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Topics of Skill Science: Overview of ten years

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Skill Science has developed for more than ten years and its theory and methodology have been taking their forms gradually. The objectives of this discipline include studying what skill is and how it develops.

We need to think where the boundary exists between normal motions as observed in our daily life and the ones with a certain level of elaboration to answer the first question, that is, what skill is. Skills can be defined externally when their intended goals are exceptional. We do not normally knead a mass of clay and find it amazing when a craftsman does it easily and quickly. Skills are thus closely related to a specialized work. The ability to do the job needs to be acquired through training and does not develop naturally. We identify a movement as a skill when its goal is exceptional and it requires a certain period of training to master.

The boundary of skills is however obscure as the tasks requiring a skill vary across societies. We also need an internal definition of skills. We notice a certain level complexity of motions when we leave all the contexts out of them. Context means the performer, the place, the time, and so on, in this case. The source of complexity includes an involvement of more body parts, a coordination pattern among body parts, an effective disengagement of unrelated body parts, and so on. All these contribute to better controlling one's body.

We need to approach to skills in two respects. We need to observe it as practiced in society to see how valuable it is to stakeholders. It is dependent to some extent on the society whether a particular motion is valued as skill. We need to take an anthropological approach in this respect. We also need to collect data of motions to study their complexities. We need a theory of complexity of motions to evaluate the level of skills appropriately.

Valuation in society and complexity inherent in motions set up a two-dimensional plane, on which we can map various motions. I show in this talk which domains we have covered in Skill Science and discuss where we need to study in future.

A Basic Study of the Influence of Auditory Stimulus on the Eye-tracking Behavior of a Driver in an Autonomous Vehicle

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Research and development for autonomous vehicle technology have been accelerated to reduce the traffic fatalities, which are the number one reason. In the autonomous vehicle, passengers likely do not pay attention to the environments in front or lateral because they are overestimate autonomous functions. However, until completely autonomous vehicles are launched, driver will be allocated to the passenger from the vehicle in case of emergency or complicated traffic condition. Then, efficient methods need to be developed for passengers to be ready for driving immediately in such conditions. What the driver acts when he/she receives the warning depends on his/her proficiency level of driving, that is an issue to develop the efficient methods. As one of the methods, human-machine (vehicle) interface is an option.

Workload with auditory interface can be lighter than with visual interface in the vehicle[1]. And also, spearcon (time-compressed speech sounds) significantly reduced total glance time toward vehicle monitor[2]. Though there are several researches to investigate the relationship between gaze behavior and audio stimuli, detailed information of the gaze behavior such as scanpath or pupil diameter are not analyzed.

In our research, first, we propose the methods of quantitative measurement of passengers' gaze behavior and develop various acoustic warnings with directional audio sources. Then we measured the gaze behaviors of driving experts and novices to examine the differences in driving experiences. In this paper, we prepared the simple experimental environment with a single screen, one projector and one headphone (Fig. 1). Head-mount eye-tracker was used to capture what the examinees saw and pupil diameter. There is a problem specific to head-mount eye-tracker that the output eye position data is affected by head movements. Then we developed the screen with invisble markers to detect the exact eye positions and corrected the effect of head movements by template matching.

We measured the gaze behavior of several driving novices and experts while they watch the driving movie taken from the inside of the vehicle with additional directional audio sources to compare the difference in the driving experiences. Fig.3 shows the eye positions after correcting the effect of the head movements. As a result, even novices watched the traffic signs, center line on the road or oncoming vehicles, which are what we should pay attention to during driving. As comments of examinees, there is a lack of reality and a sense of tension for driving. We need to analyze the eye-tracking data quantitatively and study deeply appropriate experimental environment for autonomous vehicle as future works.

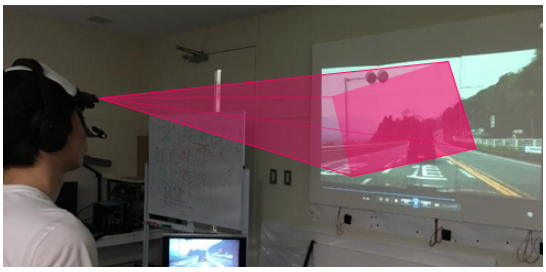

Fig. 1. Experimental environment of eye-tracking

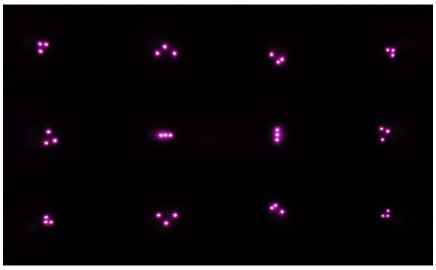

Fig. 2. Markers on the screen(filtered)

Fig. 3. Corrected eye position on the movie

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On Clustering Cellists using Acquired Data through Performance Movies Observation

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Abstract. By specifying a set of more than ten characteristic attributes related to cello playing such as "right elbow height", "vertical movement of the wrist on bow reverse action" and "the degree of left-right body trunk motion", we collect a set of data from observation of 46 cellists movies on a video site and conduct clustering and decision tree analyses to identify a set of clusters. As a result, we succeeded in obtaining five clusters which may be useful in finding a cello playing style suited for each player.

Keywords: individual differences, cellists' performance, attributes selection, data acquisition by observation, clustering, decision tree analysis, cluster characterization

1 Introduction

In performance skill acquisition, the problem of individual differences is quite serious which inhibits us to find objective rules to any performers in common. This fact causes difficulties in skill acquisition process. When trainers coach to beginners, they may stick to their own performance styles regardless to their students' styles.

As a first step to overcome this problem, we try to group professional cellists in all over the world by their performance styles. This attempt should give any hints for explaining skill diversities.

To accomplish grouping, we first specify a set of more than ten characteristic attributes related to cello playing. We then collect a set of data from visual observation of 46 cellists movies on a video web site and conduct clustering and decision tree analyses to identify clusters. As a result, we succeed in obtaining five clusters which may be useful in finding a cello playing style suited for each player. This paper reports the entire process of the cellists' clustering.

In Chapter 2, we describe how to conduct attributes selection. In Chapter 3, we state the way of acquiring data by observing movies on the web site. In Chapter 4 and 5, we introduce clustering and decision tree analysis to the acquired data. In Chapter 6, we conclude our paper.

adfa, p. 1, 2011.

2 Attributes Selection

2.1 Attributes selection by means of acquired knowledge

The problem of attributes selection is crucial in cellists clustering. If we cover all important attributes, the results would be successful. However too many unnecessary attributes might prohibit us to lead success because they may contain duplicated attributes which lead to heavy computation and possible noise in data. In our experiment, we first selected 17 attributes by subjective criteria for judgement based on personal experiences of the first and second authors. Their attributes consist of general data such as nationality, sex, body size, hand size, and more particularly cello performance data such as force generation ways in bow handling, whether one bends the right hand wrist vertically or not when one changes the bowing direction, whether one moves the body heavily or not, whether one leans the cello much or not, and so on.

2.2 Review of attributes selection

After selecting the 17 attributes, we conducted data acquisition and preliminary clustering. Through the pre-experiment, we discovered excess and deficiency of attributes and proceeded to modify the attributes set. There are three reasons for the modification: (1) unnecessary attributes due to overlapping characteristics, (2) those attributes which are hard to measure, and (3) newly discovered attributes during the data acquisition. We introduce examples below.

(1) Overlapping attributes

At the beginning, we selected “arm length” and “hand size” besides “body size”. However, those three attributes showed very high similarity in data acquisition phase and we decided to eliminate the two attributes.

(2) Attributes hard to measure

Such attributes as “force generation ways in bowing: whether we push the bow by the elbow or we pull the bow by the wrist”, “the difference of posture: whether stooping or straight or backward-leaning”, “the way of position shifting: whether elbow first, hand-first or at-the-same-time” were hard to judge and we decided to eliminate them. In case of the posture difference, it seems easy to collect data but most of the performance movies were taken from the front and there were almost no scenes taken from side, which were indispensable to judge the posture.

(3) Newly discovered attributes during the data acquisition phase

In observing performance movies, we discovered several attributes which seem to be useful in clustering as listed below.

i. Wrist Dent on Top of the Bow

ii. Left Arm Angle at the 1st Position
iii. Bow-Grasp Finger Width
iv. Right Palm Shape

Three attributes, i, ii and iv, played important roles in clustering. By observing different types of players carefully, we happened to recognize the importance of those features.

The finally selected 12 attributes are listed as follows:

1. Sex
2. Body Size
3. Elbow Height at E String
4. Wrist Vertical Bend
5. Wrist Dent on Top of the Bow
6. Neck Move
7. Head-Cello Distance
8. Cello Angle
9. Body Movement
10. Left Arm Angle at 1st Position
11. Bow-Grasp Finger Width
12. Right Palm Shape

3 Data Acquisition by Observing Performance Movies

For each player, we determined attributes' values by visual judgement. Each attribute has numerical value within 0~1, almost all were 0, 1 binary values, or 0, 0.5, 1 ternary values. Exceptions were elbow heights and Head-Cello Distance and they were treated as continuous values in between 0 to 1.

3.1 Selection of cellists

We selected a set of cellists for the clustering from an internet video site. We excluded very young cellists since their performance were quite different from others.

3.2 Data acquisition by the examiner's visual judgement

We observed each cello performance video carefully by being aware of the target attribute and determined the value. What we need is to make the measurement precise enough. To accomplish this, we need to define the measurement attributes rigorously and to prevent the measurement fluctuation.

An example of rigorous definition is "Head-Cello Distance." At the beginning, we defined the value of this attribute as binary but later we changed it as continuous. Furthermore, we defined the distance as the distance in 3D space between the head and the cello's neck and also we took the time duration of the distance degree into account.

To avoid the measurement fluctuation, the first measurement was done through every attribute for each cellist, but the second one through every cellist for each attribute. The second attempt prevented the measurement fluctuation since the same attribute was measured across players in a short period of time.

Furthermore, we measured some attributes twice to verify the measurement accuracy and for those attributes which had different results, we measured again and conducted modification. We show the result of the measurement in Fig. 1.

Cellist	Sex	BodySize	ElbowHight	Wrist Vert Bend	WristDent	Neck Move	Head Cello Dist	Cello Angle	BodyMove	Left Arm Angle	Grasp FingerWidth	Right Palm Twist
Ofla Harnoy	Female	S	0.5	No	Yes	Big	1	0.5	1	0	0.5	Flat
Madoka Hojo	Female	S	0.3	Yes	Mid	Small	0.3	0	0.5	0	0.5	Flat
Urara Urakawa	Female	S	0.6	Yes	Yes	Small	0	0.5	1	0.5	0	Flat
Tanya Anisimova	Female	S	0.5	Yes	Yes	Big	0	0.5	0.5	0	1	Flat
Mari Endoh	Female	S	1	Yes	Mid	Big	0.6	0.5	1	1	1	Flat
Osamu Kawamura	Male	S	0.5	Yes	Mid	Big	0.7	0	1	0	1	Twist
Marie-Elisabeth Heck	Female	S	0	Yes	Yes	Big	0.8	0.5	1	0	1	Twist
Yoko Hasegawa	Female	S	0.5	Yes	Yes	Big	0.5	0.5	0.5	0	0.5	Twist
Sol Gabetta	Female	L	0.5	Yes	Yes	Big	0.7	0.5	1	0	1	Twist
Tatiana Vassilieva	Female	L	1	Yes	Yes	Big	1	0.5	1	0	0.5	Twist
Hitomi Niikura	Female	S	0.5	Yes	No	Small	0.2	0.5	1	0	0.5	Twist
Yoriko Miyake	Female	S	0.7	Yes	Mid	Small	0.3	0.5	1	0.5	0.5	Twist
Jacqueline DuPre	Female	S	0.5	Yes	Yes	Big	0	0.5	1	1	0.5	Twist
Kateryna Bragina	Female	S	0.7	Yes	Yes	Big	0.5	0.5	1	1	0.5	Twist
Rinao Yaguchi	Female	S	0.5	Yes	Yes	Big	0.2	0.5	1	1	1	Twist
F.Guye	Male	L	0.7	Yes	Mid	Small	0	0	0.5	1	0.5	Flat
Jian Wang	Male	S	0.8	Yes	Mid	Small	0.5	0.5	0	0	0	Flat
Lynn Harrell	Male	L	0.6	No	Mid	Small	0.2	1	0	0	0.5	Flat
Janos Starker	Male	L	0.7	No	No	Small	0.2	0.5	0	0	0	Flat
Piatigorsky	Male	S	0.2	No	Mid	Small	0.5	0	0.5	0	0	Twist
Rostropovich	Male	L	0	No	Yes	Small	0	0	0.5	0	0	Flat
Paul Tortelier	Male	L	0.7	No	Mid	Small	0.3	0	0	0	0.5	Flat
Michaela Fukačová	Female	L	0.6	No	Yes	Small	0	0	0	0	0.5	Flat
Amit Peled	Male	L	0.7	Yes	Yes	Big	0.3	0	0	1	0	Flat
Mario Brunello	Male	S	1	No	No	Big	1	1	0.5	0	0.5	Flat
Hiroki Kashiwagi	Male	S	0.2	No	No	Big	0	0.5	1	0	1	Flat
Davide Amadio	Male	S	0	Yes	No	Big	1	1	1	0	0.5	Flat
Akiko Hasegawa	Female	S	0.5	No	No	Big	0	1	0	0	0.5	Twist
Rintaro Kaneko	Male	S	0.5	No	No	Big	0.8	1	1	0.5	0	Flat
Miklós PERÉNYI	Male	S	1	No	No	Big	1	1	1	0.5	0.5	Twist
Mischa Maisky	Male	S	0.5	No	No	Big	0	0.5	1	0	0.5	Flat
Stéphane Tétreault	Male	S	0.7	No	Mid	Big	0.5	0.5	1	1	0.5	Flat
Pierre Fournier	Male	S	0.5	No	No	Big	0.5	0	0	0.5	0.5	Flat
Ikuya Okamoto	Male	S	0.5	Yes	No	Big	0.5	0.5	0	0	0.5	Flat
Yasuiro Hasegawa	Male	S	0	No	No	Small	0.2	0.5	0	0	0	Flat
Pabro Casals	Male	S	0.5	No	Yes	Small	0	0.5	0.5	0	0.5	Flat
Michiaki Ueno	Male	S	0.7	No	No	Small	0.2	0	0.5	0	0	Flat
Dai MIYATA	Male	S	0.5	No	Yes	Big	0	0	0	0	0.5	Flat
Benedict Kloeckner	Male	S	0.5	No	Mid	Small	0.3	0.5	0.5	1	0.5	Twist
Leonard Rose	Male	L	0.5	No	Mid	Small	0.2	0	1	0.5	0	Twist
Truls Mørk	Male	L	0.8	No	Yes	Small	0	0	1	0.5	0.5	Twist
Yo-Yo Ma	Male	L	0.5	No	No	Big	0.7	0	1	1	1	Flat
Michael Schonwandt	Male	L	0.8	No	No	Big	0	0	1	1	0.5	Flat
Luka Sulic	Male	L	0.8	Yes	No	Small	0.2	0	1	1	1	Twist
Tsuyoshi Tsutsumi	Male	L	0.7	Yes	No	Small	0	0	0.5	1	0.5	Flat
Xavier Phillips	Male	L	0.7	No	No	Big	0	0.5	0	0	1	Twist

Fig. 1. Cellists performance data acquired through performance movies observation

4 Clustering

We applied k-means clustering to find a set of clusters. The most essential parameter of the k-mean algorithm is the number of clusters. To find an appropriate number of clusters, we computed the sum of the square errors within-cluster by changing the cluster number from 3 to 7. The result attained minimum when the cluster number was five as shown in Fig. 2.

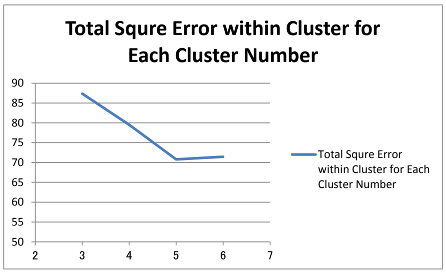

Fig. 2. The change of total square error within-cluster for each cluster number

The obtained five clusters are shown in Fig. 3, where the representative cellists of the five clusters are as follows; Cluster0: Jacqueline Du Pre, Cluster1: Mischa Maisky, Cluster2: Yo-Yo Ma, Cluster3: Leonard Rose, and Cluster4: Pabro Casals.

Cluster0		
Urara Urakawa	Sol Gabetta	Yoko Hasegawa
Tanya Anisimova	Tatiana Vassilieva	Kateryna Bragina
Mari Endoh	du Pre	Rinako Yaguchi
Marie-E. Hecker		

Cluster1		
Ofla Harnoy	Stéphane Tétreault	Rintaro Kaneko
Mario Brunello	Pierre Fournier	Miklós PERÉNYI
Hiroki Kashiwagi	Ikuya Okamoto	Mischa Maisky
Davide Amadio	Yasuhiro Hasegawa	Dai Miyata
Akiko Hasegawa	Michiaki Ueno	Xavier Phillips

Cluster2		
F.Guye	Michael Schonwandt	Yo-Yo Ma
Amit Peled	Luka Sulic	Tsuyoshi Tsutsumi

Cluster3		
Madoka Houjou	Jian Wang	Yoriko Miyake
Osamu kawamura	Piatigorsky	Leonard Rose
Hitomi Niikura	Benedict Kloeckner	

Cluster4		
Lynn Harrell	Michaela Fukačová	Paul Tortelier
Janos Starker	Pabro Casals	Truls Mørk
Rostropovich		

Fig. 3. Clustering results by K-Means Clustering

5 Characterization of Clusters by Decision Tree Analysis

In order to characterize each cluster, we conduct decision tree analysis by specifying the cluster name as the class to be decided. We use an application software called Weka, the same software for the clustering. We set the minimum numbers of the objects in each leaf of the tree as 3. The test option we adopted is "use training set". The obtained decision tree is shown in Fig. 4.

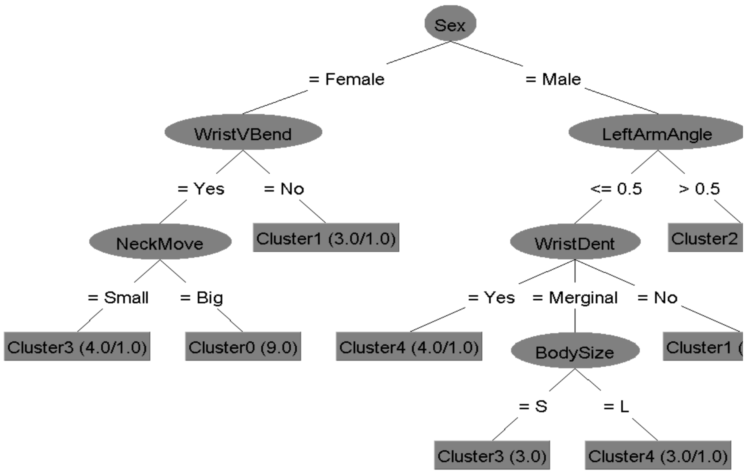

Fig. 4. Decision tree of the cellists' clusters

An oval node of the decision tree represents an attribute selected for decision at each level and the value of each arc from the node is its value. A rectangle node is a leaf node which represents the decided cluster. A rectangle node contains the decided cluster name with a number of records recognized as the cluster and also the number of miss-classified records. One measure judging the correctness of the decision tree is the accuracy rate. The accuracy rate of the decision tree sown in Fig. 4 is 84.8% and it is quite high. The decision tree shows that the top (root) node is the "sex" attribute which means it is the most important feature for the clustering. However, by careful investigation, we find that the cluster1 and the cluster3 appear both in male and female branches. To resolve the separation problem, we conduct further decision tree analysis by removing the "sex" attribute. The result is shown in Fig. 5. This decision tree shows even higher accuracy than before, attaining 87.0 %. On the contrary, the number of the leaf nodes increases from 8 to 10.

It is quite interesting that there appear three new attributes in this decision tree; they are "Head-Cello Distance", "Cello Angle", and "Right Palm Shape" among which one of the newly introduced attributes after the preliminary experiment is included. Since two other new attributes are contained in the first decision tree, three of the four new attributes are recognized as important features.

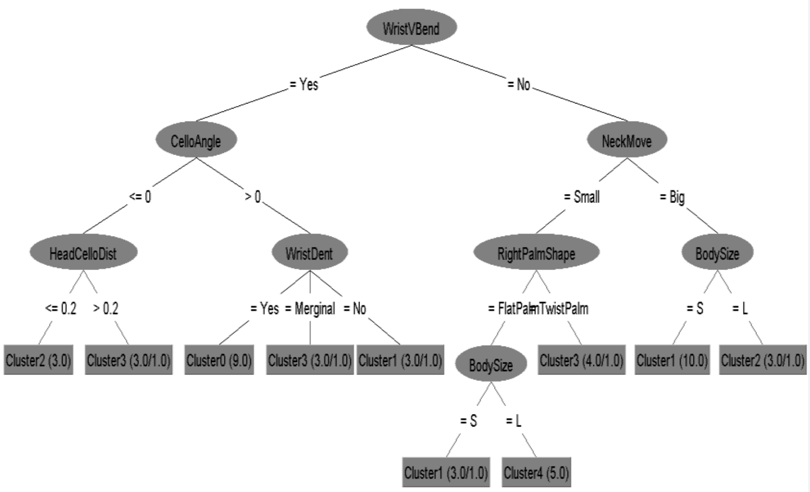

Fig. 5. Decision tree of the cellists' Clusters without the "sex" attribute

To find the similarity or dissimilarity among clusters, we computed inter-cluster distances of every pair of clusters which we defined as the average distance of each pair of records in the cluster-pair. The result is shown if Fig. 6. The two dimensional distance map is then computed by Multi-Dimensional Scaling as shown in Fig. 7. This figure shows that the cluster3 is located near the center of the gravity and may be considered as a noise cluster.

Cluster pair	Min distance	Max distance	Mean distance
2-4	2.34	6.33	4.4
3-4	1.38	7.75	4.51
1-4	1.49	8.41	4.59
0-3	2.18	7.79	4.69
1-3	2.33	7.48	4.82
1-2	2.34	8.29	5.15
2-3	2.83	7.55	5.19
0-1	2.35	8.89	5.28
0-2	4.01	7.88	5.68
0-4	2.76	9.04	6.35

Fig. 6. A list of cluster pairs sorted by average of all elements pairs square distances.

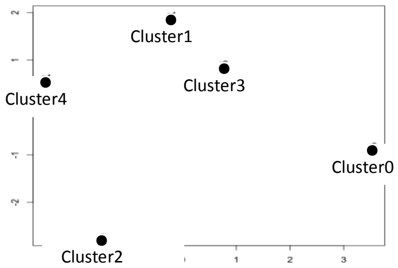

Fig. 7. Cluster locations reflecting inter-cluster distances

Now we try to characterize each cluster by carefully investigating Fig. 4 and 5.

i. Cluster0
Cluster0 is a cluster of female cellists having large amount of wrist vertical bending and also large neck motion. The representative cellist is Jacqueline duPre, who uses her small body effectively by the big body and neck motions.

ii. Cluster1
The characteristic feature of the Cluster1 cellists is that their body sizes are small and they move neck heavily and they don't bend their wrists vertically much. The last point is particularly different from Cluster0. There are both male and female players in this cluster, and the representative male player is Mischa Maisky and female player Ofla Harnoy.

iii. Cluster2
Cellists in this cluster are male, have large body and keep their left arm angle high at the 1st position. Furthermore, they lean their cellos a lot. Yo-yo Ma is the representative.

iv. Cluster3
Cellists in this cluster are generally small and they move their heads very little and keep the distance between the cello and their head far apart. They either bend their wrists vertically or twist their right palms if not. The representative player is Leonard Rose. Three Japanese female cellists are in this cluster. As indicated before, this cluster is located rather in the center of all clusters and does not have any significant characteristic features. Therefore we consider it as a noise cluster.

v. Cluster4
The characteristic feature of the Cluster4 cellists is that they don't move neck much, the left arm angle at 1st position is small, the distance between the head and the cello is small and they don't twist the right palm much. This cluster is located close to the Cluster2 as shown in Fig. 5 except the difference of the left arm height.

Those attributes which are selected as separating clusters are important to distinguish cellists types. The attribute of "Wrist Vertical Bend" is related to the way of achieving right hand flexibility, either by wrist joint or by elbow/shoulder joint. Cellists in the Cluster0 utilize mainly the vertical motion of the wrist joint and additionally neck and body vibrations. On the other hand, those in the Cluster1 utilize the horizontal move of the wrist joint and also the finger joints. The merit of the vertical motion of the wrist is its easiness to obtain large amplitude of vibration but the demerit is that the natural direction of the palm at the vertical vibration is different from the bow direction and therefore they need to twist the palm to adjust the difference of angles. It may cause deficiency of the arm torque (motion dependent torque) delivery to the bow and they tend to compensate the loss by using other parts of the body like neck and body.

The characteristic feature to keep the left elbow at high position is also notable. Since they need an extra power to keep the left elbow high, all cellists in this cluster are male and large. This posture can produce counter power to the down-bow motion and therefore it makes possible to attain strong and rapid down-bowing. On the other hand, the playing style of keeping the elbow in lower position, which is observed in Cluster1, Cluster3 and Cluster4, seems more natural and we can expect softer sound from this style.

6 Conclusion

We conducted to cluster 46 cellists. Although this number seems too small to obtain trustful outcome, the clustering result is rather surprising and very convincing. During the clustering process, the first hurdle was to determine adequate set of attributes of each player to be collected by simple visual observation. By utilizing acquired knowledge from life-long cello playing and thoughtful consideration of cello playing techniques in the skill science research, we succeeded in finding an appropriate set of attributes. Then we found the right number of clusters by simply computing the intra-clusters diversities. The obtained clusters were not known to the authors in advance and brought us a new knowledge. We knew the fact that there are several different types of cellists, but we did not know the detail. Therefore the result was very surprising.

The success of this research indicates that our clustering and decision tree analysis methods are promising in grouping performers in any fields. The utility value of the clustering result is to be investigated in future.

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We deeply express of our thanks to Keita Kinjo from Okinawa International University and Tomonobu Ozaki from Nihon University for their help in data analysis.

The effects of the theme of conversation and the place of expedition on the mental time of participants of coimagination method with expedition

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Dementia is not a normal part of ageing, but it mainly affects older adults. Hence, along with the rapid growth of ageing population, the number of people with dementia is also anticipated to increase. In the early stage of dementia, episodic memory, divided attention and planning functions start declining. Among episodic memory functions, recent episodic memory function declines first. In order to prevent the decline caused by disuse and to train the recent episodic memory function, the coimagination method with expedition is developed. In this method, there are two sessions, an expedition and a conversation session supported by coimagination method. Firstly, the expedition helps participants to face new experiences and to find topics of conversation. Secondly, coimagination method is a method of group conversation based on photos, with designated time limit and theme. The expected effects of this method are that participants utilize the functions of memorizing, retention and recall of recent episodes about expedition during conversation. When participants talk about recent experiences, they make use of their recent episodic memory functions so as to reduce the risk of decline. Based on the previous study, instead of the experiences of expedition, there are some participants of coimagination method with expedition who talk about past experiences. We need to determine what reminds participants of recent or past episodes.

The purpose of this study is to determine the suitable criteria of coimagination method with expedition to help participant utilize recent episodic memory functions during conversation by talking about recent episodes. We analyzed conversation data supported by coimagination method with expedition, by classifying the mental time of participants based on their utterances. Mental time is a time consciousness of human over past, present and future. The mental time travelling allows human to mentally travel into “nonpresent” time. Human mentally travels backward when thinking about past experiences. In this study, with the purpose of training recent episodic memory function, mental time travelling to the “past” for a long time is undesirable. We investigated the effects of the theme of conversation and the place of expedition on the mental time of participants of coimagination method with expedition. Based on the results of analysis, the recommended theme of conversation and place of expedition as follows in order to prompt older adult to talk about the recent episodes:

(1) The designated theme of conversation supported by coimagination method should be specific and detailed. If the theme is vague, it prompts the participants to connect their imagination to the past experiences.

(2) The place of expedition should be the place which is the first time visit for the participants. If the place had been visited by participants before, it helps participants to recall past experiences, and prompts them to talk about past experiences.

Toward a mechanistic account for imitation learning: an analysis of pendulum swing-up

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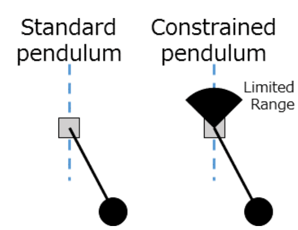
Social agents learn action repertoires from others' behaviors. This is not just a mere replication of movements, but it requires inference on intention behind actions. Empirically, past studies have reported that young children could infer the action to be completed by observing a partial and incomplete action of the demonstrator (Warneken & Tomasello 2006).

In the present study, we seek for a theoretical account for the inferential process of "successful" or "intended" actions discriminated from "unsuccessful" or "unintended" ones. Toward this goal, we ask the two basic questions:

1. How can we identify multiple seemingly different actions generated by the same motor control scheme?
2. How can we differentiate multiple seemingly similar actions generated by two different motor control schemes?

Here, we suppose that the motor control scheme or the plan of actions reflects the intention behind the actions.

To address these questions, we resorted a computer simulations of the simplest possible physical body and action repertoires — the classical pendulum swing-up task of one degree-of-freedom. We analyzed two agents controlling the pendulum movements in different control schemes given the identical pendulum with the same condition. Due to the given identical physical condition, the two pendulums' movements seem quite similar (see the top panel of Fig. 1), but their underlying control scheme are substantially different. Each of control schemes was constructed by minimizing the error function, that is minimized at the inverted position for this task. In constructing the two different control schemes, however, two different physical conditions on the pendulum were imposed: (a) a standard single pendulum without any constraint (the left in the side figure) and (b) a single pendulum with a physical constraint (the right) that prevents it from taking a certain range of posture including the inverted (the state with minimal error). We call the one with the control scheme of (a) *standard* pendulum, and the other (b) *constrained* pendulum.



To reveal latent differences in two different dynamical systems, we analyzed dimensions of the two systems by treating the generated pendulum movements as attractors. In this analysis, we employed the method proposed by Hidaka & Kashyap (2013), which numerically estimates pointwise dimension for each data point in a dataset. The estimated pointwise dimension for each time point of the standard (green) and constrained (blue) pendulum is shown in different colors in the bottom panel of Fig. 1. The result shows that both the standard and constrained pendulum show drastic changes around 5000 time steps. After 5000 time steps, the dimension of the standard one increases on average, but that of the constrained one decreases on average. As a follow-up analysis, we generated a set of multiple movements with different initial conditions for each of the two pendulums, and found that the movements of the same pendulum with different initial conditions tend to show similar patterns in pointwise dimensions. To questions (1) and (2), it suggests that this analysis on the pointwise dimension can differentiate two seemingly similar movements generated by the two different control schemes, and identify multiple seemingly different movements generated by the same control scheme.

In the past literature on the computational mechanism of motor control, the problem of interest in this paper is treated as an ill-posed inverse problem, that is by identifying the control scheme from movements, to its forward problem. The standard solution for this class of ill-posed problem is to model the constraints given by the nature of the system, namely physical laws and body structures in this case, as the prior knowledge in the estimation process (Marr 1982; Kawato 1990). In contrast to this approach, we suppose that our approach taken here is another class of approaches, that do not explicitly model the given physical constraints. Our approach assumes that the movements reflect a generic dynamical system. Then the present study demonstrated that this assumption served a sufficient basis for identification/differentiation of the systems — at least in the case concerning the simplest physical model such as a single pendulum.

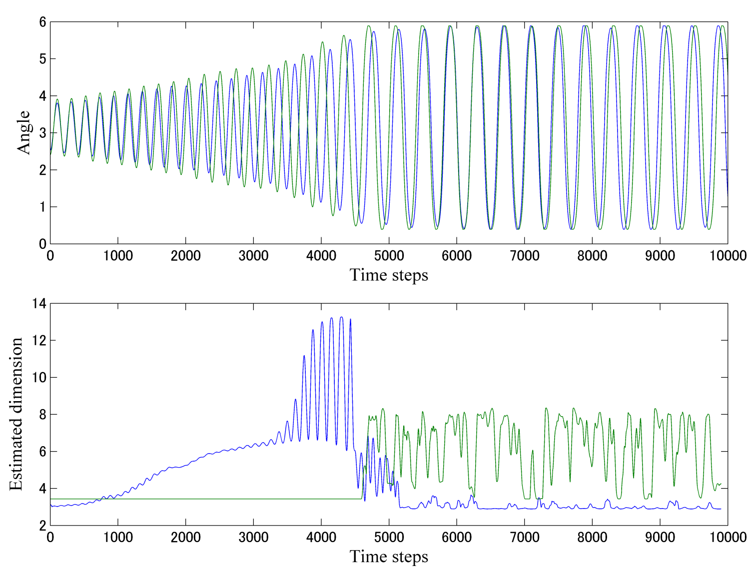


Fig. 1: Pointwise dimensions of pendulum movements

Using machine learning to help manage the "last mile" in the application of skill science

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The overall goal of skill science is to develop models and tools appropriate to the identification of the highly skilled physical performance of humans, including that related to professional musicians and athletes. The identification of physical performance models provides the basis to distinguish the difference in the physical performance of some like Yo-yo Ma the cellist, or Tiger Woods the golfer. Existing results in Skill Science have made progress by focusing on some nearly independent physical performance models, like the use of classical physics models of the acceleration of whipping action to explain the arm action of cellists; or the isolation of forearm muscles and their frequency of contraction to explain an expert cellist's ease of playing spiccato.

The next step beyond the identification of component models of physical skills includes the development of reasoning tools that can reveal special elusive dynamic models of physical behaviour. For example, it is sometimes possible to consider alternative dynamic sequences that distinguish a professional from an amateur … these special dynamic skills can be called a "knack," or a special sequence or set of motions well within the scope of a physical model, but distinguished as a preferred explanation for professional level performance.

If the development of reasoning models for discovering knacks within the envelope of a physical model is considered as a search problem, then a comparison of any individual performance that attempts to mimic that discovered knack can be thought of as a machine learning problem. Simply stated, the training or practise required to achieve knack performance can exploit simple machine learning: the idea is to use the baseline knack model to calibrate an individual performance, and then record and compare successive practise attempts and provide feedback against knack baseline performance as a learning objective.

We refer to this application of skill science and the exploitation of knacks as the "last mile" in the sense that simple machine learning calibration can help provide the feedback to help an individual achieve the "last mile" in performance goals. The delivery of incremental knack performance can be done in a variety of ways, including visualization and virtual reality modeling of physical systems, as is done in the application of machine learning to rehabilitation medicine.

Data mining of Care Life Log by the level of care required

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In the present study, to classify the vast amount of Care Life Log data that occurs in nursing in one Miyazaki Hospital Long-term Health Care Facility by level of care required, data mining was carried out. The characteristic vocabulary from the Long-term Health Care Facility's Care Life Log was used to integrate and analyze the level of care required.

There are five levels of care, with Level 1 vocabulary including recreation, toilet, morning, afternoon, etc. The level of care gradually increases from Level 1 to Level 5, which has vocabulary that includes tube, danger, treatment, removal, and discovery. The higher the level, the worse the health condition and therefore the greater care required. These levels allow for a clear analysis of a patient's condition. This analysis has led to an improvement in Quality of Life as well as a decrease in mismatches between the level of care required for patients and the level of care given by caretakers.

The nursing field requires efficiency in health care services. Because of this, improvement and continuous data collection are important. There is a need for the collection of data as a whole in the long-term building of health care services as well as large-scale data collection.

In the future, we aim to develop an electronic medical record that can be created semi-automatically in accordance with the level of care required.

Action Sports Analysis Based on Local Cross Correlation and Action Measurement Units with GPS timestamp

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This paper proposes action measurement units and an analysis method of turn and aerial maneuvers of action sports to identify skill level and type of sports. Each unit records sensing data collected from accelerometer, gyroscope, and digital compass in three dimensional space with GPS timestamp. The units can be easily attached on any part of an athlete's body without any wired or wireless connections between them, because data collected from multiple independent units can be synchronized with GPS timestamp.

To identify actions in riding based on multiple time series data collected from the measurement units, we also developed a classification method with local cross-correlation function. To measure similarity between two ridings, a cross-correlation function gave a similarity measure. However, the function was not suitable for the measure when there was a big difference between two ridings in terms of speed, although they consisted of same actions. To avoid the problem of cross-correlation function on dataset composed of different riding speeds, we introduced a local cross-correlation function, because the local function can focus on important actions and ignore time duration between the actions. The similarity measure was defined as an average of the multiple local cross-correlation values on local maximum peaks, because the peaks depict important common actions between two ridings. However, computation time for the measure tended to increase with long time series data due to calculation of convolution between two time series. To reduce the computation time, we formulated an incremental calculation of the local cross correlation.

We analyzed three action sports (i.e., skateboard, inline skate and BMX) on a big air ramp. The competition attracts much public attention in part because big air snowboarding will be part of the Pyeongchang 2018 Olympic winter games. A big air ramp is composed of a kicker ramp for making straight jumps, a vertical ramp for aerial action and a slope to get enough speed to make big jumps and "get air" on the two ramps. An athlete made a turn or air in an easy direction (i.e., clockwise or opposite) at the vertical ramp. Skill levels of athletes are classified into three categories (i.e. beginner, intermediate and advanced). The total number of recorded ridings is 43. We categorized the riding data with our method and normal cross correlation. According to the result, the clusters with normal function contain different levels and types of ridings. On the other hand, we confirm that our method is able to properly categorize the same level and type of ridings into a sub cluster. The proposed method can successfully discriminate type of sport and level of skill, because it focuses on important actions only.

Keywords: Action sports, big air ramp, skateboard, inline skate, BMX, inertial sensor, GPS timestamp, cross correlation function

The Information Scientific Stage Model of an Expertise in Embodied Knowledge

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Abstract: This research aims to elucidate information systems in terms of embodied knowledge, and constructs a mathematical model for interaction between the teacher and learner from the viewpoint of information science, such as cognitive science and artificial intelligence.

As such, it is possible to build the information scientific stage model (X, W, f, h) that will describe the coaching process. The mathematical model can potentially estimate the state of an expertise in embodied knowledge. Such approaches will not only benefit to elucidate research of embodied knowledge in cognitive science and artificial intelligence but also are applicable to coaching in sports science.

Key Words: Embodied Knowledge, Expertise, Mathematical Model, Interaction, Coaching

1. Introduction

1.1. Embodied knowledge as tacit knowledge

In recent years, there has been a growing interest in embodied knowledge because it is expected to elucidate an expertise in physical skills[1] from the viewpoints of information science, such as cognitive science and artificial intelligence. Several studies have been conducted on embodied knowledge, however, little is known about the information system through which physical skills are acquired. The reason is as follows. Embodied knowledge is tacit knowledge, which was conceptualized by Michael Polanyi[2] as bodily knowledge of how to act without any deliberation or verbalization[3]. Therefore, it is very difficult to explicate the information system of embodied knowledge.

1.2. The purpose of this study

As the first step in our study, we begin with a discussion on the coaching process. Typically, the true purpose of the teacher is not to transmit to the learner explicit knowledge such as that acquired from textbooks, but to teach and share somatic sensations which the teacher has mastered through experiences. Nevertheless, there are many cases in which it is difficult for the teacher to hand down physical skills to the learner during coaching because embodied knowledge is tacit knowledge. Therefore, the teacher gradually devises the optimal guidance for the learner, and will try to evoke somatic sensations like the teacher in the learner.

The purpose of this paper is to build a mathematical model of the interactions between the teacher and the learner in the abovementioned coaching process. It is hoped that the model will contribute to a better understanding of embodied knowledge, for example, the prediction about an expertise in physical skills and deeper elucidation related to the phenomenon of embodied knowledge according to the formula.

2. Mathematical model expressing an expertise in embodied knowledge

2.1. Process of coaching

The process by which teachers convey embodied knowledge does not require the learner to remember explicit knowledge written in textbooks or handouts. Instead, teachers pass their own physical sensations gained through their own experiences to their learners.

Although instruction is an ideal way to pass physical sensations from teacher to learner, this is often difficult in practice because the teacher has tacitly acquired that embodied knowledge. As the learner lacks this advantage, the teacher usually applies a step-by-step instruction method suited to the learner in which he copies and shares his own physical sensations.

Here, we denote the instruction of a teacher by x. Assuming that x is a continuous function, the optimal x for a learner is an extremum of this function[1]. This argument can be reasoned as follows. The semantic space of the linguistics of a teacher's instruction (hereafter referred to as the *linguistic semantic space*) is essentially a network of semantics constructed from the language. Within this linguistic network, teachers evaluate learners in the vicinity of expressions surrounding the meaning they want to convey to their learners. Therefore, by including distance or differences in the network and assuming that the network is continuous, the extreme value becomes a differential evaluation index.

Next, let us focus on the physical expression of learners who respond to x. Here, by defining the learner's physical expression as w, we can exchange x and w in stages. At each stage, work is done in moving w to the teacher's sensation (defined as x^k, where k denotes the stage). The teacher's instruction x^k is strongly correlated with the learner's physical expression w^k but is expected to differ among individuals (diversity/identity).

Now, if we suppose that we can quantify the gap between x and w, we can evaluate the level of an expertise in the learner's embodied knowledge. In fact, these two processes are equivalent. First, we express the evaluation with respect to the *kth* teacher's instruction as a function f^k. Here, we set the teacher's evaluation function because traditionally, the teachers grasp their coaching intersubjectively and impart their linguistic instruction to suit the learners. This function provides a theoretical description of this process. Such an evaluation function with respect to the teacher's linguistic instruction is justified as follows: if the content of a teacher's instruction at each stage is represented by x^k, the teacher's evaluation at that instruction stage should also be considered. A wise teacher often starts with simple instructions that are easily implemented by the learner and then gradually increases the difficulty level. The evaluation of the content instruction should increase accordingly.

Therefore, w^k must be evaluated at each stage. To this end, we define an evaluation function $h^k(w^k)$ of w^k imposed by the teacher. Note that $h(w)$ assesses the proximity to the teacher's instruction and hence determines the highest state of evaluation w. When the $h(w)$ of w^k is time-independent, it is represented by the extremum of the evaluation function.

$$\frac{dh(w)}{dx} = 0 \qquad (1)$$

Moreover, if the evaluation function w^k of physical expression depends on a parameter such as time, the problem becomes that of finding a stationary curve.

Next, it is hoped that a learner will faithfully implement and notice a word-based instruction x^k. Insufficient attention paid by the learner to the instruction will be reflected in w^k, which dictates the next instruction x^{k+1} imparted by the teacher. This yields a stage-by-stage interaction in which the learner implements x^k and outputs a physical expression w^k, which then guides the teacher's next instruction x^{k+1}, eliciting a response in the learner's physical expression w^{k+1}. This interaction is iterated until the teacher observes the learner's physical expression and

[1] Expressing a natural phenomenon as a minimum or maximum value of a fixed physical quantity echoes Aristotle's sentiment that "nature as nature is as good as it can be" in a more sophisticated form.

concludes that the learning has been accomplished.

This mathematical model comprises the teacher's instruction and its evaluation function (x^k and f^k, respectively) and the learner's physical expression and its evaluation function (w^k and $h(w)$, respectively). Thus, the constructed mathematical model is denoted (X, W, f, h), where $X = x^k$, $f = f^k(x^k(t), dxk(t)/dt)$, $W = w^k$, and $h = h^k(w^k)$ for $k = 1, 2, \ldots, n$. As shown in Fig 1, this model converges the learner's linguistic instruction and teacher's physical expressions as the stages progress.

2.2. Devising the function

As shown in the constructed mathematical model, the evaluation function is a point in the interaction between the teacher and learner. The teacher's evaluation function provides the physical sensation that the teacher wishes to explicitly impart (specifies the function parameters explicitly). At the practically verified stage, we require a method that effectively decides the evaluation functions. For this purpose, we consider the following two methods.

The first method is a sensational representation that focuses strictly on the quantifiable expressions and withholds the analysis on the physical operations. In this approach, the variable determinations are based on a complex of two standards. More specifically, the composite function of standards A_i and B_j is a tensor function C_{ij} on which the evaluation function can be based. A theoretical explanation of this approach is possible but would involve complex calculations such as those of gravity and acceleration at each stage.

The second method determines the topologies of the learner's physical expressions that are expected and definitely not expected by the teacher. In this approach, the learner's physical expression is regarded as a *physical meaning space*. For example, if the learner's sensation becomes slightly closer to the teacher's physical representation near the teacher's linguistic instruction x^1, it can be assigned a continuous variable w^1, which becomes the *physical meaning space*. In other words, by distributing the physical expressions that are close to and far from the physical sensation of the teacher along a straight line, we can evaluate the learner's physical expression.

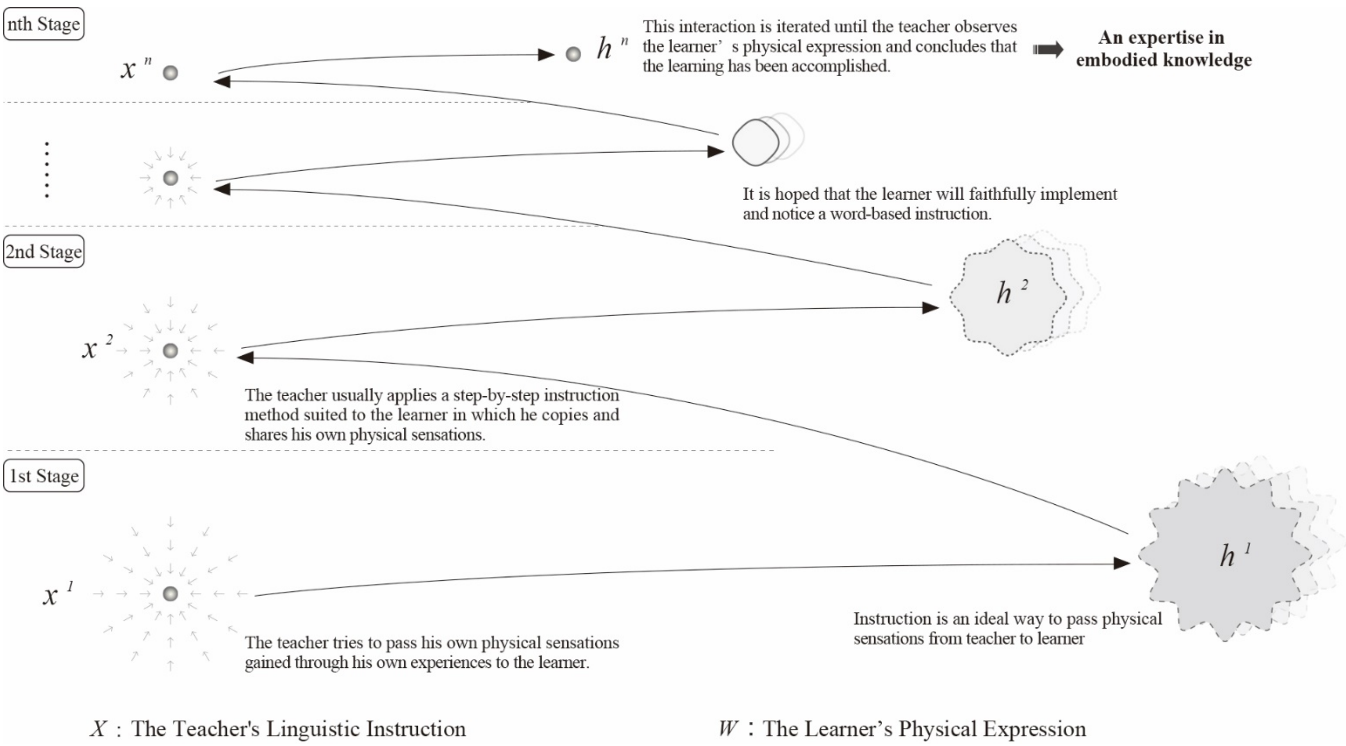

Fig 1: The information scientific stage model of an expertise in embodied (X, W, f, h) Knowledge

2.3. Stationary curve and Euler equation

When the evaluation function depends on parameters such as time, any differences between the teachers' and learners' physical sensations can be expressed by the variation principle, which seeks the stationary curve[2] of a functional as shown in Fig 2. The least-action principle is formulated by an equation that relates force and work, leading to important concepts such as potential and kinetic energy. For example, if a learner's physical representation is the evaluation function $h^k(w^k(t),dw^k(t)/dt)$, we can specify its action integral $H^k[w^k]$.

$$H^k[w^k] = \int_{t0}^{t1} h^k(w^k(t), dw^k(t)/dt)dt \qquad (2)$$

The stationary curve of this action integral can be derived from the following Euler equation and is calculable for a given evaluation function.

$$\frac{\mathrm{d}h^k(w^k(t), dw^k(t)/dt)}{\mathrm{dt}} - \frac{\mathrm{d}w^k(w^k(t), dw^k(t)\ /\ dt)}{\mathrm{d}(dw^k(t)\ /\ dt)} = 0 \qquad (3)$$

However, although this method is theoretically sound, it involves complicated calculations such as those of gravity and acceleration in practical implementation.

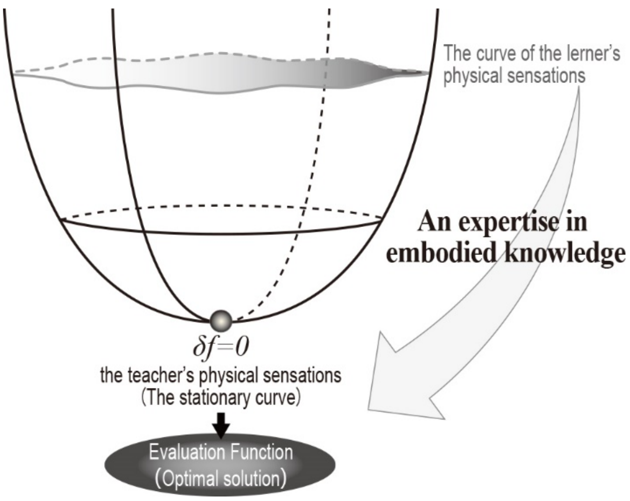

Fig 2: The stationary curve
and an expertise in embodied knowledge

3. Conclusion

For the purpose of our work, as such, it is possible to build the information scientific stage model (*X, W, f, h*) that will describe the coaching process between the teacher and the learner. The mathematical model can potentially estimate the state of an expertise in embodied knowledge. Such approaches will not only benefit to elucidate research of embodied knowledge in cognitive science and artificial intelligence but also are applicable to coaching in sports science.

A further study of the stage model of embodied knowledge should be conducted to verify the validity empirically.

Acknowledgment

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[2] The stationary curve follows the principle of least action, which states that "nature's work always takes the easiest and the shortest path;" i.e., any event occurs with the least effort[4].

A preliminary analysis of the process on floor plan recognition

Towards discovery of human's recognition mechanisms for complex structured images

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Human experts can recognize a complex structured images easily by using appropriate domain knowledge. The ultimate goal of this research is to explore the fountainhead of this ability and to identify the human's recognition mechanisms for complex images. As a preliminary case study towards the ultimate goal, we focus on images of architectural floor plan in this research. By analyzing the errors occurred in the process of a certain task on floor plan recognition, we attempt to obtain significant insights and meaningful information on complex image recognition and processing by human.

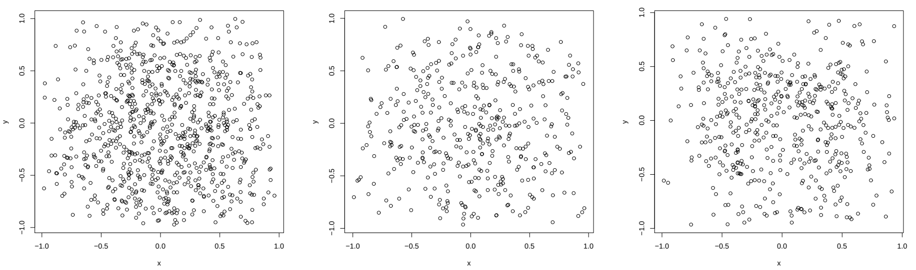
An architectural floor plan represents a whole layout of rooms. It also usually contains doors, windows and some graphical symbols representing sinks in a kitchen, wash stands, bathtubs, toilet seats and space for washing machines, etc. In addition, abbreviations of words, e.g. WIC for walk-in closet, LDK for area of living-dining kitchen, show the additional information of rooms and spaces. Since a floor plan image has rich information with a reasonable semantics as shown above, not only experts but also ordinary people can recognize the structure of the rooms and imagine the usability of the rooms easily. Due to the above reasons, we believe that floor plan images are suitable for an initial case study towards discovery of human's recognition mechanisms.

In this research, a certain task of floor plan recognition is prepared to capture the rough recognition process. In the task, given a floor plan image, subjects identify all rooms and their connectivity. Subjects are also required to specify the types of rooms such as living, kitchen and bathroom, as well as the types of the connection such as by door, by space and by wall. In other words, the objective of the task is to convert an image of floor plan to a labeled graph which consists of nodes representing rooms and edges for the connectivity.

We develop a GUI software to draw a graph on a given image by using mouse clicks and to record two kinds of log data during the task execution. The first one consists of the process of graph construction. We record the order of events on creation and deletion of nodes and edges, changing the label, and so on. The second log data contains physical conditions of subjects including head movements, eye movements, and blinks using wearable smart glasses.

As a preliminary experiment, we collect log data by three subjects using 642 of real floor plan images with size 578 x 618 pixels on average having at least

Subject A	Subject B	Subject C
Relative positions of errors in images		



example of errors with high conditional probability P(wrong label | correct label) (represented in the form of "correct label $\rightarrow$ wrong label")		
living room $\rightarrow$ LD	bathroom$\rightarrow$bath	LK$\rightarrow$living room
LDK$\rightarrow$ LD	western style room$\rightarrow$receipt	LD$\rightarrow$LDK
LD$\rightarrow$LDK	japanese style room$\rightarrow$entrance	LDK$\rightarrow$LD
kitchen$\rightarrow$receipt	LD$\rightarrow$living room	estroom$\rightarrow$bath
door$\rightarrow$wall	entrance$\rightarrow$corridor	door$\rightarrow$wall
bathroom$\rightarrow$bath	bath$\rightarrow$bathroom	entrance$\rightarrow$corridor
Veranda$\rightarrow$dining	kitchen$\rightarrow$receipt	japanese style room$\rightarrow$enterance

Fig. 1. Relative position of errors and rules with high conditional probability

three rooms. The average number of living rooms is 6.28 with standard deviation $s = 1.18$. As a result, three subjects draw 1284 of graphs in total having 27.2 vertices ($s = 7.80$) and 42.0 edges ($s = 15.19$) on average.

In this paper, we divide errors during the task execution into two kinds, noticed and not noticed by subjects, and conduct simple preliminary analysis of the former only.

The task might be difficult for the subjects and 73.8, 57.7 and 65.4 percent of graphs constructed by three subjects contained at least one error, respectively. We plot relative positions where errors occur in Fig.1. Since we cannot observe any particular tendency in the plots, we conclude that the position has no relationship on the error. In addition, we confirmed that the errors have no strong relationship with fatigue by using correlation measures on the duration time of tasks as well as the number of blinks. Some examples of errors having high conditional probability are shown in Fig.1. We can recognize that three subjects make similar errors in common.

The simple analysis of noticed errors is not sufficient for deriving strongly meaningful results. For future work, we plan to investigate on the deep analysis of the whole errors including not noticed ones by subjects for the discovery of recognition mechanisms of complex images.

Acknowledgement: In this paper, we used floor plan image dataset provided by NEXT Co., Ltd. and the National Institute of Informatics.

Adaptive Behavior Observed in Stepping-Over An Obstacle

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Keyword
Affordance, Dynamical systems approach, Synergy, Adaptation, Obstacle avoidance

The present study aims to describe the dynamics of a human adaptive behavior, stepping-over an obstacle to avoid a contact or collision in various environments. The purpose of our preliminary study is to investigate how stepping-over behavior changes depending on the height of the obstacle. Our study is based on the theoretical framework of affordance theory in ecological psychology and the dynamical systems approach (DSA) based on self-organization theory.

According to affordance theory, in order to act safely and adequately in the environment, animals must accurately perceive the relationship between environmental properties and their own body properties. In other words, environmental properties are scaled by individual animals' body properties and animals perceive them based on the relationship between each individual and its environment. For example, in a stair climbing behavior, the height of a displayed stair (an environmental property) is perceived relative to the individual's leg length (an animal's body property), and when the ratio of each property (stair height/leg length) reaches specific values, qualitative changes occur in the animal's behavioral pattern.

Conversely, within the framework of the DSA, an animal's behavioral pattern at the macro-level of the complex system can be modeled as a motion equation using a control parameter and an order parameter. The order parameter describes the low-dimensional behavior (the system's macroscopic pattern) that emerges from the high-dimensional neuromuscular system (the micro components of the system). The model predicts the behavior of a system comprising numerous mutually interacting components (degrees of freedom) at the micro-level, as the dynamics of a few order parameters. Empirical studies from the viewpoint of the DSA, however, have mainly described behaviors with variables defined by elements of an animal system but not by elements of an animal-environment system.

According to the Ecological approach, we apply the variables defined by elements of an animal-environment system to the DSA framework. In the current presentation, we propose an integrative approach using ecological and dynamical approaches and an empirical framework to examine the validity of our approach and report the preliminary data from our pilot experiments investigating adaptive behaviors in the stepping-over task with regard to how stepping-over behavior changed depending on an obstacle's height. The present study is still in progress. However, if we can reveal the dynamics of stepping-over behavior and the critical point at which the behavior destabilizes, then this knowledge may lead to better understanding of safe obstacle avoidance.

Development of a system to indicate the features of the pole works in Nordic walking

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Nordic walking, or walking with poles, is known as an effective aerobic activity that uses the whole body, including the muscles of not only the lower body but also those of the arms and the upper body. The benefits of Nordic walking are that it can easily be started regardless of the season, and the effect of the exercise is achieved within a short time. Created in Finland, Nordic walking has been increasingly becoming popular in Europe. Recently, Nordic walking has received increased attention from middle-aged people, including those in Japan. Previous studies aimed toward the scientific verification of the benefits of Nordic walking mainly focused on the alleviation of the load on the legs provided by the poles and on the energy consumption. Although a difference in the load on the legs and the energy consumption is expected to occur with technical mastery of the use of the poles, detailed research on this issue has yet to be conducted.

Therefore, we analyzed the techniques of both experts and beginners of Nordic walking to gather basic data about their differences. We developed a system to acquire data by using a three-axis accelerometer attached to the tip and grip of the poles used in Nordic walking. The sensors do not disturb body movements because they have batteries and send data to a PC via wireless connection using ZigBee. We collected and analyzed the data from both experts and beginners by using this system.

One of the results of the analysis indicated that two or more significant peaks existed in the power spectrum of the data of the experts, whereas only one significant peak existed in the power spectrum of the data of the begin- ners. The features identified will be useful indexes to differentiate between experts and beginners.

Using the results, we developed a system to analyze the data and indicate the features during the pole work. The system automatically counts the number of peaks in the power spectrum of the data recorded on the PC during the pole work, and then reports the results by sound indications. It enables the users to check their own present pole work through the indications. We believe that the developed system contributes to research on the relations between the load and the pole work and the improvement in the pole work of beginners.

The instructional support tool for the drawing learning support system for novice learners

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The purpose of this study is to explore a support system for beginners in drawing in a networked environment. Learners can receive advice and assessments from art experts without time and/or place constraints by using the proposed system. In this paper, we describe the drawing process model(DPM) and the instructional support tool using this is proposed.

The major difference between an offline drawing class and an online drawing class is the availability of instruction during learners' drawing. The instruction for the learners' drawing process is more important than instructional comments for his/her work. Therefore, quick and personalized feedback from a tutor is an indispensable function for a networked learning environment. In this study, the learner's drawing process that is recorded by a digital pen is reused to replay and refer his/her drawing process. To generate an evaluation for the drawing process automatically, these data are also reused in the system the authors propose.

The DPM consists of three types of parameters. They are the drawing step, the drawing phase and the features of the drawing strokes. The drawing step is how to draw drawing heard from tutors. The drawing phase consisted of three phases and discovered the phase from expert's drawing process. The features of the drawing strokes are six parameters based on the geometric characteristics on strokes.

Our system is working from 2013 in the art school. The instructor can instruct all the learners' drawing by using our system. However, the instruction of a learner's drawing needs time because a learner's drawing process is played back repeatedly using a drawing process viewer. By analyzing a learner's drawing process using this DPM, and showing results aims at easing instructor's instruction burden.

Keywords:
Art education, Drawing, Digital pen, Drawing process model, Drawing strokes, Drawing phases

Identifying the underlying information in body movement used in Tea Ceremony

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Traditional Tea Ceremony has been thought throughout the years in Japan. It values discipline and aesthetics as some of the most important aspects to acquire. It is learned through observation, imitation and repetition. This means it relies in transferring knowledge from master to student in ways that cannot always be represented by words. Although there is a set of rules and steps to follow in a given ceremony, regardless of the tradition of the performer, it is impossible to say that all practitioners perform in the same way.

There are several differences in the motions of what is supposed to be a set performance. Some of these differences are of order of steps, or simple mistakes that can be easily explained with words. These are in an explicit layer of information. Nevertheless, there are some things that are difficult to put into words and some that are perceived but not consciously. We think they are caused by underlying information in the movements. These layers of embedded information affect the way the performance as a whole is perceived by others. This research focuses on the perceived aesthetic value of the movements of the practitioners. The objective is to identify patterns and key motions that can be associated to beauty and high skill. This is expected to be similar between people of the same skill level and different from groups of people with different expertise.

For the experiment, a group of performers of different study groups will be observed. The group will consist of subjects that will be categorized in three groups depending on their skill level: novice, experimented, master. For each subject, information about the time he or she has been studying, frequency of practice, age, and gender will be recorded. In order to find patterns in the motion skill, subjects will be asked to perform basic staple movements of the Tea Ceremony while using movement sensors attached to their body.

These movements will also be recoded and analyzed with a motion capture array of cameras that will provide another layer of data to consider. These performances will be shown to high-ranked masters that are not part of the pool of subjects. They will be asked to identify the correct movements and the incorrect ones, as well as to give a subjective evaluation on the beauty of the performance. These results will be compared to the patterns obtained from the body sensors and motion capture cameras.