Spatio-temporal Semantic Map for Acquiring and Retargeting Knowledge on Everyday Life Behavior

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Abstract. Ubiquitous sensing technology and statistical modeling technology are making it possible to conduct scientific research on our everyday lives. These technologies enable us to quantitatively observe and record everyday life phenomena and thus acquire reusable knowledge from the large-scale sensory data. This paper proposes a "Spatio-temporal Semantic (STS) Mapping System," which is a general framework for modeling human behavior in an everyday life environment. The STS mapping system consists of a wearable sensor for spatially and temporally measuring human behavior in an everyday setting together with Bayesian network modeling software to acquire and retarget the gathered knowledge on human behavior. We consider this STS mapping system from both the theoretical and practical viewpoints. The theoretical framework describes a behavioral model in terms of a random field or as a point process in spatial statistics. The practical aspect of this paper is concerned with a case study in which the proposed system is used to create a new type of playground equipment design that is safer for children, in order to demonstrate the practical effectiveness of the system. In this case study, we studied children's behavior using a wireless wearable location-electromyography sensor that was developed by the authors, and then a behavioral model was constructed from the measured data. The case study shows that everyday life science can be used to improve product designs by measuring and modeling the way it is used.

1 Introduction

Scientists and engineers have a limited understanding of the dynamics and properties of everyday life despite its familiarity. Although standard models in scientific fields such as quantum theory and cosmology exist to explain and generate most phenomena, nothing yet exists that might represent a standard model of everyday life. Modeling everyday life requires representing it by quantitatively observing it and constructing a model from a large-scale amount of observed data. The recent development of ubiquitous sensing technology, which enables

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the observation of physical phenomena in total living space, and statistical modeling technology, which enables the construction of a model from the observed data, will open the way for the field of *science and technology of everyday life.*

An everyday life model should be considered a "reusable model" from the viewpoint of practicality as well as science, to represent the apparent phenomena in human behavior, but also to explain the underlying semantic causality among behaviors, the environment, situations, and conditions. Even if the situations and conditions are different from those for which the model was created, the model can be reused under different situations and conditions if they can be abstracted in terms of the same semantic structure. In this paper, a reusable model indicates that we can re-use the causal model to simulate human behavior under such differing situations and conditions.

This paper focuses on everyday life behavior for the following reasons. First, wearable sensors [1] and location sensors [2] are available to help quantitatively and spatio-temporally describe everyday life phenomena. Just as the Global Positioning System (GPS) [3] and the Geographical Information System (GIS) [4] software packages are useful for representing the spatial information for given positions worldwide, these ubiquitous sensing technologies will result in the proliferation of spatio-temporally indexed data sets that can be obtained from everyday life settings. These data sets can be used for assisting with the application of science and technology in studying everyday situations.

Second, statistics customized for use with spatial data, referred to as spatial statistics [5,6], have recently been developed for analyzing spatial data. Although our aim is to model a semantic structure that underlies a spatio-temporal phenomena rather than a spatial or spatio-temporal structure, we can take advantage of the spatial statistics approach as a starting point. However, we need to expand spatial statistics to acquire the reusable semantic knowledge from everyday life data that are spatio-temporally indexed. Fortunately, another statistical modeling technology has become available for acquiring reusable semantic knowledge from a large amount of data. In particular, a Bayesian network method can be used to create a realistic model [7] and therefore, it can be used for bridging the gap between a spatio-temporal data space and a semantic state space.

Finally, the use of science and technology for studying the behavior of people in everyday life is urgently required in our society. By better understanding everyday life behavior, we can better improve the quality of life. For example, as children develop their behavioral capabilities in everyday life, their rate of injury incidence rapidly increases. After a child learns to walk at around one year of age, the primary cause of death is surprisingly not illness, but injury [8]. In 2006, the World Health Organization (WHO) announced their ten-year action plan for child injury prevention [9]. Children behavior science is applicable to preventing childhood injury. Our research group has been working on childhood injury prevention [10].

This paper addresses the problem of creating a semantic model from the behavior of people in everyday life from spatio-temporally indexed data. We propose a "Spatio-temporal Semantic (STS) Mapping System", which is the general

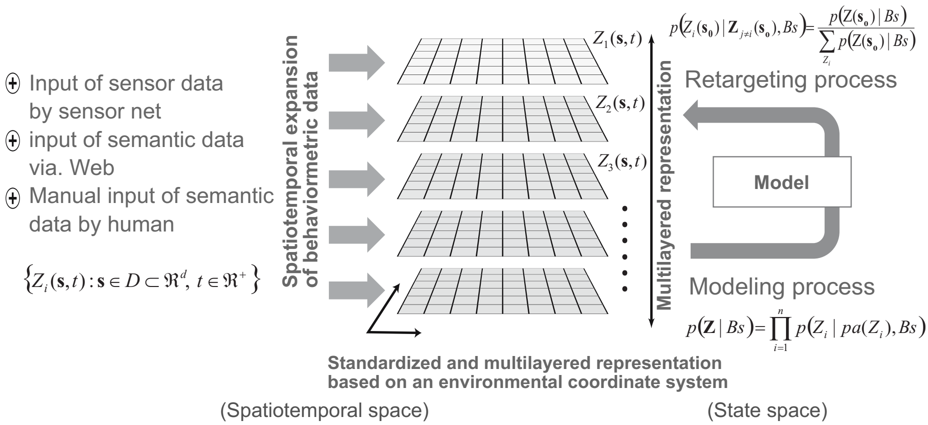

Fig. 1. Concept of spatiotemporal-semantic mapping system

framework for modeling human behavior in an everyday environment. The STS mapping system consists of a wearable sensor for spatially and temporally measuring human behavior, together with Bayesian network modeling software to acquire and retarget the gathered knowledge on human behavior. This paper also presents a case study for applying the proposed system to the development of a new playground equipment design that is safer for children, in order to show the practical effectiveness of the system. In this case study, in situ observations and measurements were made of 47 children playing with or on equipment using a wireless wearable location-electromyography sensor that was developed by the authors, and then a children's behavior model was constructed from the measured data.

2 Spatio-temporal Semantic Mapping System

2.1 Concept of STS Mapping System

Modeling human behavior, in order to develop a reusable causality model based on the behavior, environment, situations and conditions, can be divided into two components: representation of the scenario and the knowledge acquisition process.

We will begin by discussing the representation. Our environment consists of objects spatially distributed in an everyday life space. Humans exhibit a variety of behaviors by interacting with such spatially distributed objects. Therefore, the way a person behaves in their everyday life can be represented in an environmental coordinate system. A geographical information system (GIS) is well known as a representation system for describing a wide variety of information based on an environmental coordinate system. We utilize a similar representation: we standardize and structuralize human behavior in terms of a multilayered information structure by tagging them with environmental coordinates.

Next, we will discuss the knowledge acquisition process. In order to gather information on the behaviors and retarget the acquired knowledge to a new environment, we have to abstractly represent the data by expressing them in terms of a semantic state space, and then find stable structures in this space. Using a statistical modeling method can help us do this. The Bayesian network paradigm is well known as a method for developing a graphical model for a semantic state space. We utilize a Bayesian network for the knowledge acquisition.

Figure 1 presents our proposed concept for a Spatio-temporal Semantic (STS) mapping system. The STS mapping system consists of the following components: 1) a spatio-temporal extension of the behaviormetric sensor integrated with a non-location behaviormetric sensor and a location sensor, 2) a standardized and multilayered representation of information based on an environmental coordinate system, and 3) a statistical modeling process for knowledge acquisition from the represented information, and a retargeting process.

We can express the sensory data in a standardized and multilayered way, extract the knowledge using the modeling process, and then apply the extracted knowledge to a new target by using this STS mapping system.

2.2 Formulation of Behavior Phenomena in STS Mapping System

In this section we will describe the formulation of behavior phenomena in the STS mapping system. We view the observed behavior attributes as realizations from a kind of random field referred to as a spatial point process in which random variables have a kind of structure in a state space. We express the spatial point process by

$$\mathbf{Z} = \left\{ Z_i(\mathbf{s}, t) : \mathbf{s} \in D \subset \Re^d, t \in \Re^+ \right\}, \tag{1}$$

where $Z_i(\mathbf{s}, t)$ denotes the i-th attribute at location $\mathbf{s}$ at time t, D denotes a region of interest, and typically $d = 2$ or 3 and $\mathbf{s} = [x, y]'$ or $[x, y, z]'$ if we are dealing with two- or three-dimensional space.

For example, the data obtained by an ultrasonic location sensor, which is a kind of GPS, is composed of three-dimensional spatial data and temporal data. So it can be expressed by

$$\mathbf{E} = \left\{ E_i(\mathbf{s}, t) : \mathbf{s} \in D \subset \Re^d, t \in \Re^+ \right\}, \tag{2}$$

where $E_i(\mathbf{s}, t)$ denotes the occurrence of an event at location $\mathbf{s}$ at time t. Then E_i normally equals a constant 1 for all $\mathbf{s}$ and t. On the other hand, the data obtained by non-location sensors, such as a wearable electromyography (EMG) sensor, can be expressed by

$$\mathbf{Z} = \left\{ Z_i(t) : t \in \Re^+ \right\}. \tag{3}$$

By integrating the system with a location sensor expressed by Eq. (2) with a non-location sensor expressed by Eq. (3) and simultaneously measuring both data, we can obtain spatiotemporal attribute data expressed by Eq. (1). Thus we can expand the non-location sensor to a spatiotemporal attribute sensor by combining it with the location sensor. We call this integration a *spatio-temporal extension*. An example of a spatio-temporal extension of the wearable (EMG) sensor is described in detail in the next section.

There is another type of data expressed by

$$\mathbf{Z} = \left\{ Z_i(s) : \mathbf{s} \in D \subset \Re^d \right\}. \tag{4}$$

For example, this type of data can be obtained by using a three-dimensional scanner (e.g., a laser range finder equipped with stereo vision) and an environmental map (e.g., a map created by an autonomous robot system using a Simultaneous Localization And Mapping (SLAM) method [11]). If the data is stationary in terms of time, we can view it as data expressed by Eq. (1). For example, the shape data of a building can be seen as stationary in terms of time.

We can utilize a Bayesian network to create a model of causality among the observed attributes expressed by Eq. (1). The Bayesian network model is useful for not only developing the model by combining the observed data and external knowledge, but also for inferring and predicting behavior with novel targets. We can create a cross tabulation table by normalizing and quantizing the data set (Eq. 1). We can construct a Bayesian network model from this cross tabulation, utilizing several software packages for this purpose (e.g., BAYONET [12]). The Bayesian network model constructed from Eq. (1) can be expressed as a joint distribution in a state space $\mathbf{Z}$ by

$$p\left(\mathbf{Z}|Bs\right) = \prod_{i=1}^{n} p\left(Z_i|pa(Z_i), Bs\right), \tag{5}$$

where Bs denotes a probabilistic structure for the Bayesian network, $pa(Z_i)$ denotes a parent of Z_i, and n is the number of attributes. We can infer and predict desired attributes by using Eq. (5). For example, we can predict the desired attributes for one layer Z_d, given the others at location $\mathbf{s_0}$, using

$$p\left(Z_d(\mathbf{s_0})|\mathbf{Z}_{i\neq d}(\mathbf{s_o}), Bs\right) = \frac{p\left(\mathbf{Z}_i(\mathbf{s_o})|Bs\right)}{\sum_{Z_{i=d}} p\left(\mathbf{Z}_i(\mathbf{s_o})|Bs\right)}. \tag{6}$$

2.3 Advantages of STS Mapping System

The advantages of the STS mapping system are as follows: 1) both an expert and a layperson can see the relations among the behavior and environment, because most people are familiar with the representations based on an environmental coordinate system. 2) It is easy to integrate the sensory data and other data when these data are standardized by representations based on an environmental coordinate system. 3) It is possible to extract knowledge by using a modeling process and then applying this knowledge to a new target. 4) It is easy to intuitively confirm the results of the modeling and the retargeting by visualizing the results in an environmental coordinate system.

3 Application of STS Mapping System: Modeling Children's Behavior and Using Model to Design a New Product

3.1 Overview of Implemented STS Mapping System

We implemented the proposed STS mapping system to model children's behavior while playing on playground equipment. The realized system consisted of a wireless wearable location-EMG (L-EMG) sensor for conducting in situ observations and measurements of children playing, a system for representing the measured data based on an environmental coordinate system, and a Bayesian network for modeling and retargeting. Figure 2 shows the implemented system and the process flow. The details are described below.

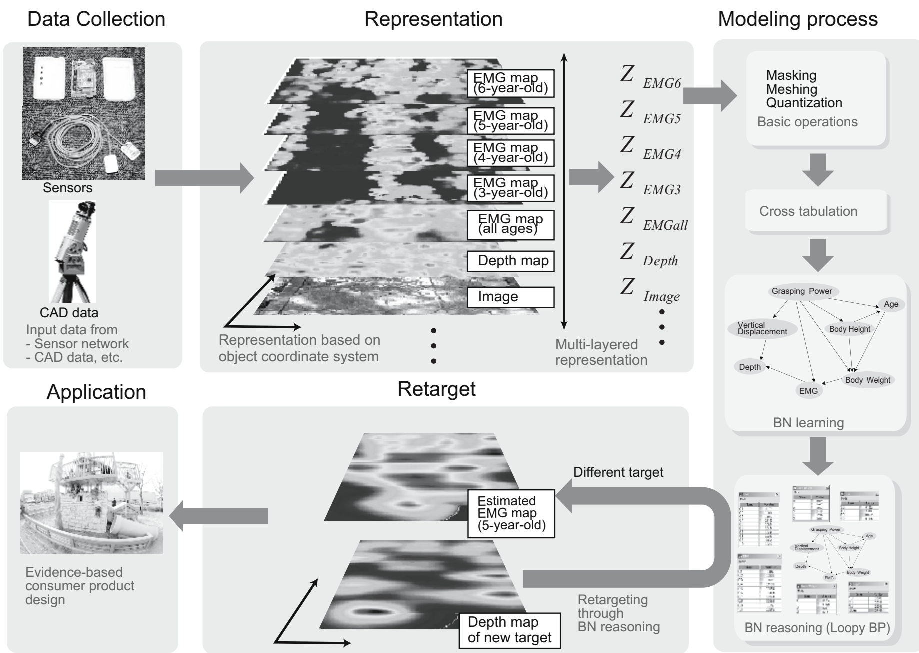

Fig. 2. Spatio-temporal semantic mapping system

3.2 Step 1: Spatio-temporal Extension of Child Behavior Measurement with Wearable Location-EMG

Development of Wearable EMG Sensor. We have developed a wearable EMG sensor to be used as a behaviormetric sensor for measuring children's physiological state [13,14]. We use the EMG sensor to measure the behavior of children for the following reasons. 1) Robustness: We can robustly obtain sensor signals related to the playing behavior because the EMG sensor can measure muscle activity. 2) Versatility: It is possible to use it to record other behavioral data; for example, it can be used to measure the electrooculogram (EOG) by placing it in a different position. The developed wireless type of EMG sensor has the following advantages. 1) The children's behavior is not disturbed because it was wearable. The measurement data was directly preserved in a personal computer (PC) via wireless communication. 2) As a result, we are able to secure sufficient storage capacity for long durational EMG measurement. 3) We developed an active electrode system that amplified the EMG signal near an electrode. We were able to begin quickly measuring EMG data because the active electrode could be easily attached to the body using an armband.

Spatio-temporal Extension of Wearable EMG Sensing. We have combined a wearable EMG sensor and an ultrasonic location sensor that was also developed by the authors [15] for spatio-temporal extension of the data from the wearable EMG sensor. This has enabled us to obtain EMG data that are spatio-temporally indexed. The ultrasonic location system consists of ultrasonic receivers, ultrasonic tags with a transmitter, and a radio controller. By attaching the ultrasonic tag to a child, we can detect and record the three-dimensional position data of the child. The ultrasonic location system can track the positions of the child within an error of 3 cm.

Observing Playing Children by Utilizing Location-EMG Sensor. We collected spatio-temporally indexed EMG data by measuring the children's playing behavior using the developed location-EMG (L-EMG) sensor in cooperation with the Kawawa nursery. Specifically, we measured children's behavior as they were climbing a stone wall, as shown in the picture on the left in Fig. 3. The L-EMG system consists of a section for recording a video image from a USB camera, a section for recording the three-dimensional position data from the ultrasonic location system, and a section for recording the EMG data. Thus, the three-dimensional position data, the video image, and the EMG signal are simultaneously measured using the L-EMG system.

The details concerning the experimental procedures are as follows. First, the electrodes were attached to the flexor digitorum superficialis muscle and the extensor digitorum of the right forearm of 47 toddlers (6 three-year-olds, 17 four-year-olds, 14 five-year-olds, and 10 six-year-olds) in the Kawawa nursery. Second, we prepared a sensor jacket in which the ultrasonic tag and the EMG sensor were embedded. Using the sensor jacket, the sensors could be easily attached to the body. The picture on the right in Fig. 3 shows a child wearing the sensor jacket and the one in the middle shows a snapshot of the data recorded by the L-EMG system software.

3.3 Step 2: Representing Spatio-temporal EMG Data and Spatial Depth Data from Stone Wall Using STS Mapping System

The EMG data measured by the L-EMG system was spatio-temporally indexed. The measured EMG data can be visualized in the stone wall coordinate system by

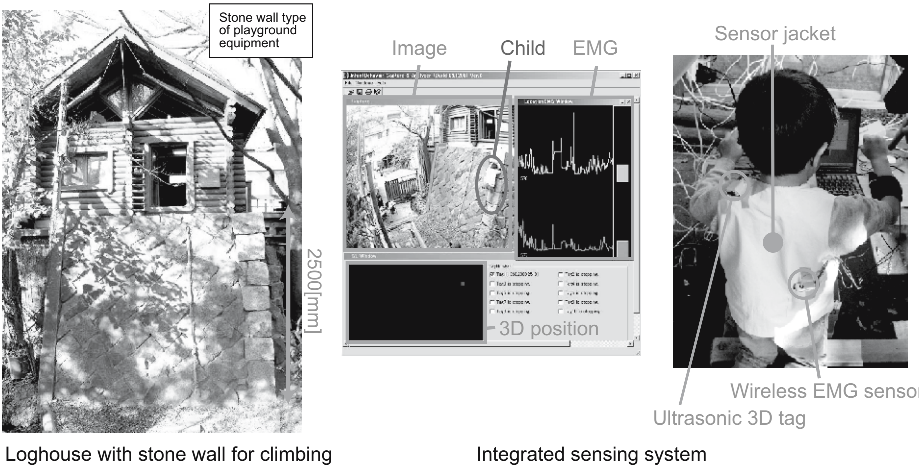

Fig. 3. Stone wall type of playground equipment

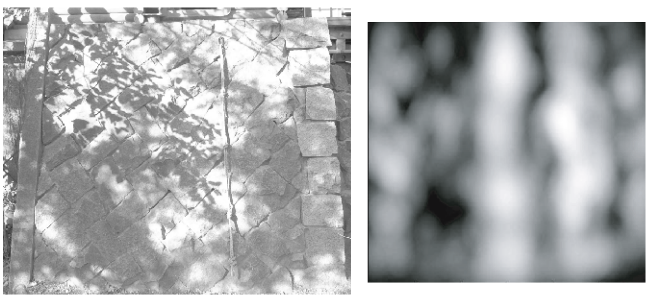

Fig. 4. EMG map that visualizes Location-EMG data

being input into the STS mapping system. Figure 4 shows an example of the measured EMG data visualized with respect to the stone wall coordinate system. This EMG map was made from the EMG data measured for all subjects aged between three and six years old. The parts in red indicate that a significant amount of muscle power was used. This figure helped us to confirm that the upper part of the wall required a significant amount of muscle power, which showed that it was difficult to climb the stone wall. We also measured the three-dimensional shape data of the stone wall using a laser scanner. We were also able to obtain the spatial data on the depth distribution using the measured shape data.

3.4 Step 3: Creating Bayesian Network Model

We conducted a mesh division for the EMG data, the depth map data, and the other data in the stone wall coordinate system. After normalizing and quantizing the mesh data, a cross tabulation table was constructed. The items in the table included the following attributes; age, weight, height, intensity of EMG, maximum grasping power, vertical displacement in playing, and depth of each block in the stone wall. The data sets that we obtained were expressed in terms of

$$
\begin{array}{ll}
Z_1(\mathbf{s},t) = Age(x,y,t), & Z_2(\mathbf{s},t) = BodyWeight(x,y,t), \\
Z_3(\mathbf{s},t) = BodyHeight(x,y,t), & Z_4(\mathbf{s},t) = EMG(x,y,t), \\
Z_5(\mathbf{s},t) = MaxPower(x,y,t), & Z_6(\mathbf{s},t) = Depth(x,y,t), \\
Z_7(\mathbf{s},t) = VerticalDisplacement(x,y,t) &
\end{array}
$$

A Bayesian network was created from the constructed cross tabulation table. We customized and used BAYONET [12] for this process. BAYONET finds probabilistic semantic structures via a kind of greedy algorithm based on one of several information criteria, such as Akaike's information criterion (AIC) [16], from the given data.

3.5 Step 4: Retargeting Bayesian Network Model: Application of Playing Behavior Model to Construct New Product Design

We used the model to create a new design for safer playground equipment. The model constructed in Step 3 above expresses the causal relation between age, weight, height, intensity of EMG, maximum grasping power, vertical displacement in playing, and the depth of each block in the stone wall. Falling from the higher part of the stone wall can cause more serious injury than falling from the lower part. The difficulty in climbing is strongly related to the risk of falling from the equipment. As stated above, the intensity of the EMG indicates the difficulty in climbing. So, we used the intensity of the EMG as a criterion for the risk of falling. Among the parameters in the product design, the depth and height of the stone wall blocks are controllable. We can infer the intensity by varying the controllable parameters and the target age as inputs to the constructed Bayesian network. More concretely, we can calculate the expectation of the EMG by utilizing Eqs. (7) and (8).

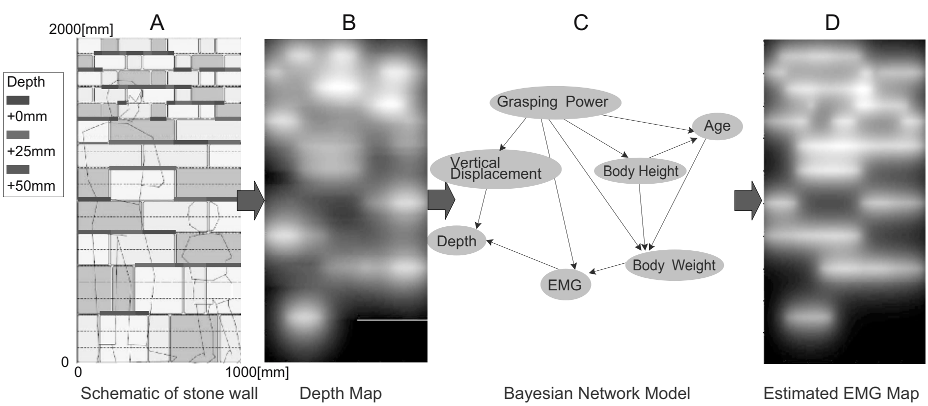

Fig. 5. Estimated EMG map using Bayesian network

$$p\left(Z_4(x,y)|\mathbf{Z}_{i\neq 4,7}(x,y),Bs\right)=\frac{p\left(\mathbf{Z}_i(x,y)|Bs\right)}{\sum\limits_{Z_{i=4,7}} p\left(\mathbf{Z}_i(x,y)|Bs\right)}, \tag{7}$$

$Z_1 = 3,4,5,6$ *years old*, $Z_2 =$ average body weight,
$Z_3 =$ average body height, $Z_5 =$ average maximum power,
and $Z_6(x,y) =$ depth map data from schematic, and

$$E(Z_4) == \sum_j A_j \times p_j\left(Z_4|\mathbf{Z}_{i\neq 4},Bs\right), \tag{8}$$

where A_j denotes the coefficient for calculating the expectation from the inferred probability distribution p_j. In general, the probability distribution inferred by a Bayesian network is a discrete distribution. Figure 5 shows an example of an estimation of the intensity of the EMG ($E(Z_4(x,y))$). In this figure, section A depicts a new schematic of the stone wall structure, section B depicts the depth map of the new schematic, section C depicts the Bayesian network model, and section D depicts the intensity of the EMG as inferred by the Bayesian network model. We used the customized BAYONET for this inference process. Figure 6 shows the results of the estimation of the EMG map for different ages. In the figure, the EMG intensity is normalized so that the maximum intensity of a three year-old becomes one. The figure shows that children can climb the wall using less strength, as they get older. By repeating the design of a new schematic and estimation of the EMG, we can interactively design a new stone wall type of playground equipment.

For this case study, we created the specifications listed below in cooperation with playground equipment makers.

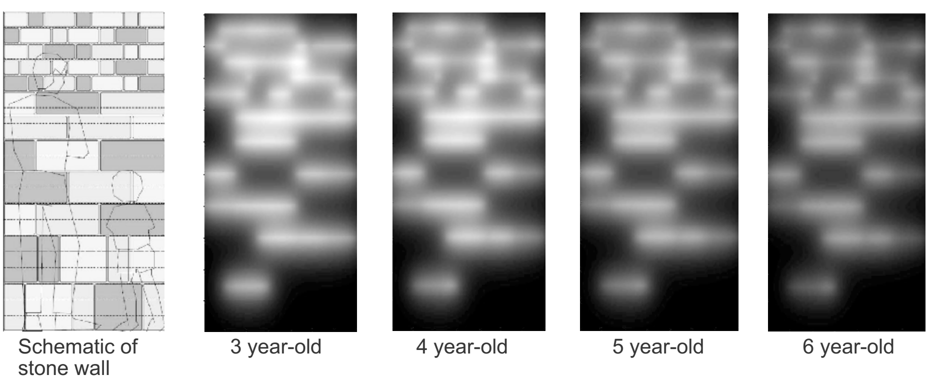

Fig. 6. Estimated EMG map of different ages (the EMG intensity is normalized so that the maximum intensity of a three year-old becomes one)

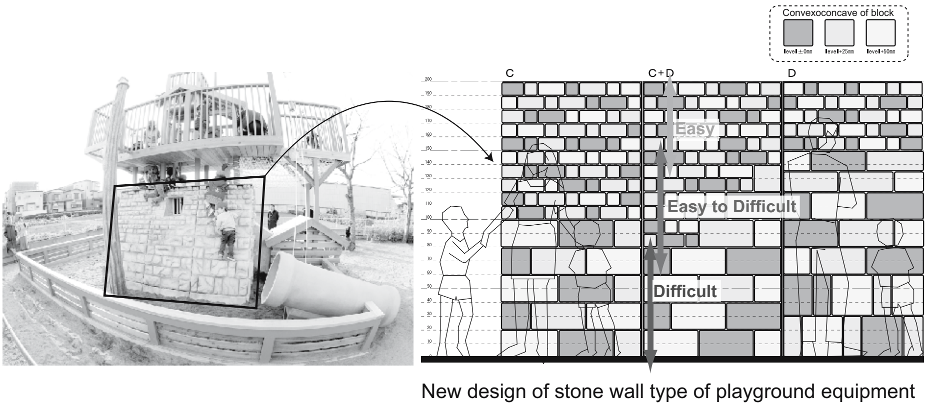

Fig. 7. Application of new type of playground equipment design

1. In order to exclude children that were 1 to 2 years of age, we designed the lower part of the stone wall to be too difficult for them to climb, i.e., so that they cannot exert the required degree of muscular power in this section.
2. To allow those children who can climb the lower section to enjoy the rest of their climb, we designed the middle part of the stone wall with a variety of difficulties.
3. To ensure safety in climbing and to help the children climb securely, we designed the upper part of the stone wall to be relatively easy for them to climb, i.e., not much strength is required.

We made some patterns for a wall that satisfied these specifications by repeating the trial design using the STS mapping system in collaboration with playground equipment designers. Figure 7 shows three examples of stone walls for playground equipment based on the created model and the constructed playground equipment based on the model.

4 Conclusion

This paper has highlighted the possibility of creating a data-driven type of an everyday life behavior model and using the model to improve everyday life. This stems from the recent development of sensing and modeling technologies. A wearable sensing technology and a statistical modeling technology make the application of science to everyday life situations feasible.

We have proposed the concept of a Spatio-temporal Semantic mapping system as one approach to dealing with knowledge acquisition based on real-life behavior data. The STS Mapping system consists of the following components: 1) a spatio-temporal extension of behaviormetric sensing with the integration of a non-location behaviormetric sensor and a location sensor, 2) a standardized and multilayered representation of the measured data based on an environmental coordinate system, and 3) a statistical modeling process for knowledge acquisition from the represented data, and a retargeting process. This paper has described the formulation of behavior phenomena in terms of a spatial point process as dealt with in spatial statistics and a concrete computation method for creating a model using the STS mapping system.

To show the effectiveness of the proposed STS mapping system, this paper reported on an implemented system and a case study using it. In the case study, we conducted in situ observations and measurements of 47 children playing with or on playground equipment by using a wireless wearable location-electromyography sensor and constructed a model of the children's behavior from the measured data. This paper also reported on a new play equipment design that had a climbing section that was suitable for the children's target age group. The new design was created using the constructed model in collaboration with playground equipment designers. The case study showed that everyday life behavior science could possibily be applied to evidence-based product design as well as indicating the effectiveness of the proposed system from a practical standpoint.

Creation of a new design as described in this paper is our first trial towards developing safer playground equipment for children. This year, our research group constructed a system for monitoring children playing in the nursery with the new equipment that has sensors installed in it. We hope that, by collecting such everyday data over a long term, we will be in a better position to clarify the relationships between injuries and children's behavior through the continuous improvement of the model and the equipment. We believe that incremental knowledge development, which means continuous improvement and application of knowledge using real data for feedback, is very important for making knowledge really useful in our society.

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