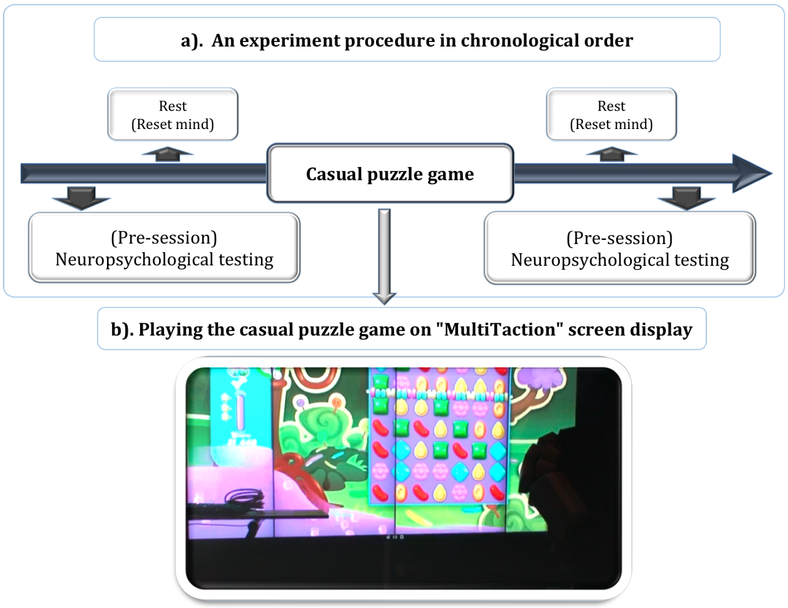

Fig. 1. An overview of experimental procedure

2.4 Experiemental procedure

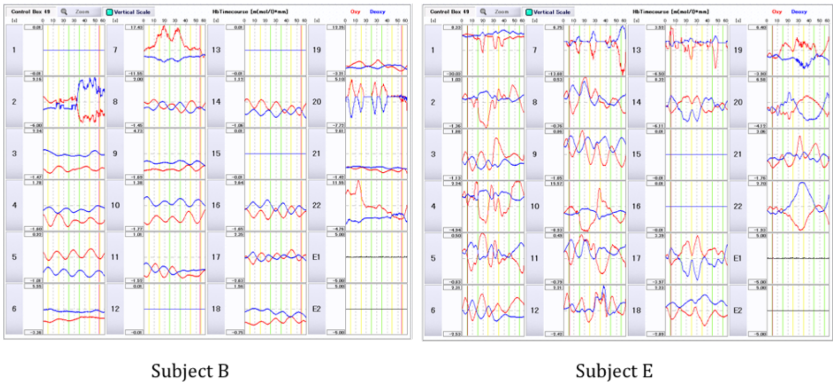

Fig. 2. Sample data of hemodynamic signal from subject B and subject E

After obtaining the consent, each subject was asked to wear the fNIRS device through the whole experiment, and sit in front of the computer display screen. During wearing fNIRs device, each subject was ensured not to lower and raised his head during each session in order to aviod noisy signals. As shown in picture a) of the Fig. 1, the experiement includes three main sessions: pre−neuropsychological test as a pre−session before the casual game playing, casual puzzle game playing, and post−neuropsychological test as a post−session after playing the casual puzzle game. The casual puzzle game used in this expersment is “Candy Crush Soda Sugar”. Each subject was asked to play this casual game for 20 minutes on “MultiTaction” device, the window operating system with 55-inch wide (16:9) Full HD 1920 x 1080 screen display as shown in picture b). of Fig. 1. Moreover, between each session during the experiment, the mind is reset by closing eyes and doing inhale−exhale for 3 rounds.

The experiement was hold in a specific room with a quiet environement, where there were only subjects and researcher.

3 Data Acquisition

3.1 Data of cerbral blood flow

With WOT-220 HITACHI device, the cerebral blood flow inclucing oxygenated and deoxygenated hemoblobin signals with 22-channels were retrieved. Some channels do not work well due to the intervention of hairs and other physical condition of each individual. As shown in the Fig. 2, the left-side picture shows the hemodynamic signals in cerebral prefontral cortex of subject B, in which the channel 1, 12 , 13, and 15 did not capture well the brain signals. The right-side picture of the Fig. 2 shows the hemodynamic signals of subject E, of which only channel 15 and channel 16 did not work well. The red lines indicate the changes of oxygenated hemoglobin (Oxy-Hb) on each channel, and the blue lines show deoxygenated hemoglobin (deoxy-Hb) of cerebal prefrontal cortex on each channel. This study, however, focuses only on oxy-Hb signals.

3.2 Normalization of oxy-Hb

In order to do a simply observation of the changes of signal between pre and post session of the casual game playing, we first implement the measurement by computing the median of the normalized oxy-Hb in both pre session and post session. The oxy-Hb signal in channel- n of subject i was nomrlized with max-min normalzation approach with the folllowing equation:

$$OxyHb'_{i_n} = \frac{OxyHb_{i_n} - min(i_n)}{max(i_n) + min(i_n)}$$

Where $min(i_n)$ is the minimum value and $max(i_n)$ is the maximum value of oxy-Hb signal in channel- n of subject i through each neuropsychological test session (pre-session and post-session).

Each signal is considered as a vector V that contains k component(with k length). The median value of each normalized signal was generated by sorting data component of each signal in ascending order and then, when k length is an odd number, the middle value of a signal is $\frac{(k+1)}{2}^{th}$. And, the median of a signal is computed by the average of two middle values, when k length is an even number.

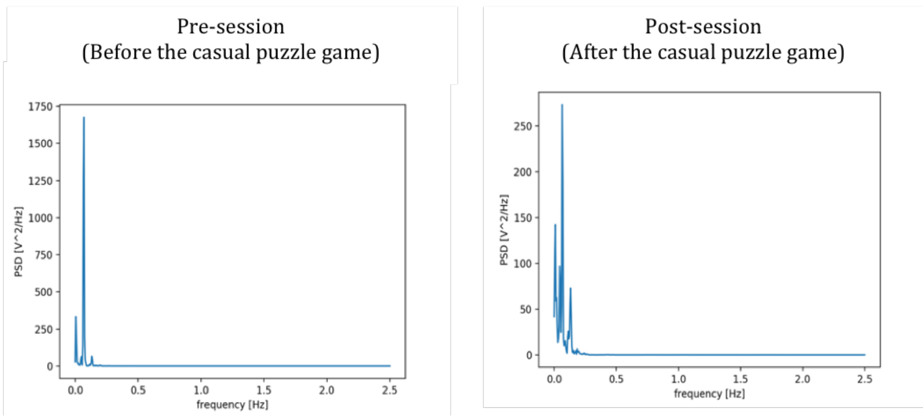

Fig. 3. The power spectral density of subject G during the mental tasks through neuropsychology testing before and after playing the casual puzzle game

3.3 Power spectral density

The power spectral density (PSD) is a point estimation of the energy variation in time series signal data as a frequency function. In this tstudy, we compute the PSD based on Welch's method [18]. The PSD is determined by averaging the windowed periodgram [19]. Regarding the Welch method, the original sequence signal is divided in multiple overlapping segments. Then, the welch method computes an array for each segment, in which each element is an average of the corresponding elements of all divided segments.

We computed PSD to extract maximum energy as the strongest variance of the oxy-Hb signal of each subject during the neurological testing in pre-session (before playing a casual puzzle game), and in the post session (after playing a casual puzzle game). We implemented on python with library SciPy. An example of the PSDs generated from oxy-Hb signal in channel 22 of subject G during his mental tasks in pre−session and post−session are shown in Fig. 3.

4 Result and discussion

4.1 Cognitive performance through neuropsychological testing

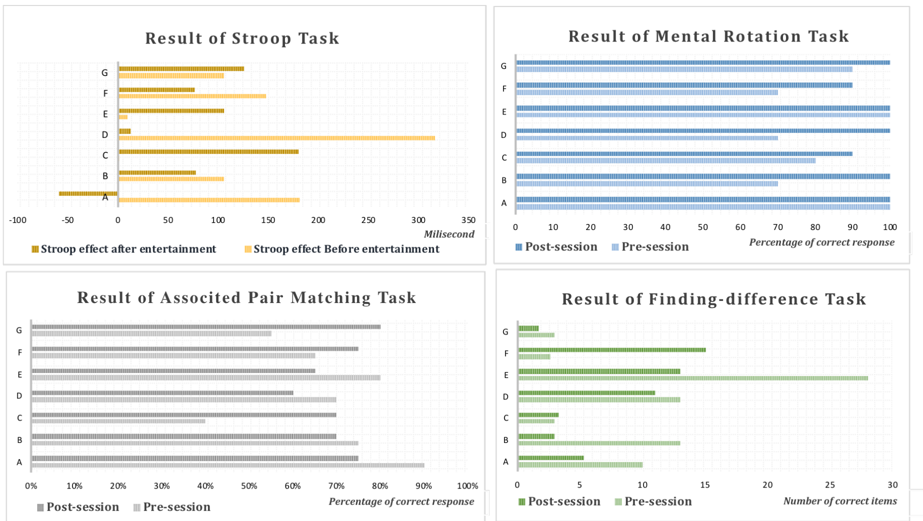

Fig. 4. Scores of neuropsychological testing

Fig. 4 shows the scores of neuropsychological testing. The results show that after a causal puzzle game playing, the ability of visuo-spatialization has been obviously improved, when the evidence through a mental rotation task shows the number of correct responses from each subject increased with less responding time (see top-right chart of Fig. 4). Similarly, stroop effect of each subject after enjoying the causal game was likely to be reduced. The score of stroop effects was computed by the average speed in correct trails of incongruent minus that in congruent. The smaller scores of stroop effect refer that individuals is faster in naming the color of ink a word is [22]. According to the top-left diagrame of Fig. 4, 60% of subjects produced lower stroop effects after playing the puzzle game. This phenomenon might refer that each control subject have the speed improvement of perceptual function after enjoying the casual puzzle game. In contrast, visaul attention ability through finding different picture was droped down. Meanwhile, the scores from experiemental result did show unstabe trends of memory performance through associated pair matching game task.

4.2 Oxy-Hb signal analysis

To illustrate the individual level, Fig. 5 shows the median values of the normalized oxy-Hb from 22-channels fNIRs for each subject during the mental tasks through neurolopsychological testing before and after playing a causal puzzle game. It is shown through the Fig. 5 that median value is missing from some channels due to the intervention of subjects' physical conditions. Thus, the common channels that well extacted hemodynamic signals from all subjects were considered to monitor the changes of brain activation in the population level.

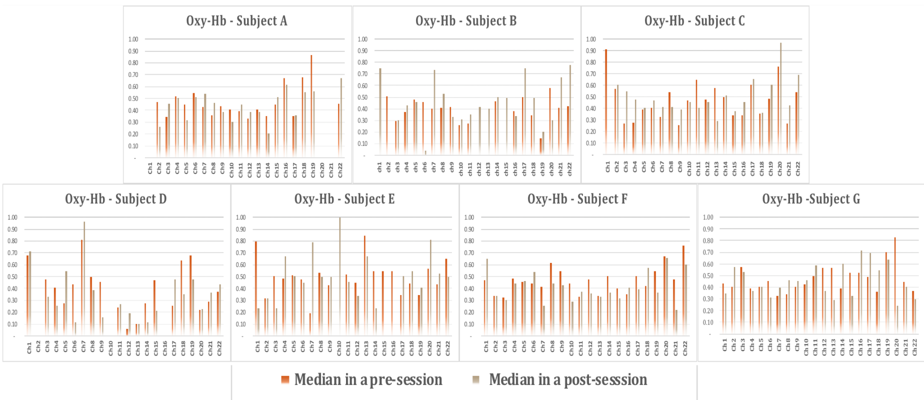

Fig. 5. Median of normalized oxy-Hb signals in 22-channel fNIRs by each subject

The channel 3, 9, 14, 19, and 22 are representatives to illustrate the changes of brain activation in this study. The change is generated by the middle values of normalized oxy-Hb signals after a causal game playing minus those before a game entertaining. The minus values of changes indicated that the medians of the normalized oxy-Hb signals after the casual game are smaller than those before the casual game as shown in the Fig. 6.

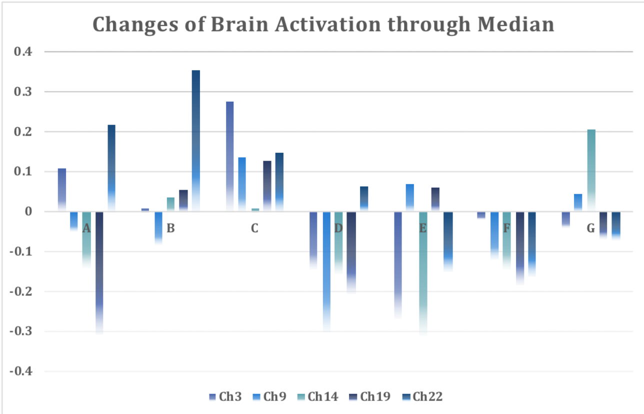

Fig. 6. Changes of brain activation through middle values of normalized oxy-Hb

The Fig. 6 shows an interesting results when all subjects excluding subject C have decreasing middle values of the normalized oxy-Hb.

Additionally, the power spectral density (PSD) of oxy-Hb signals also significantly changed after the casual game playing. The energy variation of oxy-Hb signals were reduced in the post-session, especailly, channel 19 shows a big difference of the strong varaince of oxy-Hb before and after the causal game playing.

Previous work through fNIRs-based signals indicated brain activations during a mental task of healthy control are higher than those in schizophrenic patients [21]. On the other hand, the study of observing mental workload through different levels induced the brain activations in middle and difficult level of mental tasks are higher than those in easy level [20]. In our case study with healthy control, the changes of oxygenated hemoglobin through middle values and PSD were slightly reduced while cognitive performance in mental rotation and stroop task were gradually improved.

The lower in PSD and middle values of oxy-Hb might induce the release of workload in brain function after the computer game entertainment. However, from the evidence of our experiment, indicating the correlation between oxy-Hb changes and cognitive performance is still in ambiguity. The PSD and middle values only indicated the changes of the brain activation before and after the computer casual game, while in order to clarify the relation between cognitive performance and oxygenated hemoglobin signals, the study requires larger number of samples. Moreover, our limitation in this study also related to the invetigation of fNIRs signals on four mental tasks without seperation on each task. Each mental task, for examaple mental rotation, stroop task, assiciated

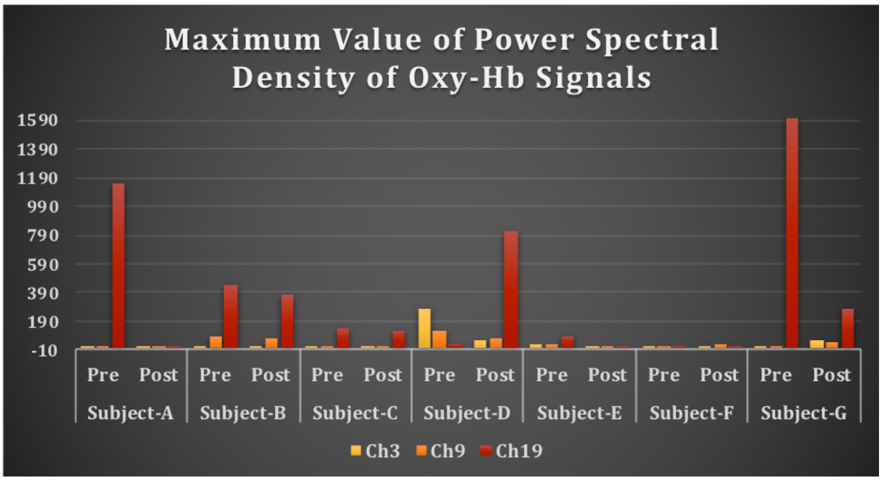

Fig. 7. Changes of brain activation through power spectral density

pair matching task as well as finding difference task, has its own charateristics, and might require different pattern of brain activation. If the oxy-Hb signals had been investigated in each signle mental task, the changes of oxy-Hb signals on a particular domain of cognitve performance would be obtained and more clearly explained.

5 Conclusion

In this paper, we investigated the cognitve performance before and after the entertainment through playing the casual puzzle game . We also investigated whether the brain activation is influenced by the casual puzzle game playing. The study suggessted that the casaul puzzle game in the form of computer version improve an immediate capacity of cogntive flexibility and visio-spatial ability, however, the short-term memory and fast eyes capacity are still in ambiguity. Moreover, the investigated features such as median of max-min normalized oxy-Hb and the power spectral density of oxygenated hemoglobin signal show the differentiation of brain activation in which oxy-Hb signals after a casual game playing have smaller variation comparing with those before the casual game. In order to infer the relation of oxygenated hemodynamic changes and the cognitve ability improvement, and understand the cognitive performance changes through oxy-Hb signals, we plan to extend our future study with larger population together with comprehensively investigate oxy-Hb signals on each type of cognitve ability, individually. Importantly, the advanced statistical machine learninig approach to interprete the changes of fNIRs oxy-Hb signals on cognitve performance is considered to be employed .

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Effects of auditory feedback for a running assist system

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Japan Advanced Institute of Science and Technology

Many people in recent years adopt running in daily life due to health-oriented influence. However, coaches are not always available for supervision in practicing a sport, thus people are often ended up with practicing alone. Sometimes it leads to breakdown at knee or waist by putting a burden on the body without proper knowledge of training. In this research, we employ a small sensor and a small computer to develop a practice assist system that supports people to exercise running through auditory feedback. This system focuses on the movement of the feet and gives users feedbacks with sound with some effects such as different amplitudes between left and right sound or tempo change based on a landing balance between the left and right feet or the foot contact time.

Expected users are people trying to run to maintain and improve their health. The exercise thus should not be intense for the modest effect of physical exercise.

The effect of metrical structure on the auditory-motor coordination of dance-like movement

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Keywords: sensorimotor synchronization, dance, rhythm, accent, meter

Since dancing to music is a universal culture of human beings, it is reasonable to assume that humans have the basic ability to synchronize their movement with auditory rhythm. The degree of synchronization is affected by various factors such as the loudness of music and the metrical structure of rhythm [1,2]. The present study investigated the effect of metrical structure on the performance of auditory-motor coordination of dance-like rhythmic movement. Since previous study showed that off-beat finger tapping was more stable in structured sound sequence condition than in non-structured sound sequence condition [3], we hypothesized that metrical structure would stabilize auditory-motor coordination of dance-like rhythmic movement.

Metrical structure can be provided by manipulating loudness, pitch, or timbre of sound consisting the beat. In order to investigate whether the effect of metrical structure differ among the features of sound providing metrical structure, we created metrical structure on metronome beats by manipulating the loudness of the metronome in experiment 1, and by manipulating the pitch of the metronome in experiment 2. In both experiments, participants synchronized their dance-like knee-bending movement with metronome beats in structural condition (repeating loud sound and soft sound alternatively in experiment 1, and repeating high pitched sound and low pitched sound alternatively in experiment 2) and in non-structural condition (repeating the same sound in both experiments). Their knee-bending movement was recorded by using a goniometer and a motion capture system. In the analysis, the stability of the synchronization and the subjective difficulty score were compared between structural condition and non-structural condition.

In experiment 1, the result of the synchronization stability showed that participants synchronized better in structural condition, and their subjective difficulty score also showed that synchronizing with structural condition was less difficult. In experiment 2, the result of the synchronization stability showed that there was no significant difference between structural condition and non-structural condition. However, the subjective difficulty score showed that synchronizing in structural condition was less difficult.

To conclude, although there was a difference in the synchronization performance between experiment 1 and experiment 2, our results suggest that metrical structure facilitates synchronizing dance-like movement with auditory rhythm.

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Invited Lecture

Dr. Eiko Matsuda,
Biologically-inspired Computing Laboratory,
Tokyo University of Agriculture and Technology

Title

Reduction of Retrograde Interference in a Motor Learning by Idiosyncratic Cross-Modal Mappings

Abstract

Humans memorize multiple movement patterns suitable for different dynamic transformations. Before the consolidation, the motor memory is easy to interfere by experiencing a contradicting motor task (retrograde interference). It has long been assumed that color cues to highlight differences between two opposing force fields can allow participants to independently form two motor memories without experiencing retrograde interference; the results were not successful (e.g., Howard et al., 2013). In the research, we showed that, if the participant chose the color cues "suitable to their impression toward the motor task", the cues worked effectively to memorize the motor task without retrograde interference.

Panel Discussion

In Search of Foundations of Skill Science - What shall we study of skills?

We discuss important topics of skill science to see what should be studied for coming years. Skill Science is concerned with actions, perceptions, and sense as well as inference and memory. Devices for collecting data such as motion capture systems enable us to study skills form objective point of view. Identifying characteristics of motions is of our interest. We are further interested to know what lead to those motions, that is, mental processes behind them. Cognition in action, however, raises several issues that require our attention. What comprise our cognition of action? What is the ontological status of them? How can we approach to them? How should we validate our findings of cognition? Each researcher presents his idea in this forum and we invite participants for discussion.

Can we rely on the sense of body?

Tsutomu Fujinami (Japan Advanced Institute of Science and Technology)

Difficulty in distinguishing input from output in human movement

Kentaro Kodama (Kanagawa University)

What kinds of roles does a somatic sensation serve in human movements?

Daichi Shimizu (The University of Tokyo)

Why not dealing with subjective thoughts and feelings for studies of embodied-ness?

Masaki Suwa (Keio University)

Application of artificial life research method for inseparability of motion and perception

Yuta Ogai (Tokyo Polytechnic University)