

Uterine environment guides organization of somatosensory area: a computational approach

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I. INTRODUCTION

Converging developmental studies have emphasized the significance experience within the uterine environment from as early as the fetal period for motor and cognitive development [1]. Notably, these studies have emphasized the importance of sensory feedback due to spontaneous movements for early development. It is therefore important to reveal how the fetus' interaction with the uterine environment guides its development in order to deepen our understanding of the underlying mechanisms for development.

Among all sensory experiences within the uterine environment, the somatosensory modality plays a central role in early development. In fact, this modality starts functioning over the whole body from as early as the 17th gestational age, before other sensory modalities [2].

Several researchers have suggested the importance of sensory stimulation generated by spontaneous fetal movements for the formation of the body map in the primary somatosensory area (S1) [3]. However, there are few studies on the mechanisms of how the S1 map is generated and what components shape its organization.

In this paper, we argue that uterine environment contributes to the guidance of the formation of somatosensory representations. We investigated the relationship between the uterine environment and the organization of S1 shaped by sensory information gathered via interaction with the environment.

II. MATERIALS AND METHODS

We ran computer simulations of human fetus models within and outside uterine environment. This fetus model have biologically plausible musculoskeletal bodies, a spinal neural network and a primary somatosensory area.

A. Body Model and Environment Model

We used human fetus models, which undergo 30 gestational weeks [4] [5] (Fig.1). The model had parameters based on actual fetus data such as size, mass, moment of inertia of each body part, joint angle limits, muscle configuration and force. The human fetus models had 198 muscles in the whole body excluding the finger and face muscles, and 1500 tactile sensor cells, whose distribution was based on human two point discrimination (Fig.1B, Table.I). To simulate tactile sensation, we used the Merkel cell model. Merkel cells are mechanoreceptors which mainly detect continuous pressure. The Merkel

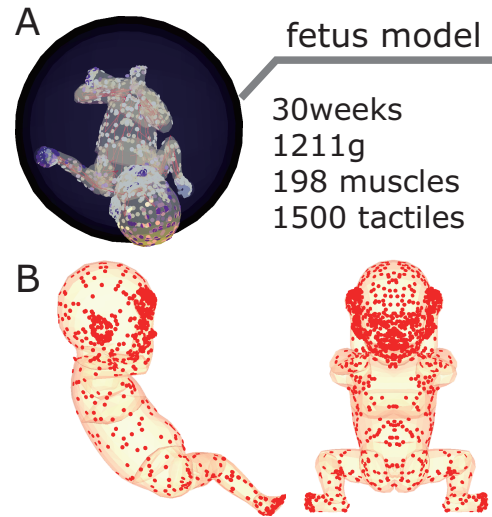


Fig. 1. Fetus model overview. (A) Fetus model appearance and fetus data. Blue circle represents uterus and white and red circles represent tactile sensors. Red one is responding tactile. (B) Tactile distribution on the fetus model.

TABLE I
THE DISTRIBUTUION OF TACTILE SENSORS ON THE
FETUS MODEL'S LEFT SIDE.

head	neck	shoulder	upper arm	lower arm
377	7	14	16	14

hand	chest	stomach	hip	thigh	calf	foot
132	34	48	22	24	15	47

cell model used in this simulation detected continuous pressure by low-pass filtering the pressure input (< 50 Hz) [6].

Inside the uterus, pressure inputs to the fetus come from its embryonic and fetal environments. We used the amniotic fluid and uterine wall models produced by Mori and Kuniyoshi [4]. In our simulations, pressure inputs could be due to (1) physical contact, (2) the uterine wall, and (3) amniotic fluid resistance. Pressure due to physical contact between body parts was distributed according to the tactile sensors distance from the colliding body part. Pressure due to the uterine membrane depends on the sensor's distance from the center of the uterus and as well as its orientation. Pressure due to amniotic fluid resistance is calculated by taking the inner product of the velocity of the body part and directional unit vector of the tactile sensor. Outside the uterus, the fetus model was only

subject to pressure due to physical contact between body parts and the ground.

B. Motion Generation Model

The neural basis for fetal spontaneous whole-body movements is believed to be Central Pattern Generators (CPGs), which are circuits mediating rhythmic behaviors such as walking and swimming in the spinal cord or brain stem [7]. We employed the spinobulbar model developed by Kuniyoshi and Sangawa [8], which includes a CPG model for generating various whole-body movements. This model receives muscle length and tension as sensory input, and outputs the degree of muscle activation as motor command.

C. Somatosensory Area Model

S1 has a somatotopic representation of the body, which largely presents the spatial organization of body parts [9]. Similar cortical representations are observed in other primary sensory areas such as the primary auditory cortex (A1) and the primary visual cortex (V1). Recently, Terashima and Okada suggested that A1 and V1 cortical representations can be explained by the common neural network model [10]. We applied the neural network model, Topographic Independent Component Analysis (TICA), to simulate the organization of the somatosensory map [11].

TICA takes the sensory inputs from tactile sensors and not only extracts the independent components using Independent Components Analysis (ICA), but also constructs a two-dimensional map in such a way that adjacent elements in the map have similar sensory representations. In other words, TICA is a variant of ICA in which the output is a sparse and topographically organized representation of the sensory inputs. To construct a two-dimensional map of m elements, an independent components vector $\mathbf{s}_t = [s_{1t}, \dots, s_{jt}, \dots, s_{mt}]^T$ is calculated as

$$\mathbf{s}_t = \mathbf{W} \mathbf{x}_t, \quad (1)$$

where \mathbf{x}_t is the vector of sensory inputs from tactile sensors, and \mathbf{W} is the weight matrix. The weight matrix $\mathbf{W} = [\mathbf{w}_1, \dots, \mathbf{w}_m]^T$ is estimated using the gradient method, which maximizes the likelihood function L for the observed time series of tactile information \mathbf{x}_t . The likelihood function L is formulated as follows:

$$c_{it} = \sum_j h(i, j) s_{jt}^2, \quad (2)$$

$$\log L(\mathbf{x}_1, \dots, \mathbf{x}_n; \mathbf{w}_1, \dots, \mathbf{w}_m) = \sum_{t=1}^n \sum_{i=1}^m G(c_{it}), \quad (3)$$

where $h(i, j)$ is binary filter function for selecting the elements that neighbor i -th components on topography. This filter makes sure that adjacent elements in the final map have similar weight vectors, allowing the map to have a topographical organization. $G(c_{it})$ denotes the probability density function of c_{it} , which we defined as:

$$G(c_{it}) = \log p(c_{it}) = -\sqrt{0.005 + c_{it}}. \quad (4)$$

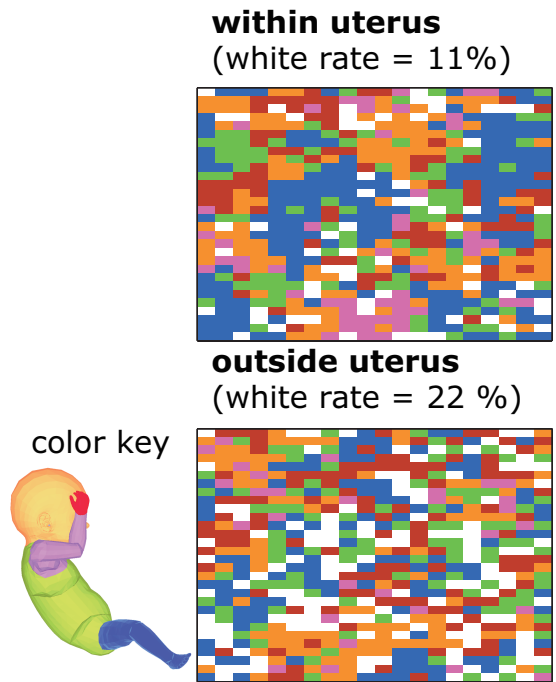


Fig. 2. Learned S1 maps. Colors represent each body parts, and white color represents somatosensory components which could not be categorized into any specific body part.

By defining the probability density function in the above fashion allowed the resulting map to be sparse. In this experiment, the dimensions of the resulting two-dimensional topographical map 30×20 elements ($m = 600$). The map had a torus configuration (opposite edges were connected) to avoid border effects.

III. EXPERIMENTS

In order to investigate relationship between the uterine environment and organization of the S1 model, we conducted fetus simulations within and outside the uterus, and then built S1 maps as defined by tactile sensory information. Therefore, we set the time step of the simulation to 1 ms, and ran the simulation for 500 s. As for tactile sensors, we used the left-side of the body. We analyzed (1) whether each component in the S1 model represent specific five body parts: head, arm, hand, torso, leg and (2) whether the S1 map is organized so that adjacent components represent the neighboring body part.

First, we determined which body part was represented by each tactile component in S1 (Fig.2). If more than half of the strongest inputs to a given tactile sensor came from one specific body part, it was categorized as being dominantly represented by that body part. We calculated the percentage of components which could not be categorized into any specific body parts ("white rate" in Fig. 2). The percentages were 11% and 22% within and outside the uterus, respectively. Figure 3 shows the array of tactile sensors contributing to the body parts represented in S1. We confirmed that these sensors tended to be spatially localized to their respective body parts.

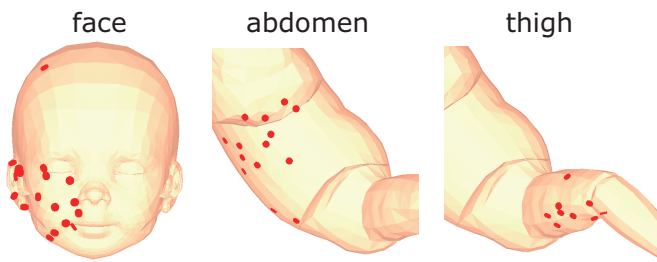


Fig. 3. Examples of cortical representation in S1. Red circle is a tactile cell, which strongly inputs one component in S1 map.

Second, to evaluate the degree of topography in S1, we investigated the degree of clustering in S1. The number of tactile components which had neighboring components also categorized into the same body part were summed. Results showed a significant increase in the number of clustered components in S1 maps created within rather than outside the uterus. The results showed that such area within uterine environment significantly increased compared with those outside uterus (Mann-Whitney test, $p < 0.005$).

IV. CONCLUSION

Animals are dynamically coupled to their environments, with environment shaping the structure of sensory input, and sensory information determining neural dynamics. In this paper, we argue that interaction structured by the environment can guide the formation of somatosensory representations in human fetuses. To test our hypothesis, we conducted computer simulations using fetus model and compared the organization of such representations within and outside uterine environment. We found that S1 within the uterus had two times the number of localized body representations than outside the uterus. Furthermore, the fetus within the uterus is significantly larger than outside the uterus in terms of somatotopic organization. Our results suggest that uterine environment possesses rich regularities that structure tactile information and guide the organization of the S1 body map.

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