

Verification Of A Classification Prediction Method For The Development Of Musical Expression In Early Childhood Using A Machine Learning Method Based On 3D Motion Capture Data

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ABSTRACT

It is widely acknowledged that children take developmental steps in performing musical expression through body movement dynamics. The author presents an approach to verify the method of classification prediction by machine learning using multiple classifiers to evaluate and classify the developmental degree of musical expressions in early childhood. The author addresses this potential solution by showing statistical analysis of full-body 3D motion captured data using such statistical analysis, and applies machine learning measures to predict developmental degrees of musical expression. In 2016, the author extracted the feature quantities of movement based on the results of the movement analysis of the musical expressions in the MEB program regarding 3-year-old, 4-year-old, and 5-year-old children (n=76). The developmental degree of musical expression was classified into three stages based on video analysis of the musical expression of each child. The 2016 training data as the feature quantity of movement (factors) and the three-stage evaluation (categorical dependent variables) were used as the model training for machine learning. Based on the results in 2017 with 2018, the classification model training results were applied to the acquired data (n=87) in 2019. The result of sensitivity analysis showed that the moving average acceleration of pelvis, the moving distance of right foot and the moving distance of right hand had a strong influence on the development of musical expression in early childhood. From those analysis results, the appropriateness of the machine learning method using decision trees for classifying the developmental degree of musical expression in early childhood was verified.

Keywords: machine learning, feature quantity of movement, musical expression in early childhood, decision tree, 3D motion capture.

INTRODUCTION

When considering music education methods that promote the development of musical expressions in early childhood, it is necessary to devise activities that take into account the developmental characteristics such as pretend and dramatization in early childhood (Rubin & Merrion, 1996; Jalongo & Isenberg, 2001; Hendy & Toon, 2005). In order to devise activities that are effective for the development in early childhood, quantitative verification from the perspective of elements of

body movement such as pretending and dramatization is hoped to be clarified developmental characteristics and actual conditions of musical expression. Previous studies have included specific activities and practices [Burton & Kudo, 2000; Jalongo & Isenberg, 2001; Schirrmacher, 2005; Ballemma, 2005; Marigliano & Russo, 2011] and experimental studies on the development of musical abilities [Hannon & Johnson, 2005; Phillips-Silver, & Trainor, 2005; Provasi, & Begue, 2003; Trainor, 2007; Zatore et al., 2007; Zenter & Eerola, 2010], but little study has been considered about the quantitative verification of musical expressions specific to early childhood.

On the other hand, the author first analyzed the movement of musical expression in early childhood in the process of music education using 3D motion capture technology, and clarified changes and characteristics of elements of body movement in musical expression [Sano, 2017; Sano, 2018a]. 3D motion capture technology has been used in adults to analyze the proficiency of specific movements such as dance [Sato et al., 2010; Burger et al., 2013] and sawing [Ando & Sumikawa, 2012] in the education field, although there are no research reports on musical expression in early childhood.

The author conducted a one-year practice of the MEB program (Musical Expression Bringing-up program) [Sano, 2015] based on the author's idea in reference to Rubin & Meriion's study [1996] and analyzed the behavior in the order of activities. The MEB program consists of four phases' activities such as "(1) Initial activities", "(2) Pantomime and improvisational expression," "(3) Story creation," and "(4) Story dramatization." From the practice process, the activities specific to each activity phase were extracted as measurement items at the time of movement analysis. The moving trace, the moving distance, the moving average velocity, the moving average acceleration, and the movement smoothness of 17 measurement sites such as the head, limbs, chest, and waist were calculated as the motion capture data.

Next, using the 13 types of data among the calculated motion capture data as feature quantities of movement, machine learning methods were used to perform classification model training, and to classify and discriminate new data of the musical expression in early childhood. The author has been trying to find a way to classify the degree of musical development [Sano, 2018b; Sano, 2019]. Machine learning [Murphy, 2012] has been used in a variety of ways in the education field, some researches showed some reports such as tracking emotions in texts from student-generated content [Kolog at al., 2019], and pursuing issues that affect student school achievement [Hey, 2018], investigation of eye movement patterns of an elementary school children regarding arithmetic education [Moreno-Estevaa et al., 2018], educational support for elementary school children's movement of horizontal bar [Matsumoto et al. 2014], and evaluation of Japanese sentences in Japanese language education [Fujita et al. 2012]. In the music field, previous studies showed research reports such as learning music performance [Widmer, 2001], classification of musical instrument performance [Young, 2008; Kashiwagi et al. 2016], player's breathing during music performance [Igarashi et al. 2001], and analysis of performance expressions [Yamagami et al. 2008], although there are no research reports that use machine learning for musical expressions in early childhood.

In 2016, the author extracted the feature quantities of movement from the movement analysis results of the measurement items related to the musical expression for the four phases of the MEB program. At the same time, the developmental degree of musical expression was classified into three stages based on video analysis of the musical expression of each child. In 2017, the acquired

data in two kindergartens were analyzed in the same manner as in 2016, and in 2018, the same analysis was conducted for the acquired data in a certified facility. The 2016 training data acquired in the fourth phase as the feature quantity(factors) for 76 children and the three-stage evaluation (categorical dependent variables) were used as training model for machine learning, and classification model training was inspected. The result of classification training model was implemented to the acquired MVN data for 2017 with 2018 during the fourth phase (n=128) to classify the developmental degree of musical expression [Sano, 2019].

In this article, the author will inspect a method for classifying and discriminating the developmental degree of musical expression by machine learning using multiple classifiers for data acquired at two nursery schools (n=87) in 2019. The author tried to explore a more appropriate classifier and verify the effectiveness of machine learning methods that contribute to music education in early childhood.

THE PURPOSE OF THIS STUDY

A common challenge in music education is that teachers accumulate massive experience and skill to evaluate children's achievements, but it is difficult to share such capabilities with comparatively unexperienced educators. Machine learning could be a practical solution for educators to utilize for predictive models of developmental degrees. The primary aim of this study is to explore a method to classify the developmental degree of musical expression in early childhood using dependent variables of three degrees of developmental stages observed by simultaneously recorded video analysis for machine learning techniques based on the feature quantities of movement dynamics calculated from motion capture data.

The author also discusses the efficient feature quantities for machine learning from viewpoint of ANOVA. In order to contribute to the development of music education methods in early childhood, it is necessary to find out a classifier more appropriate for classifying the developmental degree of musical expression.

METHOD OF THIS STUDY

Practice and Movement Analysis of MEB program

Practice of MEB program

The MEB (Musical Expression Bringing-up) program [Sano 2015] consists of four phases, with the purpose of deepening children's recognition of musical elements. The first phase is an activity that mainly focuses on the awareness of sounds in every-day life and musical sounds. The second phase focuses on the rhythmic experience of body movement beginning with the rhythm of words. The third phase is an activity that focuses on the recognition of musical elements including rhythm pattern recognition and response singing. The fourth phase is based on the activities up to the third phase, the main activity is to create the process of dramatization integrating with music experience. These activities were implemented in four phases of MEB program each year, in 2016 (n=120), 2017 (n=194), 2018 (n=90), and 2019 (n=129). 3-year-old, 4-year-old, and 5-year-old children participated in the practice of MEB program in seven facilities.

Movement Analysis Items and Participant Children in the Activity Practice Process

In the order of the four activity phases of MEB program, the characteristic activity items for each activity phase were measured by movement analysis using 3D motion capture. The first phase is an

activity that sings "Your Name (Indonesia Folk Song)", asks for a name in a song, and answers. The second phase is an activity item that plays a song of "Shopping at a bakery" (lyrics: Tomoko Sakura, composition: Tatsuyuki Ozawa). The third phase is an activity that moves the image in line with the music song of "Lion's March" (from "Saintance's" Animal Carnival ", Introduction and March of the Lion King, edited by Tsuneo Tanaka, excerpted from the theme section). The fourth phase is an activity item that performs pretending movements and responding singing while singing "Yamano Ongakuka" (lyrics: Shizen Mizuta, German folk song). During the practice of this activity, spontaneous movements appeared in the participant children.

The participant children are K nursery school (n=54), U1 nursery school (n=30), F kindergarten (n=49), Y kindergarten (n=45) in 2017, and N children in 2018, (n=45), D nursery school (n=38) and U2 nursery school (n=52) in 2019.

Movement Analysis Method Using 3D Motion Capture

The 3D motion capture used here is a wireless connection type MVN system (Awinda BIOMECH Technologies). One small and light motion tracker is provided at each of the 17 body measurement sites such as head, shoulder, pelvis, and upper and lower extremities. The MVN system catches the whole body movement by each child. Because of each individual measurement, it is necessary to attach and detach a motion tracker for each measurement. At the time of measurement, calibration is started after inputting measurement values of a predetermined body part, and recording is started. Data of body movement in musical expression performed by each participant child in accordance with the piano accompaniment is acquired in a time frame of 1/60 second. At the same time, each child's musical expression is recorded by video using the Ethernet camera and analyzed. It takes 5 to 10 minutes per person, including the measurement time (30 seconds).

Movement Analysis and Quantitative Analysis

The movement analysis of the musical expression by the MVN system was conducted, and the moving distance, moving average velocity, moving average acceleration, left and right hand interval, and movement smoothness were calculated for 17 measurement sites. The movement smoothness appears when the movement continues smoothly at a constant velocity. The movement smoothness was calculated from the ratio of moving average velocity to moving average acceleration, referring to the work of Burger [2013]. In order to examine whether there is a statistically significant difference in the average value of the calculated data, the author used a three-way ANOVA as an analysis method (non-repeated four standards as MEB phase, non-repeated seven standards as facilities and non-repeated three standards as ages).

Classification and Discrimination of Developmental Degree of Musical Expression by Machine Learning

Based on the result of the quantitative analysis, model classification training is conducted using the calculated data as the feature quantity of movement using a machine learning method. The developmental degree of the results of the video analysis for each child, which was inspected simultaneously, was evaluated and divided into three stages.

The feature quantity of movement (factors) and three-stage evaluation (categorical dependent variables) of 76 data acquired during the fourth phase of the MEB program in 2016 were used for machine learning training, and classification model training was conducted. The result of machine

learning training was implemented to classify and discriminate the acquired data during the fourth phase of MEB program in 2017 with 2018 (n=128).

Based on the results, the classification model training results for 76 children in 2016 were applied to the data of the fourth phase acquired in 2019 (n=87) to conduct classification and discrimination.

RESULTS AND DISCUSSION

The Classification Result by the Machine Learning about the Developmental Degree of the Musical Expression in Early Childhood

Herewith the author will mainly show the results of the analysis in 2019, and then compare it with the results of the analysis in 2018. Furthermore, the factors that influenced the classification of the developmental degree of musical expression were quantitatively analyzed in the actual changes from 2016 to 2019.

Results of Classification and Discrimination of the Developmental Degree of Musical Expressions regarding the Participant Children's Data in 2019

Three types of machine learning system for referable musical expression were trained and forecasted such as Decision Trees (Boosted Trees and Classification & Regression Trees), Support Vector Machine and Neural Networks (Multilayer Perceptron and Radial Basis Function).

In 2019, 87 new MVN data were acquired for 3-year-old, 4-year-old, and 5-year-old children in two nursery schools D and U2 nursery schools. Using the feature quantity of movement (factors) and the three-stage evaluation (categorical dependent variables) for 76 children acquired in 2016 as training data for machine learning, classifying model training was conducted, and 87 children in 2019 different from the training data, the relevant data was classified and discriminated. At the same time, video analysis was conducted on the musical expression of the fourth phase of each participant child, and the developmental degree was classified into three stages while confirming and sharing it with four early childhood educators. The result of machine learning was compared with the result of video analysis, and the classification accuracy was calculated.

Classification result by Boosted Trees as decision tree

Gradient boosting is a technique to improve accuracy by constructing additive regressions with randomized iterations (Friedman, 2002). Table 1-1 shows the confusion matrix by Boosted Trees, and the classification accuracy was 39.08% (High: 31, Medium: 3, Low: 0).

Table 1: Confusion matrix of classification result by Boosted Trees

Actual ↓		Predicted →		
		High	Medium	Low
	High	31	4	9
	Medium	15	3	4
	Low	21	0	0

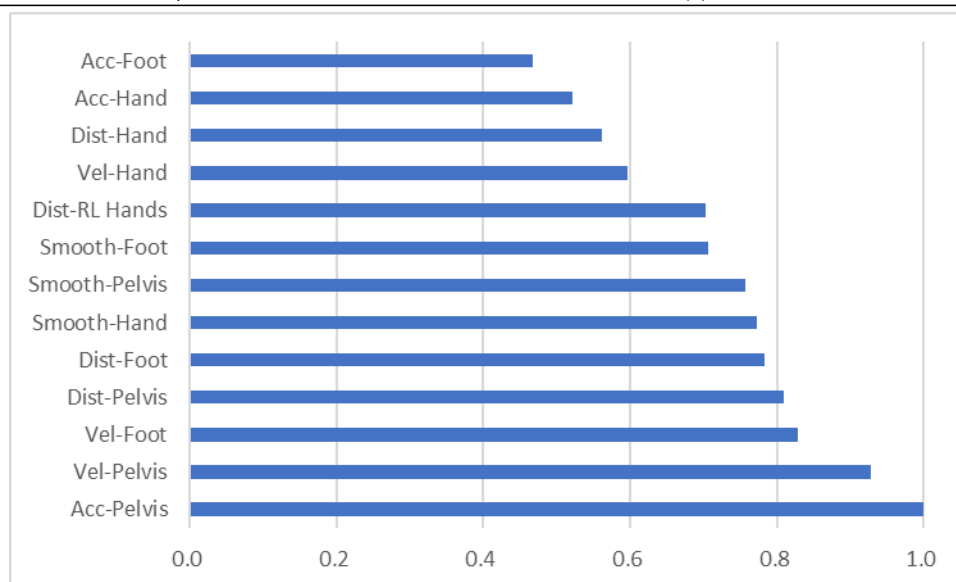


Figure 1: Results of sensitivity analysis of Boosted Trees

As a result of the sensitivity analysis, Figure 1-1 shows that the most influential factor was the moving average acceleration pf pelvis, followed more influent in the order of moving average velocity of pelvis and the moving average velocity of right foot.

(1) Classification Results by C & RT (Classification & Regression Trees) as Decision Tree
C&RT is one of strong classifier by optimizing tree partition to minimize expected loss (Chou, 1991). Figure1-2 shows classification tree diagram of the case.

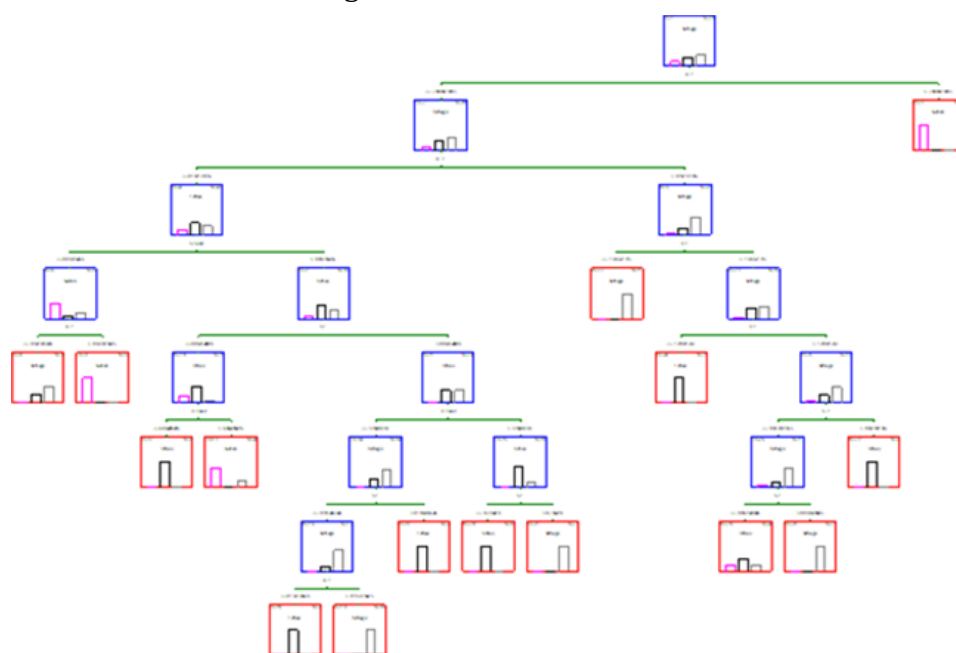
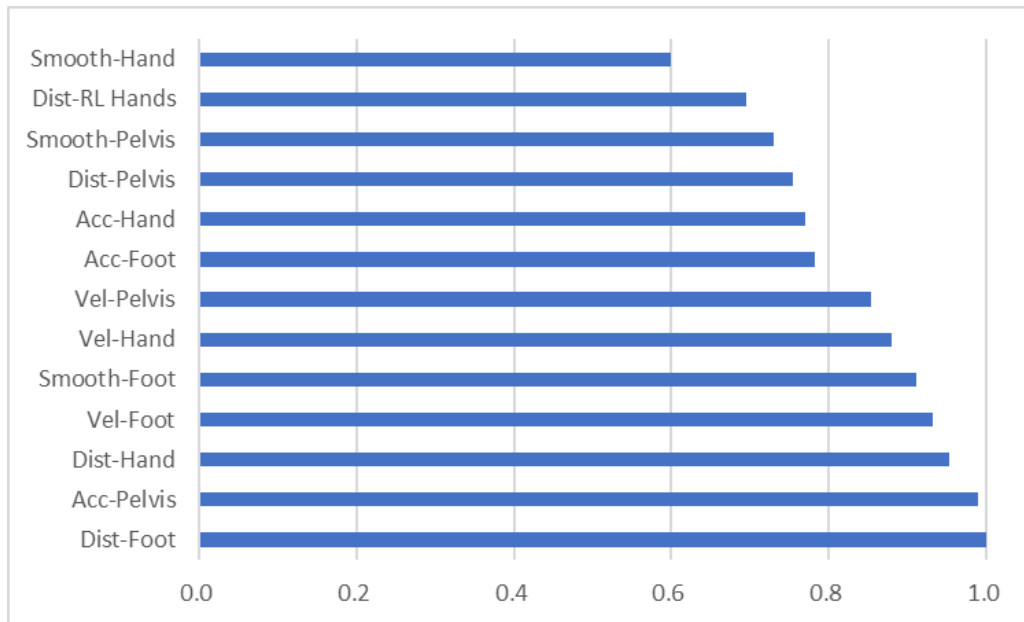


Figure 2: C & RT tree diagram

Table 1-2 shows the confusion matrix by C & RT algorithm and the classification accuracy was 42.53% (High: 13, Medium: 5, Low: 19).

Table 2: Confusion matrix of classification result by C & RT (Classification & Regression Trees)

Actual ↓		Predicted →		
		High	Medium	Low
	High	13	4	27
	Medium	2	5	15
	Low	1	1	19

**Figure 3: Results of sensitivity analysis**

As a result of the sensitivity analysis, Figure 1-3 shows that the most influential factor was the moving distance of right foot, the moving average acceleration of pelvis, and the moving distance of right hand in that order.

Classification results of Support Vector Machine

Support Vector Machine (SVM) performs regression and classification with nonlinear decision boundaries and exhibits flexibility in handling complexities.

Table 3: Confusion matrix of classification result by Support Vector Machine (SVM)

Actual↓		Predicted→		
		High	Medium	Low
	High	7	0	37
	Medium	1	0	21
	Low	1	0	20

The classification accuracy of the support vector machine was 31.03% (High: 7, Medium: 0, Low: 20) shown as Table 1-3. But classification profile was poor to identify dependent variables.

Classification results of Neural Networks (Multilayer Perceptron, “MLP-NN” and Radial Basis Function, “RBF-NN”)

In order to identify categorical developmental degrees from full body 3D movement data, neural networks such as multilayer perceptron and radial basis function were applied. 76 cases of data captured in 2016 were used to train network and 87 cases captured in 2019 were used to validate predicting power of categorization. First, to prevent overtraining of network, holding out sample was taken out from 76 cases and reassigned as testing sample. Secondly, network parameters were chosen to output similar results of prediction correctness across training, testing and holdout samples. Thirdly, such network parameter was applied to 87 cases and verified prediction results. Neural networks are constructed with feed forward diagram with distinct layered topology. MLP-NN utilizes each neural layer for transfer function and bias. On the other hand, RBF-NN utilizes bias term only at output layer level.

The classification accuracy of MLP-NN was 54.02% (High: 31, Medium: 4, Low: 12) shown as Table1-4, and the classification accuracy of RBF-NN was 27.59% (High: 1, Medium: 4, Low: 19). Among prediction algorithms, MLP-NN showed best results. Neural network has flexibility in its non-linear feature and strong power to establish accurate ruling of classification. However, specifically sophisticated modeling sometimes does not perform accurate classification. RBF-NN showed poor performance in this iteration.

Table 4: Confusion matrix of classification result by MLP-NN

		Predicted→		
		High	Medium	Low
Actual↓	High	31	10	3
	Medium	7	4	11
	Low	5	4	12

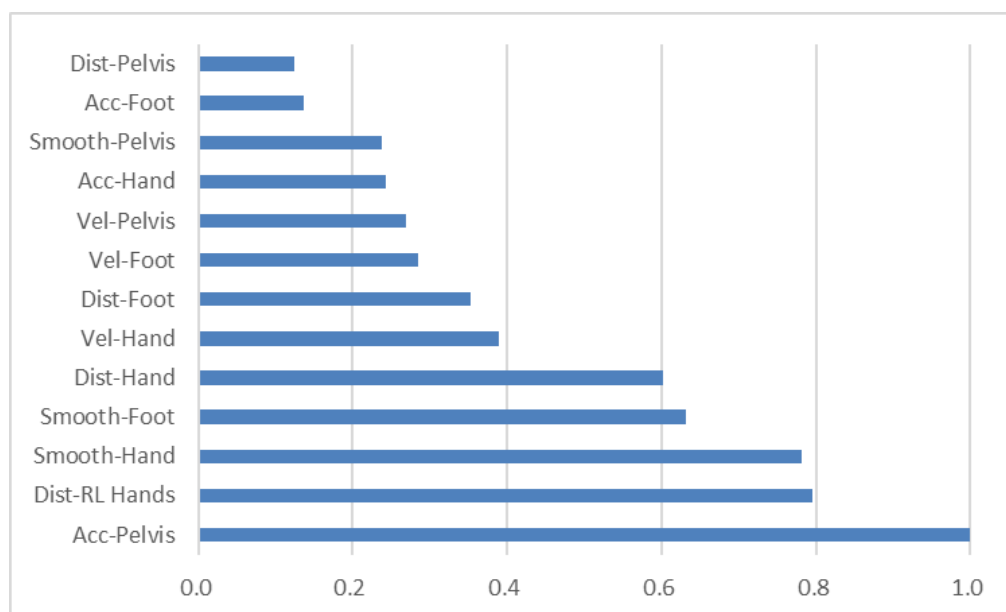


Figure 4: Results of sensitivity analysis of MLP-NN

Sensitivity of MLP-NN as Figure 1-4 shows most in acceleration of pelvis. Such result is in line with Boosted Trees and very similar with C&RT of which second largest sensitivity was the same. In addition, MLP-NN extracted sensitivity reference sharply in high range.

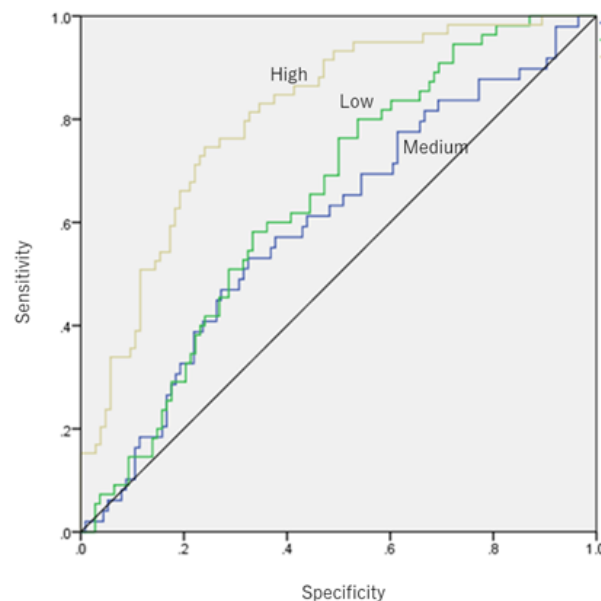


Figure 5: ROC curve

Figure 1-5 as ROC curve shows that network predicts “High” category best and “Low” category better than “Medium” category. As these 3 categories can be considered consistent in expression and varies in degrees of expression from “Low” to “High”, it can be understood network tends to predict extreme categories better.

Comparison of 2019 with 2018 regarding Classification and Discrimination Results

In 2018, 128 children in 2017 (F Kindergarten: n=41, Y Kindergarten: n=42) with 2018 (N certified facility: n=45) who were different from the training data were classified. As with the quantitative analysis in 2018, the classification model training results based on the MVN acquired data of 76 children in 2016 were applied to the acquired data in 2019 and evaluated and classified into three-stages. In the classification results in 2018, the classification accuracy was 30.5% (High: 21, Medium: 8, Low: 10) by the boosted trees of decision trees, and the classification accuracy was 33.6% (High: 2, Middle: 26, Low: 15) by MLP-NN.

Also, from the results of the sensitivity analysis, the feature quantity of movement that has an influence on the developmental degree of musical expression was the largest in the moving average acceleration of pelvis, followed by the moving average velocity of pelvis, the moving average velocity of right foot, and the movement smoothness of right foot. On the other hand, the classification accuracy of Random forest was 25.0% (High: 0, Middle: 0, Low: 32). The classification accuracy of the support vector machine was 26.6% (High: 0, Middle: 0, Low: 34). In the Random forest and the support vector machine, there was a bias that was divided into only to be “Low”.

The classification prediction of the radial basis function of the neural network was biased toward “High” (High: 42, Middle: 11, Low: 6). As a result, Boosted Trees of decision trees and MLP-NN were considered to be more appropriate classifiers.

On the other hand, according to the classification of the relevant data in 2019, the classification accuracy of C & RT(Classification & Regression Trees) was the highest at 42.53% (High: 13, Medium: 5, Low: 19), and the classification accuracy of Boosted Trees as decision tree was 39.08% (High: 31, Medium: 3, Low: 0). Among the seven facilities from 2016 to 2019, the characteristic changes of feature quantities of movement in D nursery school in 2019 were large, so quantitatively was verified that the decision tree was more appropriate classifier.

Furthermore, from the results of the sensitivity analysis in 2018 and 2019, the factor that has a large effect on the development of musical expression in early childhood was the moving average acceleration of pelvis as a feature quantity of movement, followed by the moving distance of right foot, and the moving distance of right hand. Then, the analysis result will be shown by the comparison among seven facilities about the change of the feature quantities of movement which contributes to the developmental degree of musical expression in each activity phase.

Changes in feature quantities of movement that contribute to musical development

Based on the analysis results in 2019, the average motion capture data focusing on the moving average acceleration of pelvis, the moving distance of right foot, and the moving distance of right hand as feature quantities of movement that influenced the developmental degree of musical expression in early childhood was quantitatively analyzed. A three-way non-repeated ANOVA (7 standards as facilities, 3 standards as ages and 4 standards as MEB phase) was applied to those data in order to find statistically significant difference between relevant measures.

Change of the moving average acceleration of pelvis

Table 3-1 shows the average data of moving average acceleration of pelvis for each activity phase in each participant facility.

Table 5: The average data of moving average acceleration of pelvis by activity phase of MEB program

Activity phase	Facility	Age	M	SD	N
The first phase		3-year-old	0.51	0.269	17
	K nursery	4-year-old	0.56	0.297	17
	school	5-year-old	0.59	0.253	20
		3-year-old	0.57	0.233	11
	U1 nursery	4-year-old	0.45	0.095	8
	school	5-year-old	0.63	0.416	10
	F	3-year-old	0.33	0.12	18
	kindergarten	4-year-old	0.93	2.161	14
		5-year-old	0.28	0.139	15
	Y	3-year-old	0.38	0.196	16
	kindergarten	4-year-old	0.4	0.254	14
		5-year-old	0.53	0.344	15
		3-year-old	0.39	0.199	13

		N certified	4-year-old	0.48	0.344	12
		facility	5-year-old	1.32	1.327	19
			3-year-old	1	0.625	15
		D nursery	4-year-old	1.29	1.273	15
		school	5-year-old	2.7	1.121	16
			3-year-old	0.54	0.257	16
		U2 nursery	4-year-old	0.81	0.433	12
		school	5-year-old	1.13	1.225	10
The second Phase			3-year-old	0.43	0.234	8
		K nursery	4-year-old	0.5	0.253	14
		school	5-year-old	0.55	0.19	17
			3-year-old	0.49	0.324	10
		U1 nursery	4-year-old	0.4	0.16	9
		school	5-year-old	0.63	0.215	11
		F	3-year-old	0.37	0.158	13
		kindergarten	4-year-old	0.5	0.657	14
			5-year-old	0.4	0.185	16
		Y	3-year-old	0.45	0.275	15
		kindergarten	4-year-old	0.51	0.249	14
			5-year-old	0.72	0.369	14
			3-year-old	0.57	0.451	17
		N certified	4-year-old	0.58	0.486	10
		facility	5-year-old	0.77	0.454	18
			3-year-old	1.12	0.551	18
		D nursery	4-year-old	1.91	0.827	15
		school	5-year-old	2.62	1.438	16
			3-year-old	0.5	0.257	13
		U2 nursery	4-year-old	0.77	0.504	10
		school	5-year-old	0.83	0.243	10
The third Phase			3-year-old	3.08	1.444	18
		K nursery	4-year-old	2.67	1.225	17
		school	5-year-old	2.53	1.574	18
			3-year-old	1.63	1.068	11
		U1 nursery	4-year-old	0.82	0.438	8
		school	5-year-old	3.05	1.66	9
		F	3-year-old	2.59	1.28	17
		kindergarten	4-year-old	1.69	0.841	12
			5-year-old	2.59	1.28	17
		Y	3-year-old	2.02	1.509	13
		kindergarten	4-year-old	1.54	0.622	13
			5-year-old	2.46	0.993	14
			3-year-old	2.64	1.649	16
		N certified	4-year-old	2.59	1.601	11
		facility	5-year-old	2.96	1.007	20
			3-year-old	3.54	1.321	18
		D nursery	4-year-old	3.6	1.981	16
		school	5-year-old	3.92	1.818	18
			3-year-old	1.85	1.448	15

The fourth Phase	U2 nursery	4-year-old	2.53	1.292	12
	school	5-year-old	2.37	1.264	10
		3-year-old	1.02	0.623	15
	K nursery	4-year-old	1.49	0.712	12
	school	5-year-old	1.16	0.475	19
		3-year-old	0.97	0.408	9
	U1 nursery	4-year-old	0.26	0.068	9
	school	5-year-old	0.47	0.182	10
	F	3-year-old	0.41	0.189	13
	kindergarten	4-year-old	0.39	0.313	12
		5-year-old	0.47	0.411	16
	Y	3-year-old	0.54	0.296	13
	kindergarten	4-year-old	0.54	0.24	14
		5-year-old	0.67	0.309	15
		3-year-old	0.71	0.378	15
	N certified	4-year-old	0.64	0.27	10
	facility	5-year-old	0.71	0.414	20
		3-year-old	0.54	0.256	18
	D nursery	4-year-old	3.38	3.715	14
	school	5-year-old	2.24	1.006	18
		3-year-old	0.59	0.292	16
	U2 nursery	4-year-old	1.23	1.009	11
	school	5-year-old	1.06	0.729	10

As a result of a three-way non-repeated analysis of variance on the data of the moving average acceleration of pelvis, a main effect / interaction of the test showed a statistically difference (phase: ($F(3, 1093)=221.184, p<.005$), facility: ($F(6, 1093)=50.601, p<.005$), age: ($F(2, 1093)=15.385, p<.005$), phase * age: ($F(6, 1093)=3.255, p<.005$), facility * age: ($F(12, 1093)=5.23, p<.005$), phase * facility * age: ($F(36, 1093)=2.102, p<.005$)) as shown table3-2.

Table 6: A main effect/ interaction of the test

Factor	df	F	Significance probability
Phase	3	221.184	$p<.005$
Facility	6	50.601	$p<.005$
Age	2	15.385	$p<.005$
Phase * facility	18	1.692	<i>n.s.</i>
Phase * age	6	3.255	$p<.005$
Facility * age	12	5.23	$p<.005$
Phase * facility * age	36	2.102	$p<.005$

The test simple main effect with multiple comparisons was carried out by Bonferroni method at 5% level.

Concerning the phase factor/ phase* facility* age, the simple main effect was statistically significant in K nursery school (3-year-old: ($F(3, 1093)=26.531, p<.005$), 4-year-old: ($F(3, 1093)=18.032, p<.005$), 5-year-old : ($F(3, 1093)=16.733, p<.005$)), U1 nursery school (5-year-old: ($F(3,$

1093)=15.289, $p<.005$), F kindergarten (3-year-old : ($F(3, 1093)=21.724, p<.005$), 4-year-old : ($F(3, 1093)=4.552, p<.005$), 5-year-old : ($F(3, 1093)=21.701, p<.005$)), Y kindergarten (3-year-old : ($F(3, 1093)=8.969, p<.005$), 5-year-old : ($F(3, 1093)=12.72, p<.005$)), N certified facility (3-year-old : ($F(3, 1093)=18.435, p<.005$), 4-year-old : ($F(3, 1093)=12.156, p<.005$), 5-year-old : ($F(3, 1093)=23.291, p<.005$)), D nursery school (3-year-old : ($F(3, 1093)=35.054, p<.005$), 4-year-old : ($F(3, 1093)=20.581, p<.005$), 5-year-old : ($F(3, 1093)=10.168, p<.005$)), U2 nursery school (3-year-old : ($F(3, 1093)=6.909, p<.005$), 4-year-old : ($F(3, 1093)=8.502, p<.005$), 5-year-old : ($F(3, 1093)=5.144, p<.005$)).

As a result of multiple comparison, 3-year-old, 4-year-old, and 5-year-old during the third phase in K nursery school, F kindergarten, Y kindergarten, N certified facility, D nursery school and U2 nursery school, and 3-year-old and 5-year-old in U1 nursery school showed a significant difference.

Concerning the facility factor/ phase* facility* age, the simple main effect was statistically significant in the first phase (5-year-old: ($F(6, 1093)=11.457, p<.005$)), the second phase (4-year-old: ($F(6, 1093)=4.287, p<.005$), 5-year-old: ($F(6, 1093)=9.768, p<.005$)), the third phase (3-year-old: ($F(6, 1093)=7.735, p<.005$), 4-year-old: ($F(6, 1093)=10.841, p<.005$), 5-year-old: ($F(6, 1093)=5.105, p<.005$)), and the fourth phase (4-year-old: ($F(6, 1093)=16.582, p<.005$), 5-year-old: ($F(6, 1093)=6.93, p<.005$)). As a result of multiple comparison, 5-year-old during the first phase in D nursery school, 4-year-old and 5-year-old during the second with the fourth phase in D nursery school, and 3-year-old, 4-year-old and 5-year-old during the third phase in D nursery school showed a significant difference.

Concerning the age factor/ phase* facility* age, the simple main effect was statistically significant in D nursery school (the first phase: ($F(2, 1093)=13.912, p<.005$), the second phase: ($F(2, 1093)=10.197, p<.005$), the fourth phase: ($F(2, 1093)=35.473, p<.005$)), and U1 nursery school (the third phase: ($F(2, 1093)=11.813, p<.005$)). As a result of multiple comparison, 5-year-old in N certified facility and D nursery school during the first phase, 5-year-old in D nursery school during the second and the fourth phases, and U1 nursery school and F & Y kindergartens during the third phase showed a significant difference.

As shown in Figure 3-1, the average data of 3-year-old increased during the third phase in the order of D nursery school, K nursery school, and N certified facility. The average data of 4-year-old in D nursery school was larger in both the third and the fourth phases and the average data of 5-year-old in D nursery school remarkably increased during the fourth phase of MEB program as shown in Figure 3-2.

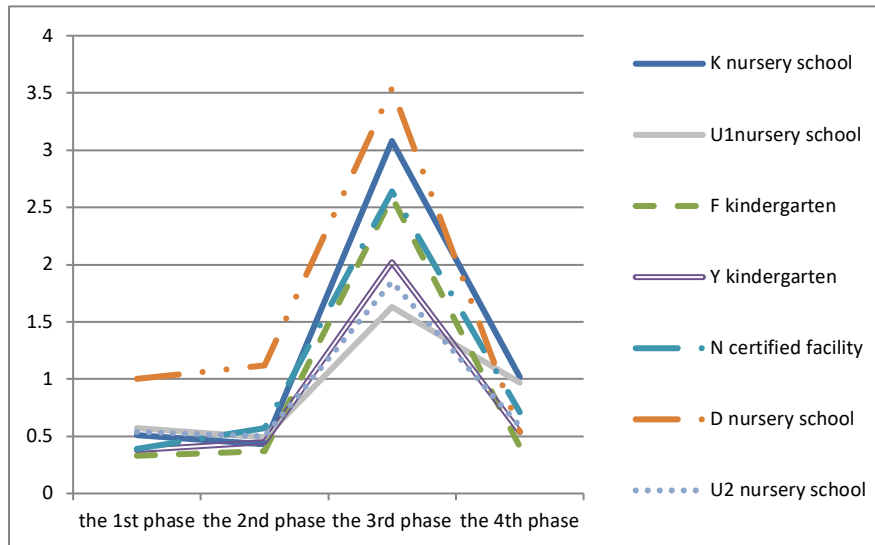


Figure 5: The moving average acceleration of pelvis : 3-year-old

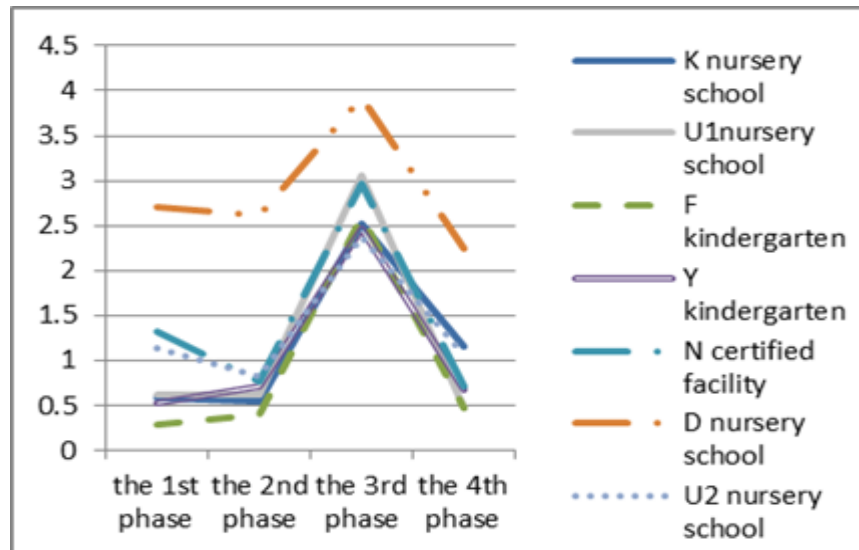


Figure 6: The moving average acceleration of pelvis:5-year-old

Changes of the moving distance of right foot

The following three-dimensional figure shows an example of the moving trace of right foot. Figure 3-3 is an example of the moving trace of right foot in the fourth phase measurement regarding 5-year-old in D nursery school.

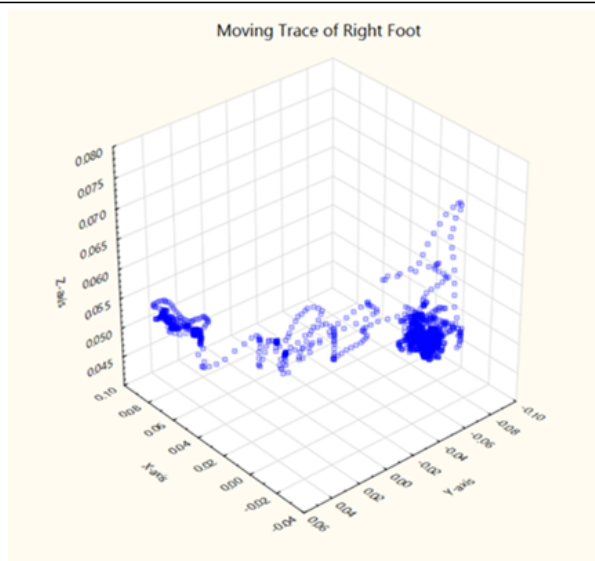


Figure 7: An example of moving trace of right foot regarding 5-year-old in D nursery school

As for the calculation data of the moving distance of right foot, as a result of a three-way non-repeated ANOVA using the same method, a statistically significance was observed in changes by age and activity phase. A main effect/ interaction of the test showed a statistically difference (phase: ($F(3, 1093) = 488.655, p < .005$), facility: ($F(6, 1093) = 31.864, p < .005$), age: ($F(2, 1093) = 7.692, p < .005$), phase* facility: ($F(18, 1093) = 12.679, p < .005$), phase * age: ($F(6, 1093) = 3.297, p < .005$), facility* age: ($F(12, 1093) = 5.431, p < .005$), phase* facility* age: ($F(36, 1093) = 4.833, p < .005$)). The test regarding simple main effect with multiple comparison was carried out by Bonferroni method at 5% level.

Concerning the phase factor/ phase * facility * age, the simple main effect showed a significant difference in K nursery school (3-year-old: ($F(3, 1093) = 59.824, p < .005$), 4-year-old : ($F(3, 1093) = 61.814, p < .005$), 5-year-old : ($F(3, 1093) = 17.24, p < .005$)), U1 nursery school (5-year-old: ($F(3, 1093) = 5.933, p < .005$), F kindergarten (3-year-old : ($F(3, 1093) = 38.871, p < .005$) , 4-year-old : ($F(3, 1093) = 5.216, p < .005$), 5-year-old : ($F(3, 1093) = 39.586, p < .005$)), Y kindergarten (3-year-old : ($F(3, 1093) = 10.839, p < .005$), 4-year-old : ($F(3, 1093) = 5.276, p < .005$), 5-year-old : ($F(3, 1093) = 16.928, p < .005$)), N certified facility (3-year-old : ($F(3, 1093) = 22.613, p < .005$), 4-year-old : ($F(3, 1093) = 58.167, p < .005$), 5-year-old : ($F(3, 1093) = 202.66, p < .005$)), D nursery school (3-year-old : ($F(3, 1093) = 43.434, p < .005$), 4-year-old : ($F(3, 1093) = 29.04, p < .005$), 5-year-old : ($F(3, 1093) = 72.522, p < .005$)), and U2 nursery school (3-year-old : ($F(3, 1093) = 24.572, p < .005$), 4-year-old : ($F(3, 1093) = 18.424, p < .005$), 5-year-old : ($F(3, 1093) = 11.535, p < .005$)). As a result of multiple comparison, a significant difference was observed in 3-year-old, 4-year-old and 5-year-old in K nursery school, F kindergarten, Y kindergarten, N certified facility and D nursery school during the third phase, and 5-year-old in U1 nursery school during the third phase.

Concerning the facility factor/ phase * facility * age, the simple main effect showed a significant difference in the second phase (5-year-old: ($F(6, 1093) = 3.508, p < .005$), the third phase (3-year-old: ($F(6, 1093) = 15.485, p < .005$, 4-year-old: ($F(6, 1093) = 28.558, p < .005$, 5-year-old: ($F(6, 1093) = 54.87, p < .005$)), and the fourth phase (4-year-old: ($F(6, 1093) = 3.429, p < .005$)). As a result of multiple

comparison, 5-year-old in D nursery school during the first and the second phase, 3-year-old in K nursery school, 4-year-old in K nursery school, N certified facility and D nursery school, and 5-year-old in K nursery school, N certified facility and D nursery school during the third phase, and 4-year-old in D nursery school during the fourth phase showed a statistically significant difference.

Concerning the age factor/ phase * facility * age, the simple main effect showed a significant difference in the third phase (K nursery school : ($F(2, 1093)=21.639, p<.005$), F kindergarten : ($F(2, 1093)=14.124, p<.005$), N certified facility : ($F(2, 1093)=71.5, p<.005$), D nursery school ($F(2, 1093)=14.576, p<.005$)), and the fourth phase (D nursery school ($F(2, 1093)=6.451, p<.005$)). As a result of multiple comparison, 3-year-old and 4-year-old in K nursery school , 5-year-old in U1nursery school, Y kindergarten, N certified facility and D nursery school, and 3-year-old and 5-year-old in F kindergarten during the third phase showed a significant difference. 4-year-old in D nursery school was large during the fourth phase of MEB program.

In this way, the moving distance of right foot was larger for 3-year-old children in the order of K nursery school and D nursery school, and for 4-year-old children, up to the third phase, N certified facility, K nursery school, and D nursery school were larger, and in the fourth phase, the average data of D nursery school was large. The average data of 5-year-old were larger in the order of N certified facility and D nursery school.

Changes of the moving distance of right hand

As for the calculation data of the moving distance of right hand, as a result of a three-way non-repeated ANOVA using the same method, a statistically significance was observed in changes by age and activity phase. A main effect/ interaction of the test showed a statistically difference (phase: ($F(3, 1093)=238.589, p<.005$), facility: ($F(6, 1093)=28.853, p<.005$), age: ($F(2, 1093)=25.501, p<.005$), phase* facility: ($F(18, 1093)=12.259, p<.005$), facility* age: ($F(12, 1093)=8.793, p<.005$), phase* facility* age: ($F(36, 1093)=3.903, p<.005$)). The test regarding simple main effect with multiple comparison was carried out by Bonferroni method at 5% level.

Concerning the phase factor/ phase* facility* age, the simple main effect was statistically significant in K nursery school (3-year-old : ($F(3, 1093)=38.666, p<.005$), 4-year-old : ($F(3, 1093)=50.554, p<.005$), 5-year-old : ($F(3, 1093)=13.783, p<.005$)), U1 nursery school (3-year-old ($F(3, 1093)=5.514, p<.005$)), F kindergarten (3-year-old : ($F(3, 1093)=18.438, p<.005$), 4-year-old : ($F(3, 1093)=5.875, p<.005$), 5-year-old : ($F(3, 1093)=17.825, p<.005$)), Y kindergarten (4-year-old : ($F(3, 1093)=6.046, p<.005$), 5-year-old : ($F(3, 1093)=17.503, p<.005$)), N certified facility (3-year-old : ($F(3, 1093)=15.032, p<.005$), 4-year-old : ($F(3, 1093)=29.358, p<.005$), 5-year-old : ($F(3, 1093)=77.745, p<.005$)), D nursery school (3-year-old : ($F(3, 1093)=16.844, p<.005$), 4-year-old : ($F(3, 1093)=39.32, p<.005$), 5-year-old : ($F(3, 1093)=37.439, p<.005$)), and U2 nursery school (3-year-old : ($F(3, 1093)=11.48, p<.005$), 5-year-old : ($F(3, 1093)=7.902, p<.005$)).

As a result of multiple comparison, 3-year-old, 4-year-old and 5-year-old in K nursery school, F kindergarten, Y kindergarten and N certified facility during the third phase, and 3-year-old in U1 nursery school during the fourth phase showed a significant difference. The average data were large

regarding 3-year-old during the third phase, 4-year-old during the fourth phase, and 5-year-old during the third and the fourth phase.

Concerning the facility factor/ phase* facility* age, the simple main effect was statistically significant in the third phase (3-year-old: ($F(6, 1093)=12.802, p<.005$), 4-year-old: ($F(6, 1093)=24.445, p<.005$), 5-year-old: ($F(6, 1093)=20.037, p<.005$)), and the fourth phase (4-year-old: ($F(6, 1093)=18.462, p<.005$), 5-year-old: ($F(6, 1093)=20.327, p<.005$)). As a result of multiple comparison, 5-year-old in D nursery school during the first phase, and the third phase, 3-year-old and 4-year-old in K nursery school showed large value, followed by 5-year-old in N certified facility and D nursery school. The average data were large of 4-year-old and 5-year-old in D nursery school during the fourth phase.

Concerning the age factor/ phase* facility* age, the simple main effect was statistically significant in the first phase (D nursery school: ($F(2, 1093)=5.831, p<.005$)), the third phase (K nursery school: ($F(2, 1093)=14.725, p<.005$), Y kindergarten: ($F(2, 1093)=9.49, p<.005$), N certified facility: ($F(2, 1093)=25.817, p<.005$), D nursery school: ($F(2, 1093)=14.403, p<.005$)), and the fourth phase (U1 nursery school: ($F(2, 1093)=6.496, p<.005$), D nursery school: ($F(2, 1093)=67.147, p<.005$)). As a result of multiple comparison, the results showed a statistically significant difference in 5-year-old in D nursery school during the first phase, 3-year-old and 4-year-old in K nursery school, and 5-year-old in Y kindergarten, N certified facility and D nursery school during the third phase. The average data was large of 3-year-old in U1 nursery school, and 4-year-old and 5-year-old in D nursery school.

In this way, regarding the moving distance of right hand, in the 3-year-old children, K nursery school was large until the third phase, and U1 nursery school was large during the fourth phase as shown figure 3-4. 4-year-old regarding K nursery school and N certified facility were larger in order until the third phase, and D nursery school increased further in the fourth phase. Regarding 5-year-old, the average data were larger in the order of N nursery school and D nursery school up to the third phase and the average data in D nursery school were larger in the fourth phase as shown Figure3-5.

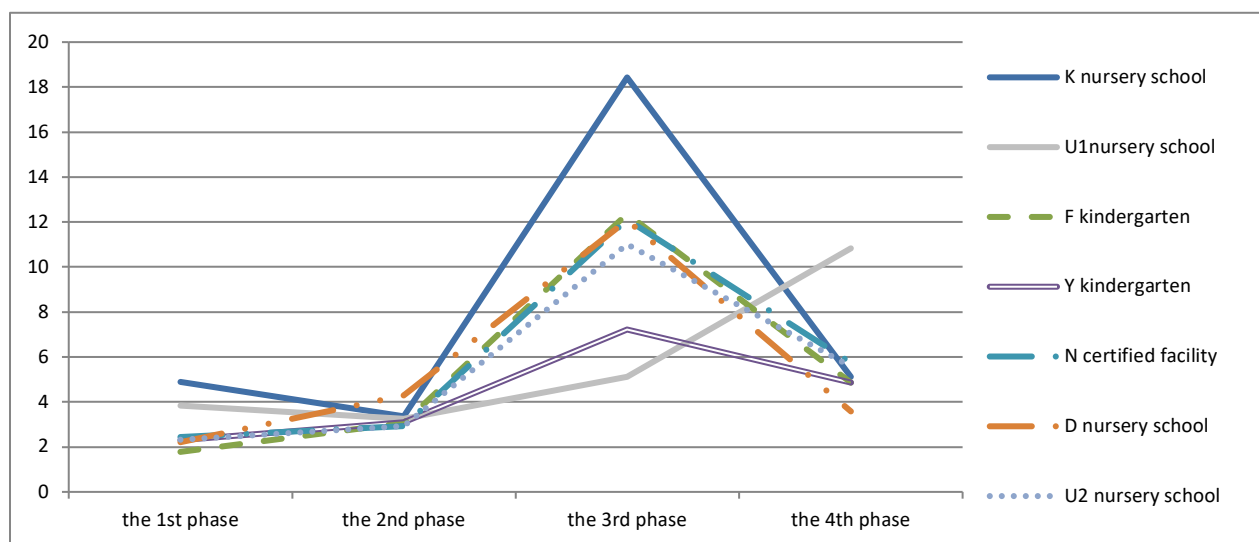


Figure 8: The moving distance of right hand : 3-year-old

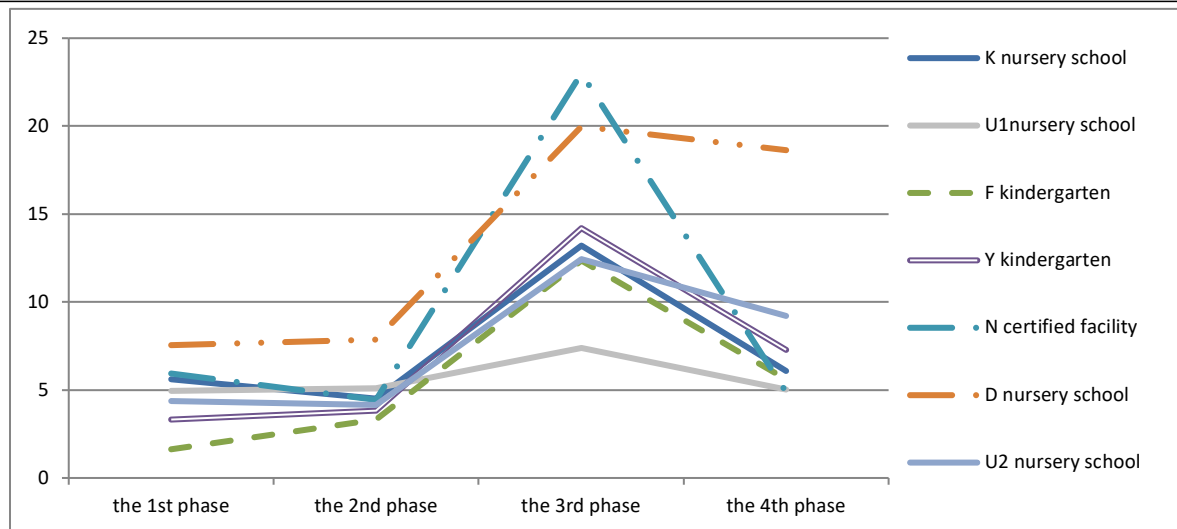


Figure 9: The moving distance of right hand: 5-year-old

The moving distance of right hand remarkably increased during the third phase which mainly aimed to encourage the recognition of musical elements in early childhood. The average data regarding 3-year-old in U1 nursery school and 4-year-old in D nursery nursery school increased during the fourth phase. The average data regarding 5-year-old in D nursery did not decrease very much although the average data of other facilities generally decreased as shown figure 3-5. The average data regarding 3-year-old in U1 nursery school as shown figure 3-4, showed the movement of the right hand due to representation such as pretending and dramatization increased toward the fourth phase, and the change of average data regarding 4-year-old in D nursery school showed a similar tendency.

It was implicated that change of the average data regarding 5-year-old in D nursery school was relied on the movement smoothness and the moving average acceleration regarding right hand. The movement smoothness of right hand showed the increase with the perception of regularity such as a constant beat and rhythm pattern included in music related with the recognition of musical elements. The moving average acceleration of right hand showed increase of pretending related to image of music.

CONCLUSION

The author inspected the results of movement analysis using 3D motion capture technology for musical expressions in early childhood from 2016 to 2018, and conducted the classification and discrimination of the developmental degree of musical expression by machine learning using the feature quantities of movement. Those results were implemented to the data newly acquired in 2019. As a result, it was found that classification accuracy by the decision tree was relatively high in discriminating acquired data different in 2018 and 2019.

The classification accuracy of Multilayer Perceptron (MLP-NN) was 33.6% for the analysis data in 2018 and 32.18% for the analysis data in 2019, whereas the classification accuracy of the Boosted trees for decision trees was 30.5% in 2018, increased to 39.08% in 2019. Using the decision tree C & RT, a classification accuracy showed 42.53% in 2019.

Furthermore, as for objective criteria for classification/ discrimination, a characteristic feature quantity of movement as a factor affecting the developmental degree of musical expression was extracted by sensitivity analysis.

As a result, it was the moving average acceleration of pelvis that showed the greatest influence using any classifier. Next, the ones having the greatest influence were the moving distance of right foot and the moving distance of right hand. For these three types of feature quantity of movement, seven facilities' data were compared using a three-way non-repeated analysis ANOVA among activity phases, participant ages, and participant facilities, using acquired data from 2016 to 2019. As a result, the moving average acceleration of pelvis generally increased remarkably in the third phase of the activity. Specifically, numerical values of 5-year-old in D nursery school were characteristic. Regarding the moving distance of right foot, 3-year-old in K nursery school and D nursery school, and 4-year-old in N certified facility, K nursery school and D nursery school were large up to the third phase.

4-year-old in D nursery school showed a large numerical value during the fourth phase. The numerical value of 5-year-old in N certified facility and D nursery school were large. Regarding the moving distance of right hand, the average data of 3-year-old and 4-year-old in K nursery school was large up to the third phase, and the average data of 4-year-old in D nursery school further increased during the fourth phase. Regarding 5-year-old, the average data were large of N nursery school and D nursery school during the third phase and the average data of D nursery schools were larger during the fourth phase. In this way, regarding the D nursery school in 2019, the increase of average data affecting the feature quantity of movement was characteristic. In particular, for the musical expression during the fourth phase, many participant children largely expressed spontaneous movements, and when quantitatively inspected in the three-stage classification, as tended to classified to be "high" by the decision tree.

Implication to Music Education

From the above inspection, it was found that the developmental degree of musical expression can be predicted and verified that the classification prediction is effective using a machine learning method. Based on these results, it is necessary to conduct the measurement using a plurality of music pieces having different musical characteristics and to extract a new feature quantity extracted from the music characteristics (rhythm, tonality, etc.) in the future. In this way, by machine learning using new feature quantities, being able to objectively evaluate the developmental degree of musical expression in early childhood, it will be possible to provide more appropriate musical experiences to individual early childhood child. In this regard, it is thought that it contributes to the evolution of music education methods in early childhood.

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References

Akira, F., Hiroshi, and F., Naoyoshi, T. (2012) Automated evaluation as Japanese compositions based on features along Japanese education and construction of the individual evaluation model, *Journal of natural language processing*, 19(4): 281-301.

- Ando, A., Sumikawa, Y. (2012). Development and function evaluation of teaching materials for “sawing” observation by using motion capture and the virtual world, *Japan Journal of educational technology*, 36(2): 103-110. <https://doi.org/10.15077/jjet.KJ00008274459>
- Ballema, G. (2005). *Year’ round dramatic play, Michigan*: Frank Schaffer Publications.
- Burger, B. (2013). Move the way you feel: Effects of musical features, perceived emotions, and personality on music-induced movement, University of Jyväskylä, Jyväskylä, Finland.
- Burger, B., Thompson, M., Saarikallio, S., Luck, G., Toiviainen, P. (2013) Influences of rhythm and timbre-related musical features on characteristics of music-induced movement, *Frontiers in Psychology*, 4(183): 1-9. doi: 10.3389/fpsyg.2013.00183
- Burton, L., Kudo, T. (2000) *Sound play: Understanding music through creative movement* (1), Rowman & Little field Education.
- Cauwenberghs, G., Poggio, T. (2001). Incremental and decremental support vector machine learning. *Advances in Neural Information Processing Systems*, Cambridge MA: MIT Press, 13(5): 409-412. http://isn.ucsd.edu/papers/nips00_inc.pdf
- Chou, P. (1991). Optimal partitioning for classification and regression trees. *IEEE Transactions Pattern Analysis and Machine Intelligence*, 13 (4): 340-354. doi:10.1109/34.88569
- Friedman, H. (2002). Stochastic gradient boosting. *Computational. Statistics & Data Analysis*, 38(4): 367–378. [https://doi.org/10.1016/S0167-9473\(01\)00065-2](https://doi.org/10.1016/S0167-9473(01)00065-2)
- Hannon, E., and Johnson, S. (2005). Infants use meter to categorize rhythms and melodies: Implications for musical structure learning, *Cognitive Psychology*, 50: 354- 377. doi:10.1016/j.cogpsych.2004.09.003
- Hendy, L., and Toon, L. (2001). *Supporting drama and imaginative play in the early years*, Buckingham, Philadelphia: Open University Press.
- Heys, J. (2018). Machine Learning as a Tool to Identify Critical Assignments, *Chemical Engineering Education*, 52 (4): 243-250. <http://journals.fcla.edu/cee/index>
- Igarashi, S., Ueno, K., and Furukawa, K. (2001). Analysis of Respiration during Musical Performances by Machine Learning, *SIG Technical Reports*, MUS, (82(2001-MUS-041)), 27-32.
- Jalongo, M., and Isenberg, J. (2001). *Creative expression and play in early childhood*, New Jersey: Merrill Prentice Hall.
- Kashiwagi, Y, Ochi, Y., and Iguchi, N. (2016). Estimation approach of a touching finger pattern for guitar performance using machine learning, *IEICE technical report* : 116(351): 11-14.
- Marigliano, M., & Russo, M., (2011) Moving bodies, building minds: Foster preschooler’s critical thinking and problem solving through movement, *Young Children*, 66(5): 44-49. <https://www.jstor.org/stable/42730771>
- Matsumoto, A., Mikami, H., and Kojima, A. (2012). Support for motor learning by clustering of sports forms: Examine effective image features as a target children back hip circle, *ITE technical report*, 38, 51(0): 9-12.
- Moreno-Estevea, E., White, S., Woodc, J., and Blackc, A. (2019). Application of mathematical and machine learning techniques to analyze eye tracking data enabling better understanding of children’s visual cognitive behaviours, *Frontline Learning Research*, 6(3) Special issue: 72 – 84. <https://doi.org/10.14786/flr.v6i3.365>
- Murphy, K. P. (2012). *Machine learning: A probabilistic perspective*, Cambridge: MIT Press.
- Phillips Silver, J., and Trainor, L., (2005) Feeling the beat: Movement influences infant rhythm perception, *Science*, 1.308: 1430. doi: 10.1126/science.1110922
- Provasi, J., and Begue, A., (2003) Spontaneous motor tempo and rhythmical synchronization in 21/2 and 4 year old, *International Journal of Behavioral Development*, 27(3): 220-231. doi.org/10.1080/01650250244000290
- Rubin, J., and Merrion, M. (1996). *Drama and Music Methods*, Portsmouth: Linner Professional Publications.

- Sano, M. (2015) Characteristics of musical expressions showing the formation process of beat perception in early childhood: Through the practice of musical expression bringing-up program for 5-year-old children in K nursery school, *Japanese Journal of Music Educational Practice*, 12(2): 120-131. https://doi.org/10.20614/jjomep.12.2_120
- Sano, M. (2017). Analysis of elements of movement in musical expression in early childhood, *Japan Journal of Educational Technology*, 41: 5-8, <https://doi.org/10.15077/jjet.s41003>.
- Sano, M. (2018a). Development of a quatitative methodology to analyze the growth of recognition of musical elememts in early childhood from a viewpoint of change of body movement, *Asia-Pacific Journal of Research of Early Childhood Education (International)*, 12(1): 61-80. <http://dx.doi.org/10.17206/apjrece.2018.12.1.61>.
- Sano, M. (2018b). Statistical analysis of elements of movement in musical expression in early childhood using 3D motion capture and evaluation of musical development degrees through machine learning, *World Journal of Education*, 8(3): 118-130. <https://doi.org/10.5430/wje.v8n3p118>.
- Sano, M. (2019). Predicting developmental degrees of music expression in early childhood by machine learning lassifiers with 3D motion captured body movement data, *Journal of Educational Research and Reviews*, 7(7): 155-168. <https://doi.org/10.33495/jerr.v7i7.19.128>
- Sato, K., Kaiga, T., and Watabe, S. (2010). The utilization of motion capture to support proficiency of the dancing, *Japan Journal of educational technology*, 34: 133-136. <https://doi.org/10.15077/jjet.KJ00007086695>
- Schriimacher, R. (2005). *Art and creative development for young children*, New York: Thompson.
- Trainor, L., (2007) Do preferred beat rate and entrainment to the beat have a common origin in movement?, *Emprical Musicology Review*, 21: 17-20.
- Widmer, G. (2001) Using AI and machine learning to study expressive music performance: project survey and first report, *Ai Communications*, 14(3):149-162.
- Yamagami, S., Tajima, Y., and Kotani, Y. (2008). Analysis and attach of musical expression by machine learning using analysis of musical structure, *IPSJ SIG technical reports*, MUS, 74: 71-76.
- Young, D. (2008) Classification of Common Violin Bowing Techniques Using Gesture Data from a Playable Measurement System, *Proceedings of the 2008 Conference on New Interfaces for Musical Expression (NIME08)*, Genova, Italy.
- Zatore, R., Chen, J., and Penhune, V. (2007). When the brain plays music: Auditory-motor interactions in music perception and production, *Nature Reviews Neuroscience*, 9: 547-558. doi: 10.1038/nrn2152
- Zentner, M., and Eerola, T., (2010) Rhythmic engagement with music in infancy, *PNA*, 1073: 5768-5773. doi: 10.1073/pnas.1000121107