A cognitive developmental scenario of transitional motor primitives acquisition.

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Abstract

Motor primitive is one of the keys for human behavior generation and motor control with enormous degree of freedom of human body. Our purpose in this paper is to present a cognitive developmental scenario of motor primitives acquisition from the interaction between the body and the surrounding environments with cognitive properties of infants. The hypothesized scenario is that (1) infants explore their own body and environments, (2) categorize stable perceptual states extracted from sensory information, (3) memorize transitional movements between the states, and (4) make brief representation of each transitional movement as motor primitive. We have conducted an infant musculoskeletal computer simulation experiment to examine this scenario. Our result is that stable states, which are provided within the body and the environment dynamics, are detected from probability distribution of sensory data with the exploration. Transitional movements are found for the exploration, and brief motor commands are extracted by a statistical analysis. The extracted motor commands can realize the respective movements. We conclude that the scenario is validated from perspective of computational possibility.

1. Introduction

Motor primitive are general representation utilized for multiple purposes in human motor control (Schaal, 2006). The representation should be motor unit that has functionally minimum configuration for motor control. If motor primitives are acquired and represented in general form in a brain, variables for realization of movements are reduced. Therefore, the reduction of variables would provide dramatically decrease of number of the experience for learning. Or, learning would be no longer necessary, because reusing and combining motor primitives provides achievements of motor tasks at once.

The concept of the primitive is similar to "synergy" proposed by Bernstein (Bernstein, 1996). However, motor primitives do not only represent muscle coordination for specific motor tasks, but also be able to be combined for other complicate motor tasks generally.

Some researchers have studied about human motor primitive. Rohrer et al. defined submovements, which are regarded as motor primitives, as segmented trajectory from human arm movements based on a smoothness criterion (Rohrer and Hogan, 2003). Schaal mathematically designed motor primitives as attractors of trajectories, which are used for robotic imitation tasks, based on computational neuroscience (Schaal, 2003). He and his collaborators also conducted a fMRI brain imaging research to investigate what kinds of types are represented in brains as motor primitives (Schaal et al., 2004). According to the research, motor primitives consists of two different types of movement: cyclic movements and discrete (transitional) movements. However, no research has answered what kind of movement should be acquired as motor primitives in human brains, and how to acquire them.

Humans develop through the interactions among a brain, a body and surrounding environments. In particular, the physical interaction between the body and the environment is important for behavior generation (Thelen and Smith, 1994). However, this aspect of development has not been much studied quantitatively. Motor primitives in the brains are probably acquired in the interactions. We have expected that the developmental view provide an insight for the motor primitive acquisition.

Our purpose in this paper is to present a developmental acquisition scenario of transitional motor primitives. The important properties for acquisition of transitional motor primitives are probably exploration (Bly, 1994), categorization (Goswami, 1998), contingency detection (van der Meer et al., 1995) and memorization (Rovee-Collier et al., 1992). The scenario is basically based on the cognitive properties. However, it would be also shown in this paper that body morphology affects the primitives under the scenario.

In the next section, we reviewed developmental researches that studied about infants' cognitive properties, and we also proposed the scenario based on the properties. In the Experiments and analyses, we confirmed computational possibility of the scenario by an infant musculoskeletal model simulations and statistical analyses. The infant model is driven by appropriate motor command generation rule called as Random walk with a drift. The movements of the model are analyzed from a viewpoint of a probabilistic structure in sensory information. By the analyses, we segmented transitional movements, and extract effective muscles for the movements by use of discriminant analysis with Fisher weight maps (Shinohara and Otsu, 2004). Finally, we realized the movements by only extracted muscles.

In the Discussion, we discussed the result and future works on related developmental issues, which are a concept acquisition and construction of developmental neural model.

2. Motor primitive acquisition scenario

2.1 Motor and cognitive properties of infants

2.1.1 Exploration of movement

Infants move constantly while they are awake. Their movements that appear involuntary with chaotic manner are known as General movement (Gentaro Taga and Konishi, 1999). Autonomic movements such as General movement probably contribute to explore the body and the environments dynamics. They should move involuntary to know dynamics of own bodies and an environment for acquisition of motor skills in early development, before infants learn something with their own aim.

2.1.2 Categorization of perception

Infants are attracted to novel situation. For example, when a new toy is presented in front of an infant, s/he gaze the object. But infants gradually lose interest in the toy, as the infant becomes accustomed to it. A term for the former case is dishabituation, and a term for the latter case is habituation. These things are confirmed by various experiments in which novel multimodal stimuli are presented for infants (Goswami, 1998).

These phenomena require an ability of categorization for perception and a preference of novel situations or objects. Therefore, infants should have the ability and the preference. We believe that these natures, in which infants pay attention to changes of environments, contributes not only visual memory, but also motor memory, because of the infatnts' modality general cognitive properties such as habituation.

2.1.3 Contingency detection and memorization

It is observed that 5 months old infants succeed interactions to the surrounding environments. Moreover, they try to keep producing fun activity (Bly, 1994). Therefore, it is probably that infants tend to know connections between their own movements and the reactions, called as "contingency".

Some experiments were composed so as to confirm that infants detect and memorize contingency easily. Van der Meer et al. (van der Meer et al., 1995) observed infants' movements when they watch their own hand via a TV monitor. According to their research, only watched hand's movement occurred even when head direction is counter side of watched hand. This implies that infants detect contingency of own motor command and tend to repeat the movement. It also indicates that infants extract motor commands for the movement because they do not move unwatched hand actively.

Rovee-Collier et al. (Rovee-Collier et al., 1992) discovered that infants memorize contingency with their own movements. When they tied one of infant's legs to a mobile which is attractive toys, they observed that movement of the infant's leg which is tied to the mobile was gradually increasing. A few weeks later, when they composed same experiment, the infant moved the leg earlier than first experiment with same visual configuration such as a baby bed, the mobile and so on.

In both above cases, infants attracted to an object (their own hand or mobile) moving and try to keep it moving. There are two important functions in those cases. The first is ability of detecting contingency. The second is ability of finding changes of surrounding environment. Infants have an ability to find substantial changes in sensory input, which is the same for habituation and dishabituation.

To summarize above experiments and observation, infants explore surrounding environment, categorize perceptual information, detect and memorize own movement for change of the information, and extract necessary motor commands for the movement.

2.2 The acquisition scenario

From above properties, we hypothesize a behavioral developmental scenario of transitional motor primitives acquisition as follows.

1. **Exploration:** Exploring dynamics of own body and surrounding environment.

2. **Categorization:** Detecting unchanged perceptual information.

3. **Memorization of transitional movements:** motor commands for the transitional movement to obtain novel perceptual information.

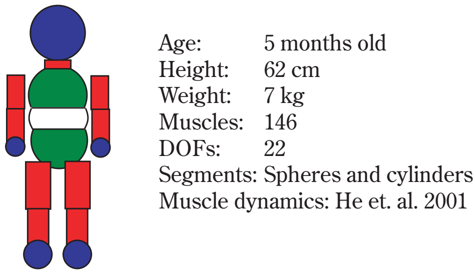


Figure 1: The infant model's body configuration.

4. **Acquisition of motor primitives:** Extracting minimum configuration of motor commands as motor primitives for each movement.

It is expected that an infant's movements are naturally and automatically segmented into useful components useful. the criterion of the acquisition should refer only internally perceptible sensory information within the exploration, because there is none to teach segmentation points in the movements in the brain. The model does not have a clear external criterion for movement segmentation such as smoothness.

In next section, we consider computations which should be solved for the above scenario. These were done using a simulation of the infant musculoskeletal system (Kuniyoshi and Sangawa, 2006). The items in the above list correspond to the following section: Item 1 to section 3.2, item 2 and item 3 to section 3.3 and item 4 to section 3.4, respectively.

3. Experiments and analyses

3.1 The simulation environment

The infant musculoskeletal developmental model used in this research has a head, a body, arms and legs, which are constructed by spheres and cylinders (see (Kuniyoshi and Sangawa, 2006) for details). It has 198 muscles, attached at the head, the body stem, the arms and the legs. Particularly in this research, the neck joint is fixed, and the muscles which are terminated at the head and the body are eliminated, because it must be simulated that an infant's head is held up for data analyses. So available number of muscles is 146 in following experiments. The muscles are modeled by detailed equations which have activation dynamics and mechanical properties depending on muscle length and contraction velocity (He et al., 2001). Input (motor command) for muscle is neural impulses frequency normalized $0-1$.

Based on previous papers including Sun et al. (Sun and Jensen, 1994), the model parameters including lengths, masses, muscle strengths for each parts can be configured by setting a infant's age. The age range in which it can generate plausible parameters is between 0 months old and 12 months old. In following experiments, a 5 months old infant model is simulated. The parameters includes weighting 7.0 [kg] and 62.0 [cm] height.

3.2 The exploration experiment

This experiment is composed to confirm what kind of property motor commands should have, and How the commands influence exploration of body and environment dynamics. In order to achieve sufficient exploration, motor commands must have appropriate signal frequency for inertia of body segments, muscles dynamics and so on. So we designed motor command generation rule that is suitable for the body properties.

The proposed rule is represented by random walk with a drift, by which a motor command randomly change from previous motor command, and gradually decrease to 0. In this research, we have adopted random behavior to focus our investigation on the interaction between a body and an environment straightforward, while infants' movements are observed to be chaotic (Gentaro Taga and Konishi, 1999).

The rule is defined by following equations.

$$P\left(\Delta a_i(t+\Delta t)\right) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{\left(\Delta a_i(t+\Delta t)+B\right)^2}{2\sigma^2}\right) \tag{1}$$

$$a_i(t+\Delta t) = m_i(t) + \Delta a_i(t+\Delta t) \tag{2}$$

$$m_i(t+\Delta t) = \begin{cases} 1.0 & (a_i(t+\Delta t) > 1.0) \\ 0.0 & (a_i(t+\Delta t) < 0.0) \\ a_i(t+\Delta t) & \text{otherwise} \end{cases} \tag{3}$$

Motor command $m_i(t)$ is independent from the commands for the other muscles. Parameters for the rule are Δt, B and σ, which are an interval time of motor command change, a drift parameter, and a magnitude of the motor command change, respectively.

According to computational neuroscience (Wolpert and Ghaharamani, 2000), it is known that motor commands from a brain tend to correlate with recent commands. Minimum torque change criterion (Uno et al., 1989) can explain smooth human natural arm trajectory. Moreover, comparing minimum commanded torque change criterion and minimum muscular tension criterion (Nakano et al., 1999), Neural signals from a central nervous system to a muscle are hard to change. So the above motor command generation rule concerning neural signal is consistent for the computational biological model.

Fig.3 represents motor commands generated by Random walk with a drift (Δt = 20[msec], B = 0.02, σ = 0.1), and fig.4 represents probability distribution of the motor commands. For comparing experiments, another motor command is generated by shuffling the above time series. It does not have time correlation any longer, but the same probability distribution remain to it. Fig.7 represents the result, which implies that the time series changes rapidly.

The simulation results with the 5 months old infant model are represented as probability distribu-

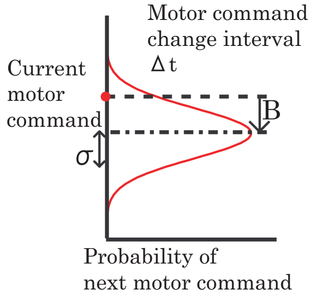


Figure 2: Random walk with a drift. The generation rule has three parameters $(\Delta t, B, \sigma)$.

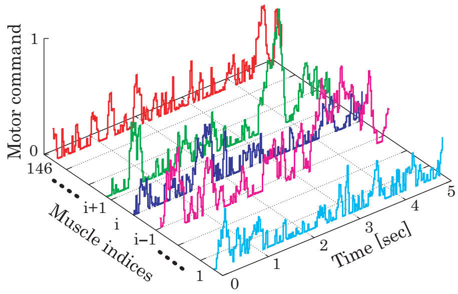


Figure 3: Motor Command sequences (Random walk with a drift, Δt = 20[msec], $B = 0.02, \sigma = 0.1$).

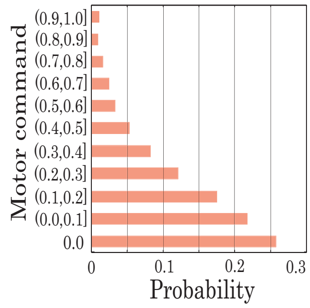


Figure 4: Probability of motor command (Δt = 20[msec], $B = 0.02, \sigma = 0.1$).

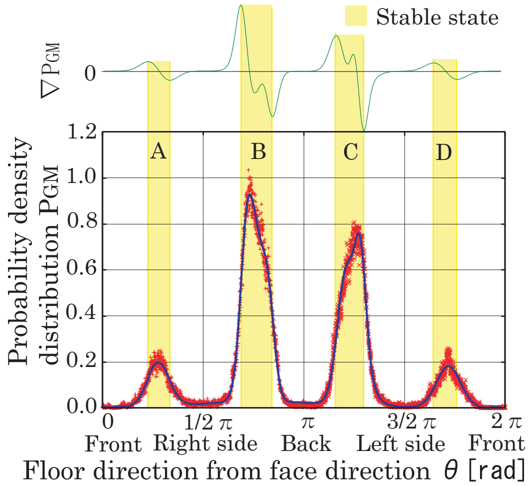
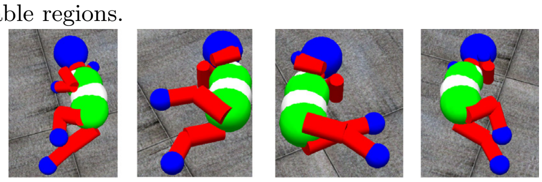


Figure 5: A probability distribution of floor direction from face direction while 5 months old model is driven by Random walk with a drift for 3000 [sec] simulation time. Yellow bands with labels (A, B, C, D) are detected stable regions.



(a) State A (b) State B (c) State C (d) State D

Figure 6: Examples of posture at corresponding stable states.

tion of gravity direction on head. Fig.5 and fig.8 represent the results with the rule and without the rule. The measure is 0 when the face direct to floor. Red points in these figures represent frequency, which is converted to a probability density, of head position divided into 3600 area, and blue lines are approximated distribution by mixture of gaussians. According to these results, the motor commands by Random walk with a drift produce a distribution with several peaks, while the time uncorrelated commands produce a distribution with only one peak. The fact indicates that the time correlated motor command sequence is suitable for exploration.

The peaks are considered as stationary or stable position for the infant's body. From cognitive perspective of view, if infants are in these stable positions, they do not pay attention to the situation. Once they move out of the stable state to another, they tend to memorize the causality of the transition to the subsequent state. Because it is attentional situation for the infants.

Table 1: Numbers of transitional movements. A, B, C and D correspond to the labels in fig.5

AtoB	BtoC	CtoD	DtoA
8	17	5	1
BtoA	**CtoB**	**DtoC**	**AtoD**
10	17	6	1

3.3 Detection of stable states and segmentation of transitional movements

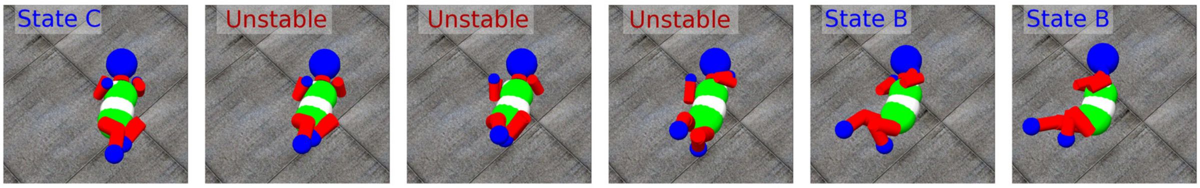
In order to detect the infant's state, the head direction was measured and analyzed. the direction simulates a sense of a three semicircular canal. Moreover, it is regarded as the infant's own gaze. The information from the direction is not completely sufficient to know whole body state, however it can represent almost whole body dynamic movement because of constraint of infant's own body. In this section, stable states are detected by estimating existence probability distribution of head direction and transitional movements are segmented by head direction sequence from one stable state to another.

In order to detect stable states and segment the transitional movement, the following algorithm was used.

1. Approximate probability distribution $P_{MG}(\theta)$ (head direction: $0 \leq \theta < 2\pi$) by mixtures of gaussians distribution by EM algorithm (Number of gaussians is decided by Minimum description length)

2. Find all peaks $\theta_{p,i}$, $(1, \cdots, i, \cdots, N_p)$ of the distribution $(\theta_{p,i} < \theta_{p,i+1})$.

3. Decide boundaries of stable area for i-th peak by



(a) 0.0 sec (b) 0.2 sec (c) 0.4 sec (d) 0.6 sec (e) 0.8 sec (f) 1.0 sec

Figure 9: Extracted rolling over movement (State C to State B).

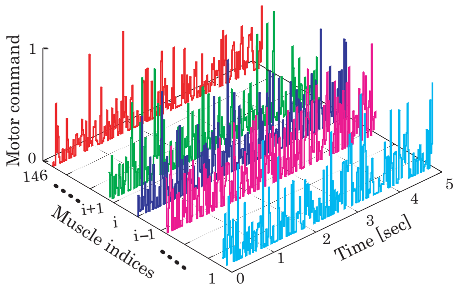


Figure 7: Motor command sequences (No time correlation). Same probability distribution as fig.4.

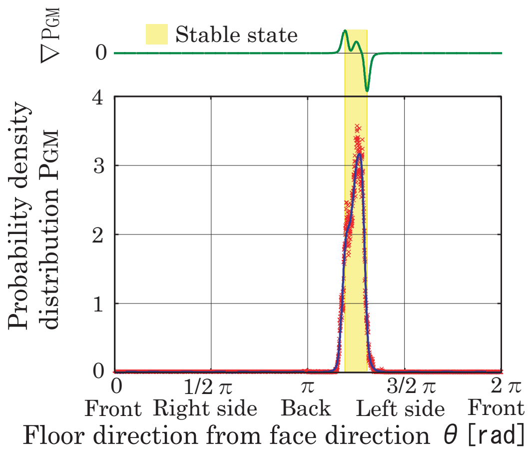


Figure 8: A probability distribution of floor direction from face direction while 5 months old model is driven by no time correlated motor commands for 1000 [sec] simulation time. Only one stable region is detected.

following equation.

$$\theta_{min,i} = \arg\max_{\theta} \nabla P_{MG}(\theta)$$
$$\begin{cases} \theta_{p,N_p} - 2\pi < \theta < \theta_{p,1} & \text{if } i = 1 \\ \theta_{p,i-1} < \theta < \theta_{p,i} & \text{otherwise} \end{cases} \quad (4)$$

$$\theta_{max,i} = \arg\max_{\theta} \nabla P_{MG}(\theta)$$
$$\begin{cases} \theta_{p,N_p} < \theta < \theta_{p,1} + 2\pi & \text{if } i = N_p \\ \theta_{p,i-1} < \theta < \theta_{p,i} & \text{otherwise} \end{cases} \quad (5)$$

$\theta_{min,i}, \theta_{max,i}$ are boundaries of minimum and maximum, respectively.

4. Segment movements for which $\theta(t)$ moves from $\theta_{max,i}$ to $\theta_{min,i \pmod{N_p}+1}$ and $\theta_{min,i}$ to $\theta_{max,(i-2) \pmod{N_p}+1}$.

Detected stable states are displayed as yellow bands in fig.5 and fig.8. According to fig.5, detected

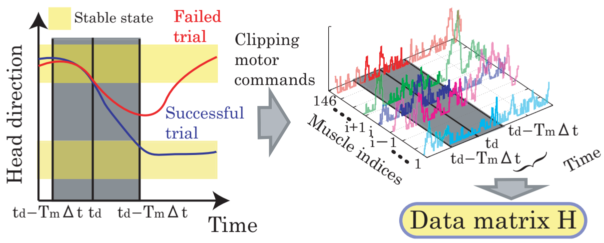


Figure 10: Successful or failed trial as a transitional movement, and definition of data matrix $\boldsymbol{H}$. Movements in which head direction moves from a stable state to another are regarded as successful movement. Movements in which head direction comes back to initial stable state after a deviation from the state are regarded as failed movement.

stable state are four (A, B, C, D) and segmented transitional movement patterns are eight. Fig.6 indicates typical postures on the stable states. Numbers of transitional movements are displayed in table 1. Fig.9 shows one of the extracted transitional movements. The movement, which is automatically segmented, is considered as rolling over movement.

3.4 Acquisition and utilization of motor primitives

In the foregoing section, we have extracted the eight transitional movements (table 1). In this section, six movements (AtoB, BtoA, BtoC, CtoB, CtoD, DtoC) are targets of construction of motor primitives by statistical analyses, because DtoA and AtoD movements occurred only once.

3.4.1 Discriminant analysis with Fisher weight maps

According to the scenario, motor primitives should be a minimum configuration of motor commands for movements. In this section, effective muscles for each transitional movement are detected by 2-class discriminant analysis with Fisher weight maps (Shinohara and Otsu, 2004). This analysis is a operation which transforms an original data to another space suitable for discrimination. In solving the problem, a vector Fisher weight map is derived, and each weight in the map is expected to be useful not only for discrimination, but also for selection of effective muscles for successful transitional movements. Fig.10 shows a definition of successful trial and failed trial and a way to segment motor com-

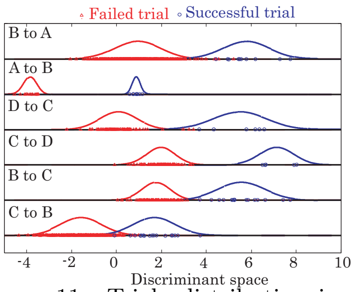


Figure 11: Trials distribution in discriminant space.

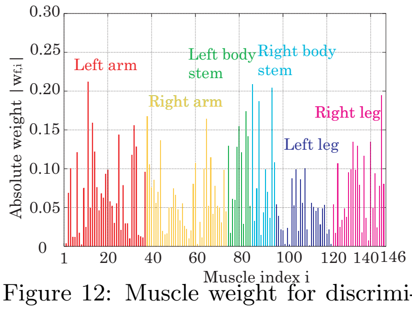


Figure 12: Muscle weight for discrimination(CtoB).

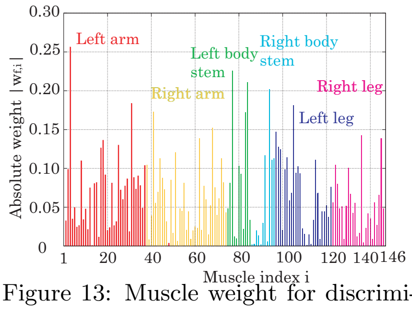


Figure 13: Muscle weight for discrimination(BtoC).

mands for a statistical analysis.

Fisher weight map $\boldsymbol{w}_f$ is defined as

$$\boldsymbol{x} = \boldsymbol{H}^T \boldsymbol{w}_f. \tag{6}$$

$$\boldsymbol{H} = [\boldsymbol{m}(t_d - T_m \Delta t) \dots \boldsymbol{m}(t_d) \dots \boldsymbol{m}(t_d + T_p \Delta t)] \tag{7}$$

represents a data matrix in which motor commands are ordered by time. $\boldsymbol{m}(t)(= [m_1(t), \cdots, m_i(t), \cdots, m_M(t)]^T)$ represents motor commands for muscles. M (=146) is muscle number. t_d is a moment at which head direction deviate from a stable state. T_m (=50) and T_p (=50) are time window, and Δt (=20[msec]) is time interval. $\boldsymbol{x}$ is a feature vector from data matrix $\boldsymbol{H}$ by $\boldsymbol{w}_f$. So $\boldsymbol{w}_f$ transform the data $\boldsymbol{H}$ to suitable feature $\boldsymbol{x}$ for the discriminant analysis. Generally, each element of $\boldsymbol{w}_f$ represents importance of corresponding muscle and scale of data. In this case, it represents purely contribution for a transitional movement, because statistical properties of all element in $\boldsymbol{H}$ are same as Fig. 4. Finally, $\boldsymbol{x}$ is analyzed by common 2-class discriminant analysis to be transformed to discriminant space.

According to (Shinohara and Otsu, 2004), This problem is solved as a maximizing problem of

$$J(\boldsymbol{w}_f) = \frac{\boldsymbol{w}_f^T \boldsymbol{\Sigma}_B \boldsymbol{w}_f}{\boldsymbol{w}_f^T \boldsymbol{\Sigma}_W \boldsymbol{w}_f} \tag{8}$$

with the constraint

$$1 = \boldsymbol{w}_f^T \boldsymbol{\Sigma}_W \boldsymbol{w}_f. \tag{9}$$

$\boldsymbol{\Sigma}_W$ and $\boldsymbol{\Sigma}_B$ are within-class scatter matrix and between-class scatter matrix, respectively.

$$\boldsymbol{\Sigma}_W = \frac{1}{N_s + N_f} \Bigg\{ \sum_{i=1}^{N_s} (\boldsymbol{H}_{s,i} - \bar{\boldsymbol{H}}_s)(\boldsymbol{H}_{s,i} - \bar{\boldsymbol{H}}_s)^T + \sum_{i=1}^{N_f} (\boldsymbol{H}_{f,i} - \bar{\boldsymbol{H}}_f)(\boldsymbol{H}_{f,i} - \bar{\boldsymbol{H}}_f)^T \Bigg\} \tag{10}$$

$$\boldsymbol{\Sigma}_B = \frac{1}{2} \Big\{ (\bar{\boldsymbol{H}}_s - \bar{\boldsymbol{H}})(\bar{\boldsymbol{H}}_s - \bar{\boldsymbol{H}})^T + (\bar{\boldsymbol{H}}_f - \bar{\boldsymbol{H}})(\bar{\boldsymbol{H}}_f - \bar{\boldsymbol{H}})^T \Big\} \tag{11}$$

$\boldsymbol{H}_{s,i}$ are data matrices in cases that head direction reach to another stable state from original state, and $\boldsymbol{H}_{f,i}$ are data matrices in cases that head direction go back into original stable state eq. (10). N_s and N_f are successful and failed trial number, respectively. $\bar{\boldsymbol{H}}$, $\bar{\boldsymbol{H}}_s$, and $\bar{\boldsymbol{H}}_f$ are averages of whole $\boldsymbol{H}$, $\boldsymbol{H}_s$, and $\boldsymbol{H}_f$ for each transitional movement, respectively.

The maximizing problem can be solved as a generalized eigenvalue problem

$$\boldsymbol{\Sigma}_B \boldsymbol{w}_f = \lambda \boldsymbol{\Sigma}_W \boldsymbol{w}_f. \tag{12}$$

In the solution, $\boldsymbol{w}_f$ is a eigenvector that has maximum eigenvalue.

After solving $\boldsymbol{w}_f$, the 2-class discriminant analysis is solved with transformed data $\boldsymbol{x}$ with the fisher weight map. Fig.11 shows that distributions of successful and failed trial in discriminant space are clearly separated each other. The most distant motor commands from average of failed trials in the discriminant space are adopted as a set of motor commands to acquire motor primitives for each movement, because they are regarded as the most successful trials for the movement patterns.

Fig.12 and Fig.13 show fisher weight maps for BtoC and CtoB movements, which indicate that there are muscles which have high contributions and low contributions. So unnecessary muscles for each movements can be eliminated.

3.4.2 Extraction of motor commands and realization of movement by motor primitives

Here we define accumulated contribution

$$C_p = \frac{\sum_{i=1}^{p} w_{f,i}}{\sum_{i=1}^{M} w_{f,i}}, \quad w_{f,i} > w_{f,i+1}. \tag{13}$$

$w_{f,i}$ are elements of $\boldsymbol{w}_f$ in descending order. p is rank-order. The accumulated contribution is a value not only for discrimination, but also movement generation without muscles that have low weight $w_{f,i}$ $(p < i)$. Fig.14 implies muscle number in the cases that muscles are reduced for each movement by each accumulated contribution. According to the result, 90 % accumulated contribution needs about 65 % muscles in all movements.

If the set of motor commands with the remaining muscles realizes corresponding movement, we consider the set as one of motor primitives. Fig.15

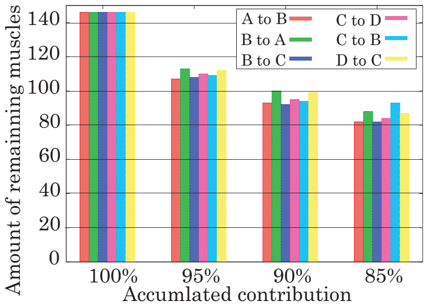


Figure 14: Amount of remaining muscles.

shows head direction time series when two motor primitives (CtoB and BtoC) are combined. Input to muscles that are not included in the sets are average motor command of fig.4 (=0.18). In the 90 % accumulated contribution case, motor primitives generate the transitional movements similarly to the movements by original motor commands. But, in 85 % accumulated contribution motor commands, they are not realized.

Finally, we tried to realize six motor primitives (fig.16). All pattern are realized by original motor primitives, but by 95 % contributed motor primitives, some of the movements are not realized.

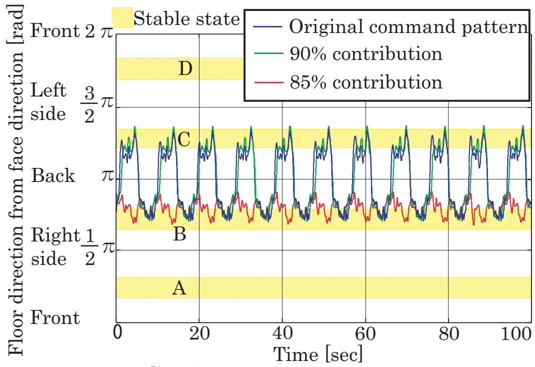


Figure 15: Combining two motor primitives.

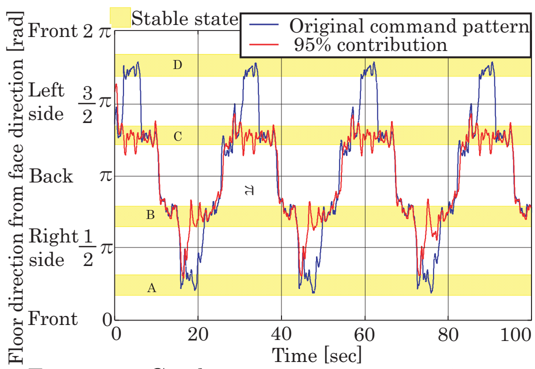


Figure 16: Combining six motor primitives.

4. Discussion

In this research, we studied how infants acquire motor primitives. We have showed that motor primitives like rolling over can be obtained in an information structure through a physical interaction between the infant's body and the environment with cognitive properties of infants. the scenario seems to be useful not only for rolling over, but also for more delicate movement such as pick-and-place movement. For realization of such kind of movement, goal-drected exploration and stabilization mechanism should be embedded in the acquisition system.

The scenario does not include an explicit representation of utilization of morphological properties of infants. However, the result is clearly affected from the infant model's own body morphology used here. The probability distribution of head direction (fig.5) depends on a shape of the model's body trunk: spheres different from real infant's shape (fig.1). Moreover, it is not necessary that the infant model is located at exact the same body status physically so that extracted motor command sequences are able to achieve the respective movements. This is because there is a constraint by body morphology to move. The result suggests that real infants exploit their own body morphology to acquire motor primitives. The morphology of infant body, called as embodiment, likely affects every level of development.

Technically, some movements are not realized by reduced motor command sets in section 3.4.2. This is likely because the motor commands sets were based on the most successful trials, but not improved for the movements. As the future work, we plan to make a sufficient statistical analysis and a learning algorithm to execute motor control robustly. Another problem is that the all analyses here were performed without reference to time. So we will develop an algorithm which is able to take time development into account.

Babies develop social and motor skills through exploring and interacting with the surrounding environment through their own bodies (von Hofsten, 2007). They also acquire concepts within a cycle process of behavior and perception (Thelen and Smith, 1994). A recent physiological research found mirror neuron system (Rizzolatti and Arbib, 1998). A mirror neuron in one's brain fires when s/he executes a motor task like object handling. Moreover, the neuron fires when s/he observes the same movement. The important point is that the neuron does not respond to details of movements but to a movement class. This does not only provide an evidence for motor primitives in brains, but also provides a new view for acquisition of concept and language, because it is found in broca's area. Motor primitive acquisition and concept and language acquisition can be described as common in the sense of segmenting the world and combining the segments in a consistent manner. We believe that the motor primitives acquisition scenario in this paper contributes to investigate the common system acquisition through human development.

We are interested in how the neurological system in humans can acquire and utilize motor primitives. A developmental neural model of the scenario in this paper must be constructed for understanding human development. First, we have to investigate a computational brain model with body development with reference to time for the scenario. Second, it is necessary to construct a neural network model which is equivalent to above the computational model. Finally, an integrated model for motor control and language has to be proposed for an aim of understanding higher brain function.

5. Conclusion

Our research have showed one of the acquisition scenarios along human development. The motor command sets considered as motor primitives were extracted by statistical analysis. The analysis are probably enough for our purpose, so almost all movements can be achieved by the motor primitives while few movements cannot be achieved.

This paper is still beginning of elucidation of motor primitives. We believe that a perspective of development plays a important role to reveal the secret.

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