Infant Behavior Simulation: Computational Approach to Infant Safety

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***Abstract*— A computational approach must be taken in order to comprehensively understand the behavior of infants and children. This approach is also required for the clarification of the dynamics of a system that includes behavior-related accidents. The present paper describes an infant behavior model for simulating infant behavior in a virtual environment. The determinant factors of infant behavior are classified into internal factors, such as the physical and cognitive capabilities estimated from the age of the infant, and external factors, such as visual stimuli from surrounding objects. An infant behavior simulator that models the causal connections among these internal and external factors is described herein. The present paper reports the performance evaluation of the developed simulator and describes its perspective. This simulator will enable the analysis of infant accidents at home from an engineering perspective and will facilitate the design of rooms and houses that are safer for infants. Furthermore this simulator can be used as a starting point for developing a robot behavior model for the living environment and the care of humans.**

***Keywords*— Computational theory of behavior, Infant behavior simulation, Infant behavior model, Unintentional injury, Infant accident**

I. Introduction

A recent report [1] states that unintentional injury is the leading cause of death among children younger than 14 years of age, even though the rate of injury has declined approximately 40% over the last ten years. In the United States, unintentional injury claims more than 5,600 lives a year, or an average of 15 children each day. In Japan, unintentional injury is also the leading cause of death among children and accounts for 21.7% of child fatalities. The present report clarifies the necessity for recognizing child injury as a preventable public health issue, rather than as the result of uncontrollable "accidents".

When we consider accidents of any type, all accidents are comprised of three phases; 1) Before the accident 2) At the time of the accident, and 3) After the accident. Before an accident, we must focus on prevention. When an accident has happened, we must focus on emergency treatment. After an accident, we must focus on healing and rehabilitation. The most economical of these three actions is prevention.

In order to prevent the unintentional injury of children and design safer environments for children, we must develop techniques for understanding child behavior. However, despite our familiarity with infant behavior in a living environment, we possess a limited understanding of the dynamics of child behavior in a living environment and accident-related behavior among children.

Research on infants[1] has been carried out in the medical field. Statistical data on infant accidents [2] and on the development of infant behavior are available; thus, many preventive measures have been proposed. However, since no accurate tool has been developed for observing the wide variety of infant behaviors that occur in a living environment, we lack quantitative data on infant behavior in a living environment. This results in difficulty in comprehensively understanding infant behavior that occurs in a living environment.

Conversely, in the field of cognitive science, research on infant behavior has been carried out. For example, detailed investigation of infant vision, has clarified the following facts. The use of stimulus information for stereoscopic depth perception appears to develop between 3 and 4 months of age [3], [4], while the use of stimulus information for pictorial depth information appears to develop between 6 and 7 months of age [5]. To individuate objects around themselves, infants can use shape information at 7 months, texture information at 11 months, and color information at 12 months [6]. It is also known that the distance to objects, the size and shape of objects, and whether objects are moving or not have an affect on the reaching behavior of infants [7]. Despite this research, the infant behaviors or capabilities addressed in this field are very limited when compared with the diversity of infant behaviors that occur in a living environment.

As a consequence, there is a considerable gap between

[1] In this paper, the term "infant" refers to children under three years of age

the behavioral phenomena investigated in neuroscience and cognitive science and the statistical investigation of the occurrence of accidents. To bridge this missing link, infant behavior and infant-behavior-related accidents must be described ”mesoscopically,” namely, more macroscopically than is the case in neuroscience and cognitive science, and more microscopically than is the case in the investigation of statistical data on accidents.

The present research uses a computational approach in which a computer is used to generate an explanation of the phenomena from the viewpoint of information-processing and computational theory. This allows the mesoscopic investigation of infant behavior by integrating the existing knowledge on infant behavior from various research fields and analyzing infant behavior more comprehensively than is currently possible in research fields such as cognitive science or the developmental behavior of children. The present study attempts to establish both a computational approach to comprehensively and mesoscopically understanding child behavior and the dynamics of a system that takes infant behavior into account. This paper also emphasizes the necessity of using sensing technology in order to describe infant behavior mesoscopically in accordance with the computational approach to infant behavioral science.

This paper presents an infant behavior model for simulating infant behavior in a virtual environment. This paper is organized as follows. In Section II, we describe the possibility of developing a new computational theory of infant behavior as a key component of the infant behavior simulator. Herein, we broaden our perspective to include a computational theory of human behavior and describe why we should now be able to undertake the difficult task of developing such a theory. In Section III, we analyze the factors related to infant injury accidents in the home and clarify the key factors to be considered in infant behavior simulation. Section IV shows the infant observation system for tracking not only an infant but also the objects handled by the infant in order to analyze infant behavior in a living environment. Section V presents the developed infant behavior model for infant behavior simulation. A performance evaluation of the developed simulator is shown in Section VI. In Section VII, we describe the perspective of the infant behavior simulation. Our conclusions are described in Section VIII.

II. Computational Theory of Human Behavior

Computational theory is a concept for explaining human activities from the information-processing perspective advanced by Marr [8]. In order to simulate human behavior in a virtually created environment, it is necessary to develop a computational theory of human behavior not only for describing human behavior but also for explaining and generating it. Before explaining how this problem can now be addressed, we will briefly describe the history of the computational theory of human.

The history of the computational theory of human can be described from the following three perspectives: 1) the emergence of a new observation device, 2) the emergence of a medium for representing human behavior, and 3) a mesoscopic phenomena to be investigated.

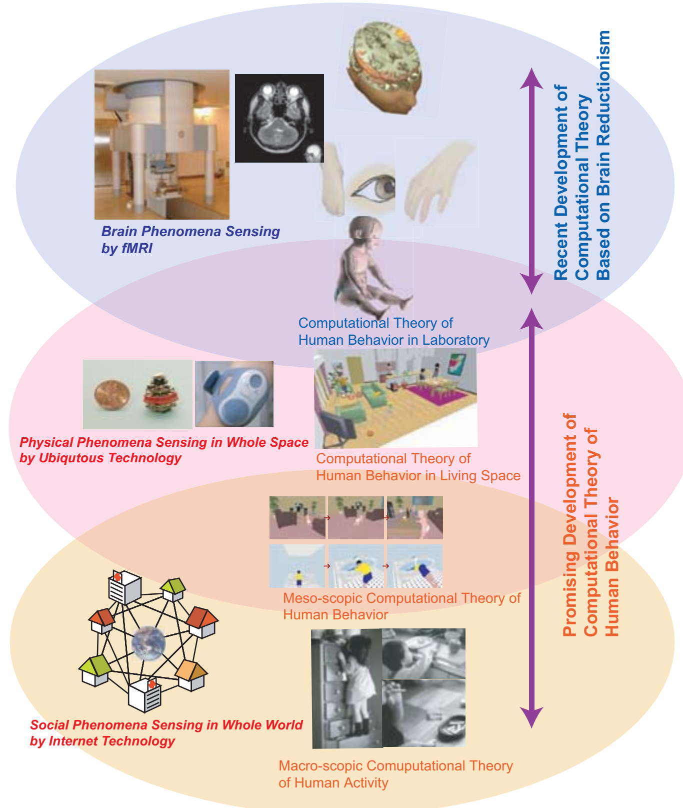

Fig. 1. Computational theory of human behavior

The emergence of fMRI, which enables us to observe brain activity in a living human, and computers enabling us to model and represent brain activity, has lead to the recent development of the computational theory for explaining mesoscopic phenomena between neurons and brain activity. In addition, the emergence of robots, which enable us to represent both brain activities and body activities, has lead to the computational theory for explaining the mesoscopic phenomenon of physical embodiment. Today, it can be said that ”brain reductionism”, which refers to the trend in research of attempting to describe phenomena at the level of brain activity, has become a strong paradigm in the computational theory of human.

Recently, two new forms of observation technology have emerged; ubiquitous sensing technology [9], [10] and World Wide Web technology [11]. Ubiquitous sensing technology enables us to observe physical phenomena in a whole space using multiple sensors embedded in the space. It can be used for observing human behavior in a living environment from the microscopic perspective[2]. In contrast, Web technology

[2]Micro-, meso-, or micro- are relative concepts. In Section I, we refer to behavior description by ubiquitous sensing as ”mesoscopic”. However, herein, we refer to it as ”microscopic” in comparison with the macroscopic descriptions created from statistical data.

enables us to observe social phenomena across the world by collecting a large amount of data via the Web. It can be used for observing human activities from a macroscopic perspective. In addition, game technology has become available as a medium for representing human behavior. Today's game technology has rich capabilities for expressing human behavior as computer graphics.

The emergence of these technologies implies that we can develop a new computational theory of human behavior in a living environment, which is a mesoscopic phenomenon that exists between microscopically described human behavior and macroscopically described human activities. The authors believe that a computational theory of human behavior, comparable to that of human brain science, will be developed.

The present paper deals with infant behavior for the following reasons. Firstly, developing a computational theory of infant behavior is not only a new aim in academic research but is also an aim strongly requested by aging or aged societies. As infants have the highest rate of unintentional-injury-related death, aging or aged societies are deeply concerned about infant accidents.

The second reason is that a computational theory of infant behavior will be one of the most effective methods for scientifically approaching the problem of infant injuries or accidents that occur in a living environment, as it is impossible to analyze accidents by creating "artificial accidents." In addition, a number of accidents occur due to a combination of multiple factors, such as infant abilities, environmental factors, and parental behavior. Computational representation enables us to comprehensively integrate these factors using a computer and conduct an analysis-by-synthesis in order to investigate and clarify the dynamics of a system of accidents.

The final reason for developing a computational theory of infant behavior is that we are likely to succeed in developing such a theory. The data, knowledge, and sensing technologies required for developing such a theory are available. For example, the developmental behavior of infants has been clarified [12], [13]. As mentioned above, infant injuries or accidents that occur in a living environment are phenomena that can be described microscopically and macroscopically using available sensing technologies. Microscopic description should be performed by observing infant behavior in a living environment using ubiquitous sensing devices, while macroscopic description should be performed through the collection of accident data from hospital databases. In addition, in the earliest stage of the science of infant-related accidents, overly complex factors, such as the high level of cognitive abilities of adults, are avoidable without deteriorating the usefulness of the model. These complex factors can be integrated into the computational theory incrementally following the development of the basic theory.

The present paper describes our research on the creation of a computational theory of infant behavior as a key component of infant behavior simulation.

III. Infant-Behavior-Related Accidents

A. Classification of infant accidents

From the viewpoint of interaction with objects and other persons, infant accidents at home can be classified into three groups.

- *Accidents due to interaction with objects*
  This group includes accidents due to single objects (e.g., being burned by a stove), and accidents due to multiple objects (e.g., an infant steps on a toy on the floor, and hits his or her head on a desk while falling.)
- *Accidents due to interaction with others*
  Examples of this group of accidents include being bitten, or kicked by a brother or sister.
- *Accidents due to a combination of interaction with objects and others*
  An example of this type of accident results when an infant is pushed by another young child and falls down the stairs.

This paper focuses on accidents due to interaction with objects since this type of accident occurs most frequently according to statistical data. Moreover, these accidents are addressed first because they involve the fewest factors.

B. Analysis of infant accidents due to interaction with objects

Let us consider a concrete example of an accident in order to analyze key factors in infant accidents due to interaction with objects.

"A child wanted to drink orange juice and found a cup in the cabinet. He climbed up on a chair to get the cup, but he couldn't reach it. So he stood on tiptoe. Then he lost his balance and fell to the floor. He hit his forehead against the floor."

From this example, it can be seen that the accident is deeply related to the objects around the infant and his capability of performing behaviors. In this case, objects such as the cup, the chair, the cabinet, and the floor were involved in the accident. The boy grew until he could walk, climb, and stand on his tiptoes. This fact suggests that we must model both environmental factors and developmental behavior factors.

C. Key factors in infant accidents due to interaction with objects

1) Environmental factors: In our research, we believe that an object has three types of functions for modeling environmental factors in infant accidents: 1) psychological/cognitive function, 2) physical function, and 3) physiological function. Figure 2 shows our concept of object functions.

Object functions are related to the "Cause of the infant's intention", "Cause of the physical realization", and "Cause of the accident", respectively. The "Cause of the infant's intention" means that an infant performs an action because he or she is attracted to an object. For example, when an infant finds a ball on which his favorite animated character is printed, he or she will enthusiastically try to reach it. The "Cause of the physical realization" means that infant uses an object for realizing his or her intention. For example, if the ball is put on a shelf, he or she will try to reach it using a chair. The "Cause of the accident" means that the infant is injured by an object. For example, an infant can be injured by the corner of a shelf if he or she hits his or her head when falling from a chair. Thus, object functions are related to infant's behaviors and accidents.

This view of objects in the environment is based on the concept of affordance [14], which refers to the environmental property that makes a person do or not do something. The authors believe that this perspective is one of the available perspectives for modeling the environment. Moreover, this perspective is useful for application in the present research because we are able to concretely define such functions using accident data collected by hospitals.

Of the three object functions, this paper deals with the psychological/cognitive function of objects as the first step in modeling all functions. In Section IV, we analyze the relationship between an infant's interest in an object and the distance to the object.

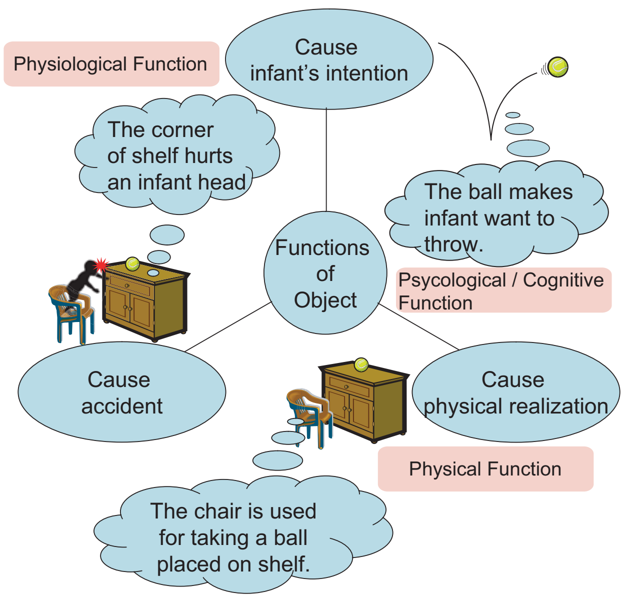

Fig. 2. Object functions

2) Developmental behavior factors: As indicated above, infant accidents are related to the developmental level of infant behavior. Statistical data also shows this fact. Figure 3 shows the recent trend in the cause of death among children. The figure indicates that the leading cause of death among children is not disease but unintentional accidents. Figure 4 indicates more clearly which age group of children is more likely to be involved in accidents.

The behavioral ability of infants develops more rapidly than that of both older children and adults. Therefore, even though their behavior is much simpler than that of adults, it is difficult for parents and even infants themselves to predict infants' behavior and its results.

This paper utilizes the knowledge of the development of infant behavior that is known in the medical field. In Section V, we describe the details of how we model developmental behavior factors.

Age	First (%)	Second (%)	Third (%)	Fourth (%)	Fifth (%)
0	Birth defect / Chromosomal aberration (36.3)	Respiratory disturbance / Angiopathy (16.1)	Sudden death syndrome (8.1)	Accident (8.1)	Fetal homorrhagic disorder (4.1)
1 - 4	Accident (24.8)	Birth defect / Chromosomal aberration (17.6)	Malformation neoplasma (7.5)	Heart disease (6.0)	Pneumonia (5.0)
4 - 9	Accident (35.0)	Malformation neoplasma (17.2)	Birth defect / Chromosomal aberration (7.9)	Heart disease (5.5)	Murder (3.8)
10 - 14	Accident (22.0)	Malformation neoplasma (21.2)	Heart disease (9.5)	Suicide (9.2)	Birth defect / Chromosomal aberration (6.5)

Fig. 3. Resent trend in the cause of death among children in Japan

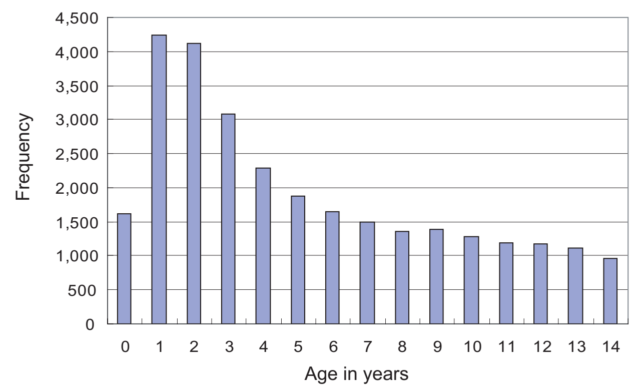

Fig. 4. Relationship between the frequency of injury and age in Victoria, Australia from June 2002 to July 2003 (This data was provided by the Monash University Accident Research Center (MUARC))

IV. Observation and Analysis of Infant Behavior in a Living Environment

A. Development of an infant behavior observation room

Observing infant-object interaction is important in order to create a model of how objects affect infant behavior. Therefore, we constructed a behavior observation room in order to study how infants interact with objects and furniture. This section briefly introduces the developed observation hardware and analysis software. This section also presents the obtained data on infant behavior transition and the relationship between an infant's interest and his or her distance from an object as typical examples of the results of infant behavior analysis. These findings were utilized in order to create a computational model of infant behavior. The details of this model are described in Section V.

Figure 5 shows an experimental behavior observation room, in which ultrasonic location sensors [15] [16] and a camera are installed. The ultrasonic location system consists of an ultrasonic receiving system, an ultrasonic transmission system, a time-of-flight measurement system, a network, and a personal computer. The ultrasonic receiving system receives ultrasonic pulses emitted from the ultrasonic transmitters and amplifies the received signal. The time-of-flight measurement system records the travel time of the signal from transmission to reception. The network synchronizes the ultrasonic location system and collects time-of-flight data from the ultrasonic receiving system. The positions of objects are calculated based on more than three time-of-flight results. The sampling frequency of the proposed ultrasonic location system is 50 Hz. The proposed system can detect the positions of objects and infants within 30 mm for all objects or infants to which ultrasonic transmitters are attached. The transmitter is shown in Fig. 6.

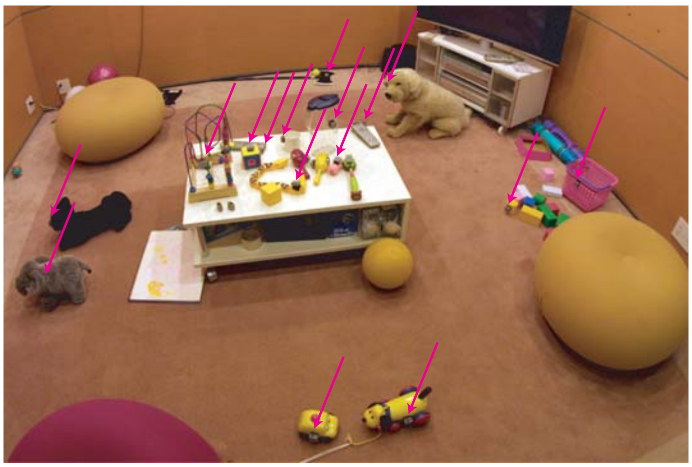

Fig. 5. Behavior observation room equipped with ultrasonic location sensors and a camera

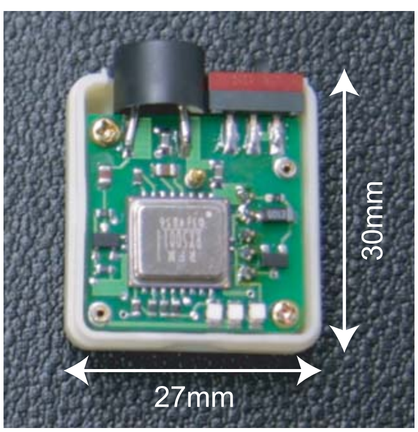

Fig. 6. Ultrasonic location sensor developed by the authors

B. Analysis of infant behavior data

1) Data analysis software: Figure 7 shows the software that we developed in order to analyze infant behavior. The software has functions for capturing video images from a camera equipped with a fish-eye lens and for collecting synchronous infant and object position data from the ultrasonic location system. The software also has a function that helps the user to label behavior while replaying the captured images and trajectories. The labels indicate semantic information such as ”Sit”, ”Stand”, ”Run”, ”Interest in Object”, and ”Interest in Mother”. These labels were selected in order to reduce difficulty in differentiating labels among analyzers. Specifically, these labels were selected because they showed correlation coefficients over 0.7 in both intra-observer and inter-observer reliability evaluations [17]. The labels are recorded by associating the video frame number with the time. Figure 8 shows examples of the infant activities captured by the fish-eye camera. Figure 9 shows an example of the measured trajectories of an infant, a mother, and objects. The lower image shows video data captured from a camera installed on the ceiling. The upper left image is zoomed in on the infant using information from a sensor that is attached to the back of the infant. The upper right image shows the infant’s trajectory.

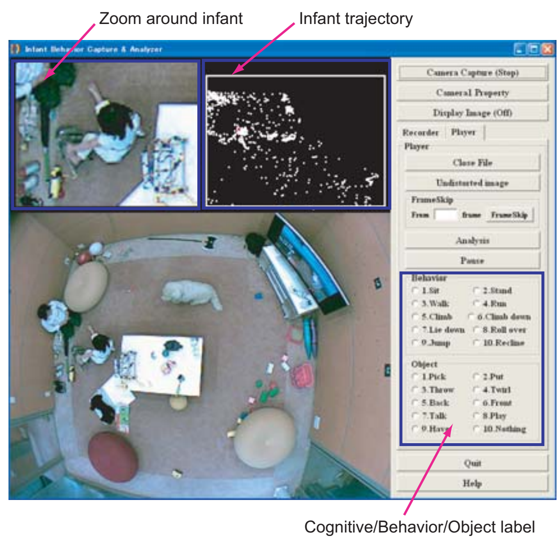

Fig. 7. Software for capturing and analyzing infant behavior

2) Results of analysis: Figure 10 shows an example of a state transition diagram obtained from the observation of a 2-year-old infant.

Figure 11 shows the time rate of infant’s interest. It indicates that the infant maintained an almost constant interest in objects. In this paper, we indicated that the infant is interested in an object if he or she looks at the object, although we can not be certain whether the infant is actually interested in the object. Figure 12 shows the interest induction of an object in relation to the infant’s distance from the object. The y-axis is calculated using the following equation to eliminate the effect of the arrangement of the objects.

$$P(Interest|Distance) = \frac{P(Interest \cap Distance)}{P(Distance)}$$

The conditional probability $P(Interest|Distance)$ is utilized

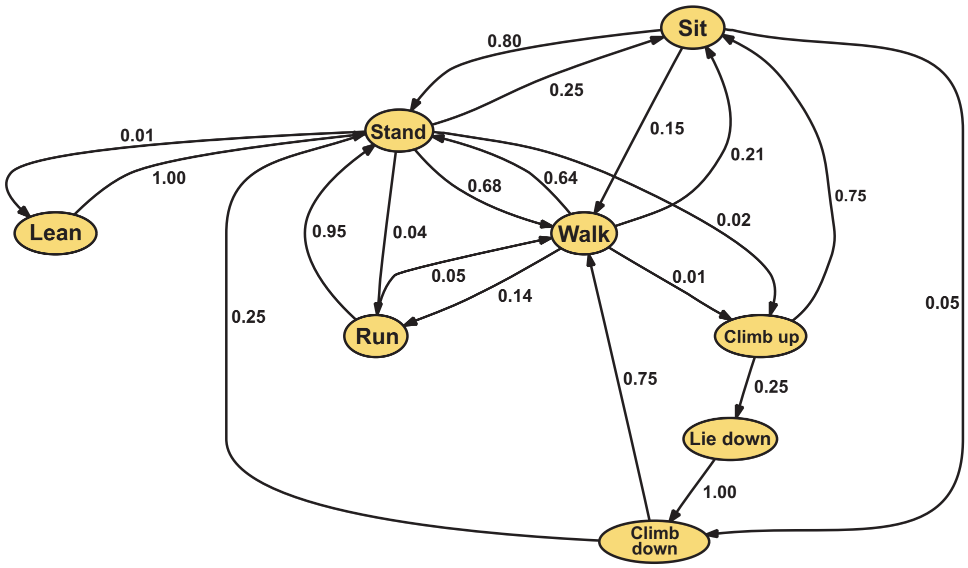

Fig. 10. State transition diagram of experimental data gathered during 2 hours of monitoring a 2-years-old subject

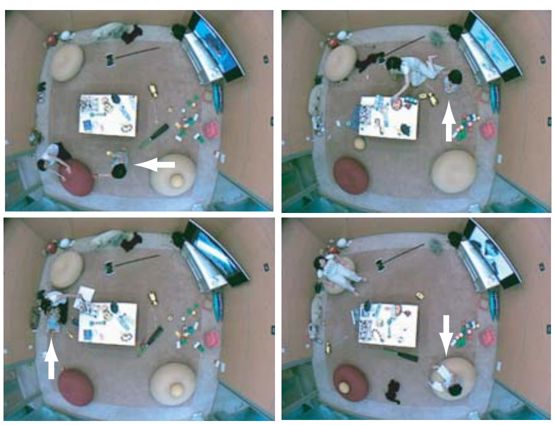

Fig. 8. Examples of infant activities

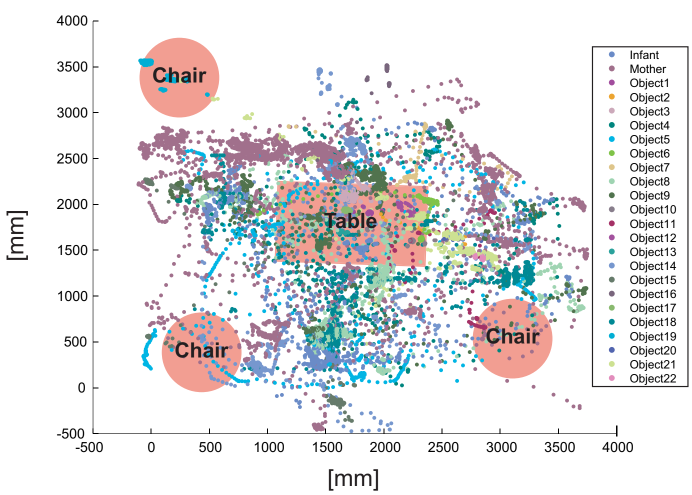

Fig. 9. Example of the measured trajectory for a 1.5-year-old child and handled objects

in order to create the computational model of infant behavior in Section V.

Figure 12 confirms that infants are more likely to be interested in nearer objects while maintaining interest in the mother independent of the distance to the mother. The lower part of Fig. 13 shows an example of the visualization of an infant's interest distribution in a case in which the infant, the mother, and the objects are arranged as shown in the upper part of the figure.

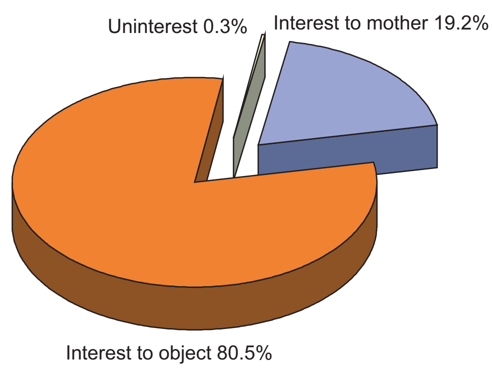

Fig. 11. Infant's interest in objects and mother

V. Development of an Infant Behavior Simulator

A. Probabilistic model of infant behavior

This section describes the developed model of infant behavior. The developed model was created by integrating the environmental model and the developmental behavior model. Figure 14 indicates the causal connection that we assumed in the creation of the model. The model is expressed as a probabilistic model by Eq. (1). The equation expresses the joint

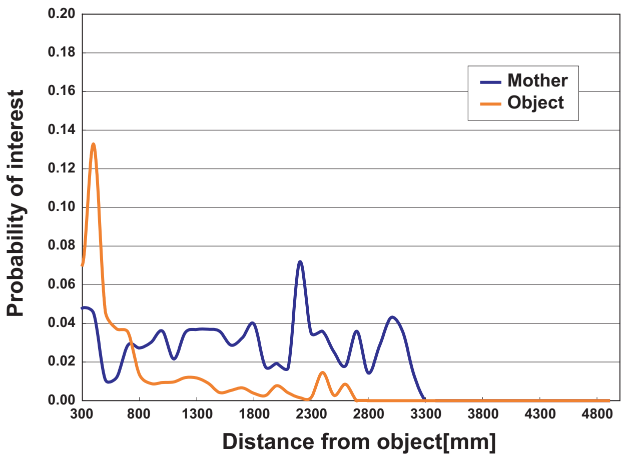

Fig. 12. Analysis of the interest induction of an object in relation to the infant's distance from the object

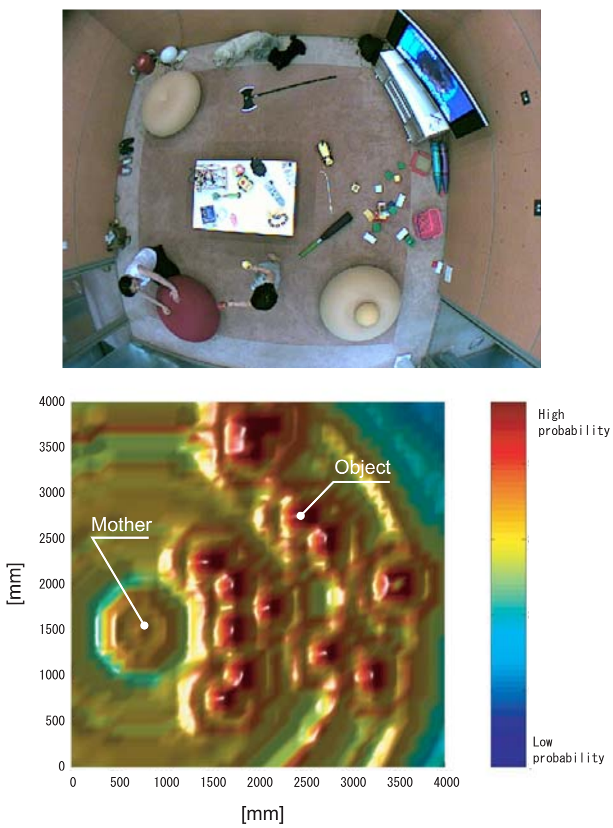

Fig. 13. Visualization of an interest distribution in a living environment

probability of a behavior according to time t ($Behavior_t$), environmental factors ($Variables_{env}$), and developmental behavior factors ($Variables_{dev}$).

$$P(Behavior_t, Variables_{env}, Variables_{dev}) \quad (1)$$

A presumable application of the developed model is one that allows a user who wants to design a safe environment

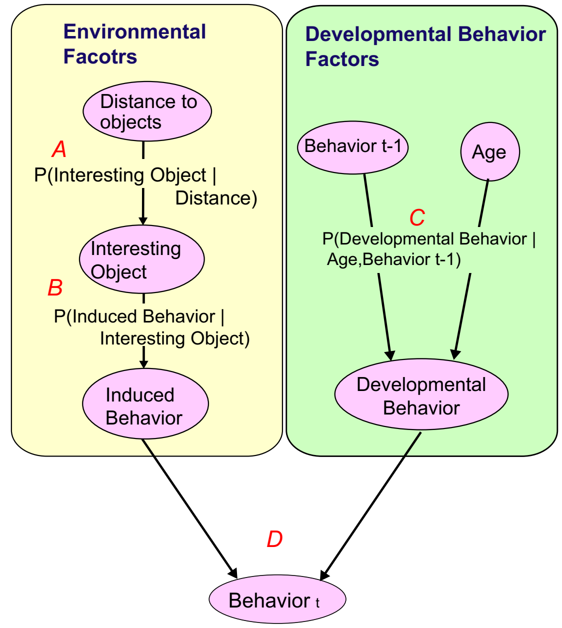

Fig. 14. Causal connection of infant behavior

for infants to predict infant behavior and infant injuries stemming from infant behavior. Such an application would allow parameters such as age, kinds of objects and furniture, and arrangement of the objects and furniture to be changed in a virtually created environment.

In this paper, based on the concept of affordance [14], which refers to the environmental property that makes a person do or not do something, we assume that an infant performs a behavior if he or she has the capability for performing the behavior induced by the affordance property of the environment. To model infant behavior from this viewpoint, we assume that environmental and developmental behavior factors are independent of each other. Therefore, Eq. (1) can be rewritten as follows.

$$\begin{aligned} P(Behavior_t, Variables_{env}, Variables_{dev}) = \\ P(Behavior_t, Variables_{env}) \times \\ P(Behavior_t, Variables_{dev}) \end{aligned} \quad (2)$$

Below, we explain the details of the environmental factors and the developmental behavior factors that this paper is focused on and show a concrete calculation of Eq. (2).

B. Modeling environmental factors

This paper is concerned with the distance of an infant to an object ($Distance$) and the object that the infant is interested in ($InterestingObject$) as environmental factors ($Variables_{env}$). Using $Distance$ and $InterestingObject$, we created a model for explaining the behavior that the infant can perform in a certain environment. Specifically, we created a model expressed as $P(Behavior_t, Distance, InterestingObject)$.

1) Modeling interest induced by objects (A in Fig. 14): The interest that the infant has in a certain object can be explained by various factors such as shape, color, size, weight, and whether the object is moving or not. In this paper, as the first step to modeling the interest induced by objects, we focused on the distance between the infant and the object since this can be measured by a sensor and is a much more significant factor when compared with the weight and the size of the object. Therefore, we can model the interest induced by objects using the conditional probability $P(InterestingObject|Distance)$ mentioned in Section **??**.

2) Modeling behavior induced by objects (B in Fig. 14): Based on the concept of affordance, we created the model for explaining behavior induced by objects. We assumed that behavior is induced only by interesting objects. Hence, we can model behavior induced by objects using the conditional probability $P(InducedBehavior|InterestingObject)$.

Using the above assumptions, we can calculate $P(Behavior_t,\ Distance,\ InterestingObject)$ as follows.

$$\begin{aligned} P(Behavior_t, Distance, InterestingObject) = \\ P(Behavior_t|InterestingObject) \times \\ P(InterestingObject|Distance)P(Distance) \end{aligned} \tag{3}$$

C. Modeling developmental behavior factors(C in Fig. 14)

Here we model the behavior that the infant whose age is Age can perform at a certain time t. We focus on the previous behavior of the infant ($Behavior_{t-1}$) and the infant's age (Age) as the developmental factors ($Variables_{dev}$), and create the model expressed by $P(Behavior_t, Age, Behavior_{t-1})$. If we assume that $Behavior_{t-1}$ and Age are independent of each other, we can rewrite $P(Behavior_t, Age, Behavior_{t-1})$ as follows.

$$\begin{aligned} P(Behavior_t, Age, Behavior_{t-1}) &= \\ P(Behavior_t, Age) \times P(Behavior_t, Behaviort_{t-1}) &= \\ P(Behavior_t|Age)P(Age)\times & \\ P(Behavior_t|Behaviort_{t-1})P(Behaviort_{t-1}) & \end{aligned} \tag{4}$$

1) Utilization of knowledge of behavior development: We based constraints stemming from behavior development according to the DENVER II [12], [13], which was originally used for evaluating the developmental level of infant behavior. Figure 15 shows a section of the DENVER II developmental evaluation sheet. Some examples of rough-and-large behavior of the entire body by infants indicated in the DENVER II are "lie on one's front", "roll over", "lie face up", "crawl", "sit", "stand", "fall", "walk", "run", "jump", "pull oneself up", "walk backward", "climb up", "kick", "throw", "stand on one foot", and "pick up". Some examples of rough-and-large behavior of the hands are "place hands together", "reach for an object using the hands", "rake with the hand", "hold an object in both hands", "change hands", "pinch with the thumb", and "move only the thumb". This knowledge is utilized in modeling developmental behavior factors. Below, we describe the details of each conditional probability in Eq. (4).

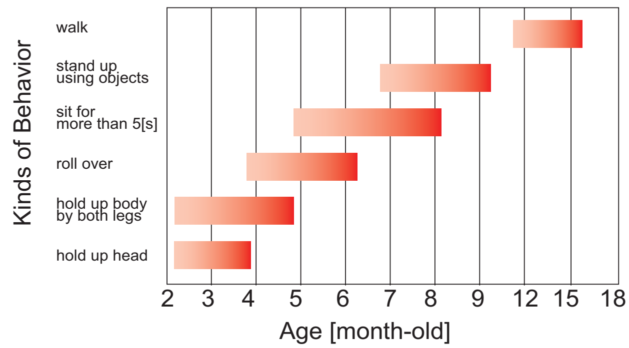

Fig. 15. Example from the DENVER II

2) Constraints stemming from behavior development: When the DENVER II was created, many factors such as age, race, parental income, and geometry were considered. Age was found to be the most significant factor [12]. Based on this fact, in the present research, we assumed that the possible behavior at a certain age Age depends only upon age and created the conditional probability $P(Behavior|Age)$ using the DENVER II.

3) Physical constraints in behavior transition: The behavior at time t is constrained by the previous behavior at time $s(s < t)$. For example, a person cannot "run" directly from the "sit" state without going through the "stand" state. Here, we assume that behavior transition has the Markov property, namely, that future behavior at time t depends only upon the present behavior at time $t-1$. Therefore, the following equation can be derived,

$$\begin{aligned} P(Behaviort_t \quad | \quad & Behaviort_s, s < t) = \\ & P(Behaviort_t|Behaviort_{t-1}). \end{aligned} \tag{5}$$

We defined $P(Behaviort_t|Behaviort_{t-1})$ using the DENVER II. In our current model, each value of the conditional probabilities was defined as 0 or 1. An example of the state transition is shown in Fig. 16. The state transition changes largely depend on age, as shown in Fig. 17. In this figure, the left-hand side of each of the six figures indicates the state transition related to rough-and-large behavior of the hands, and the right-hand side of these figures shows the state transition related to rough-and-large behavior of the entire body. The figure indicates that the transition becomes complex as the infant becomes older.

D. Probabilistic integration of environmental factors and developmental behavior factors

Here, we describe the concrete calculation of Eq. (2). The following are the factors that this paper focuses on.

$$Variables_{env} = \{Distance, InterestingObject\} \tag{6}$$
$$Variables_{dev} = \{Age, Behaviort_{t-1}\} \tag{7}$$

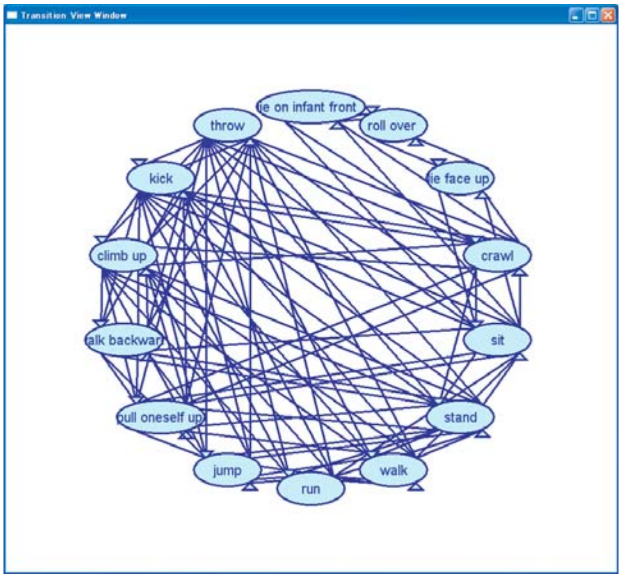

Fig. 16. State transition for the case of a 1.5-year-old infant

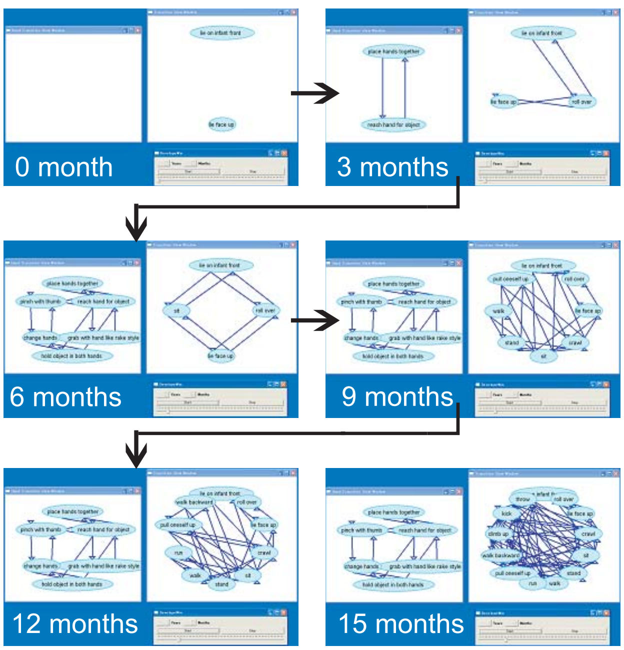

Fig. 17. Change in the state transition of behavior with respect to infant age

Therefore, we can rewrite Eq. (2) as follows.

$$\begin{aligned} P(Behavior_t, Distance, InterestingObject,& \\ Age, Behaviort_{t-1}) &= \\ P(Behavior_t, Distance, InterestingObject) \times& \\ P(Behavior_t, Age, Behaviort_{t-1}) & \quad (8) \end{aligned}$$

By substituting Eqs. (3)(4) into Eq. (8), we can derive the following equation.

$$\begin{aligned} P(Behavior_t, Distance, InterestingObject,& \\ Age, Behaviort_{t-1}) &= \\ P(Behavior_t|InterestingObject) &\times \\ P(InterestingObject|Distance) &\times \\ P(Behavior_t|Age) &\times \\ P(Behavior_t|Behaviort_{t-1}) &\times \\ P(Distance)P(Behaviort_{t-1})P(Age) & \quad (9) \end{aligned}$$

Using Eq. (9), for example, we can calculate the conditional probability of behavior ($Behavior_t$) with respect to Age, $Behavior_{t-1}$ and $Distance$. Since we assume Age, $Behavior_{t-1}$ and $Distance$ are independent of each other, we can derive the equation of conditional probability as follows.

$$\begin{aligned} P(Behavior_t, InterestingObject|& \\ Distance, Age, Behaviort_{t-1}) &= \\ P(Behavior_t, Distance, InterestingObject,& \\ Age, Behaviort_{t-1}) &/ \\ (P(Distance)P(Behaviort_{t-1})P(Age)) &= \\ P(Behavior_t|InterestingObject) &\times \\ P(InterestingObject|Distance) &\times \\ P(Behavior_t|Age) &\times \\ P(Behavior_t|Behaviort_{t-1}) & \quad (10) \end{aligned}$$

VI. Performance Evaluation of Developed Simulator

A. Simulation method

To evaluate the effectiveness of the developed infant behavior model, we simulated infant behavior using the developed model and compared the output of the simulation with data measured in the infant observation room mentioned in Section IV. We assume that the measured data are correct.

The simulation procedure was comprised of the following. We substituted the positions of an infant, a mother, furniture, and objects into Eq. (10) and calculated the conditional probability of each behavior at the next moment. For example, we calculated the conditional probability $P(Behavior_t = "Stand", InterestingObject = "Cup" \mid Distance = "1024mm", Age = "14month-old", Behaviort_{t-1} = "Walk")$, and then sorted the output behaviors in descending order and selected some of the most likely behaviors as the behavior candidates. In this evaluation, we used the measured data from two infants aged 14 months and 26 months.

B. Evaluation method

Recall and precision index are widely used for performance analysis in the field of information retrieval [11] as the indexes are similar to type 1 and type 2 errors in statistics. Recall and precision are defined as follows.

$$Recall \equiv \frac{\text{The num. of relevant ones of the candidates}}{\text{The num. of the whole relevant things}} \quad (11)$$

$$Precision \equiv \frac{\text{The num. of relevant ones of the candidates}}{\text{The num. of output candidates}} \quad (12)$$

Recall is used for evaluating how well a system can find a selected item, while precision is used for evaluating how well a system can reduce the number of unnecessary items. Both indexes are a trade-off.

Fundamentally, this paper utilizes recall and precision in order to evaluate the performance of the developed model. While the precision index was expanded to correspond with our purpose, recall was used without modification. Our system outputs behavior with corresponding probability values. Therefore, we must evaluate not only the correctness of the behavior output but also the correctness of the probability of the behavior output. K. Järvelin and J. Kekäläinen proposed Discounted Cumulative Gain (DCG) [18] as a new precision index which can be used for such a purpose. Based on DCG, we defined and used "ranking precision" (RP) as a new precision index. The use of recall and ranking precision in this paper are described as follows.

The n-th recall is expressed by

$$R_n = \frac{\text{The num. of relevant behavior}}{\text{The num. of the whole relevant behavior}}. \quad (13)$$

The n-th ranking precision is expressed by

$$RP_n = \frac{\text{Probability of relevant behavior}}{\text{The sum. of probabilities of behavior candidates}}. \quad (14)$$

The average recall is expressed by

$$\bar{R} = \frac{1}{M}\sum_{n=1}^{M} R_n, \quad (15)$$

where M denotes the number of evaluations.

The average ranking precision is expressed by

$$\overline{RP} = \frac{1}{M}\sum_{n=1}^{M} P_n. \quad (16)$$

Additionally, in this paper, we used F-value [11] for comprehensive evaluation. F-value is defined as follows.

$$F = \frac{1}{\alpha\frac{1}{\overline{RP}} + (1-\alpha)\frac{1}{\overline{R}}},$$

where α is a weighting value. We used 0.5 as α, which means that we consider the importance of both index R and index RP to be the same.

Furthermore, we compared the performance among simulations under the following conditions.

- 1st condition
  Simulation in which all behaviors are output with the same probability
- 2nd condition
  Simulation using the integrated model, which consists of the developmental behavior model, the behavior transition model, interest induction model, and behavior induction model
- 3rd condtion
  Simulation using the integrated model without the developmental behavior model
- 4th condition
  Simulation using the integrated model without the behavior transition model
- 5th condition
  Simulation using the integrated model without the interest induction model
- 6th condition
  Simulation using the integrated model without the behavior induction model

C. Results and discussion

1) Results of evaluation: Figures 18 and 19 show the results of the recall and ranking precision of the simulation for an infant aged 14 months. Figures 20 and 21 show the results for an infant aged 26 months. The x-axis of each graph indicates the number of behavior candidates.

Naturally, recall was 100% under the 1st condition, which indicates that all possible behaviors were output as behavior candidates. Under the other conditions, recall rose gradually and finally reached 100% as the number of candidates increased. The reason why recall rose steeply at some points was that our simulator often output the same probabilities among several behaviors; thus, in such cases, we could not increase the number of candidates one by one.

Ranking precision was 5% under the 1st condition. Under the other conditions, ranking precision decreased gradually as the number of candidates increased. However, ranking precision under the 2nd to 5th conditions was 1.7 to 3.7 times as high as that under the 1st condition. This means that each of the developed models contributed to explaining infant behavior. In the case of the infant aged 14 months, the developmental behavior model was found to be the most influential. In the case of the infant aged 26 months, after averaging ranking precision, the behavior transition model was found to be the most influential.

Figure 22 compares F-values among the simulations under different conditions. The results of this comparison show that the F-value of the integrated model (the 2nd condition) was more than two times as high as that of the random model (the 1st condition).

VII. Perspective of the Infant Behavior Simulation

This section describes the perspective of the proposed infant behavior simulation. The relatively short-term goals of the simulator are the following.

- *To be helpful in educating parents for the purpose of preventing accidents*
  Knowledge applicable to individual homes can be obtained in order to help prevent injury accidents. Effective education is made possible by combining the simulation with realistic graphics.
- *To be helpful in designing an environment that is safe for infants*
  In designing ordinary homes, nursing homes, daycare centers for children, and kindergartens, for example, the

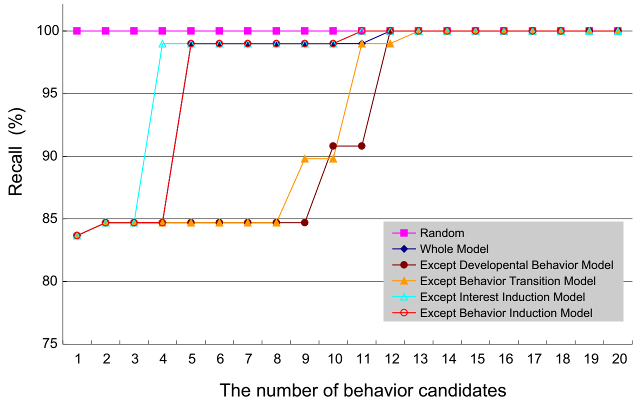

Fig. 18. Evaluation of recall in the case of an infant aged 14 months

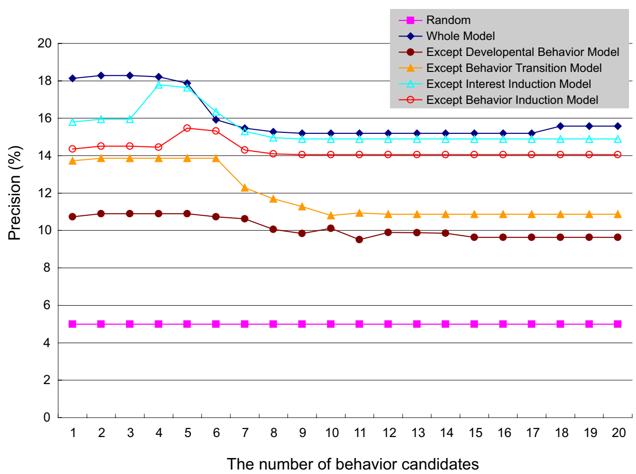

Fig. 19. Evaluation of precision in the case of an infant aged 14 months

safety of such environments can be evaluated in advance. The proposed simulator will also make it possible to improve existing homes in order to reduce the risk of injury accidents involving infants.

To realize the above two applications, we are developing a function for visualizing infant behavior and infant accidents using game technology [19]. Examples of visualized results are shown in Fig. 23. Visualization is realized using Virtools™ [20], which is originally a rapid prototyping software for creating video games that can run on Microsoft™ Internet Explorer. Virtools™ features are as follows: 1) It is easy to add new functions using the C++ language. 2) It is possible to distribute the developed software with no additional royalties. 3) A free downloadable player is available as a plug-in for Microsoft™ Internet Explorer. These features will be very useful for efficiently disseminating the simulator as digital content on the Web allowing the public to evaluate the effectiveness of the developed simulator for parents.

The longer-term goals for the simulator are the following.

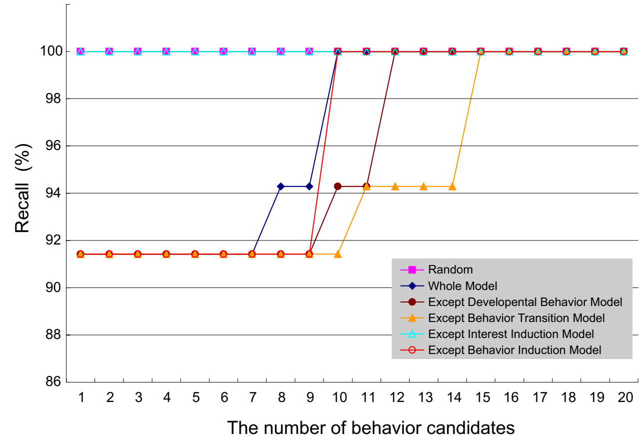

Fig. 20. Evaluation of recall in the case of an infant aged 26 months

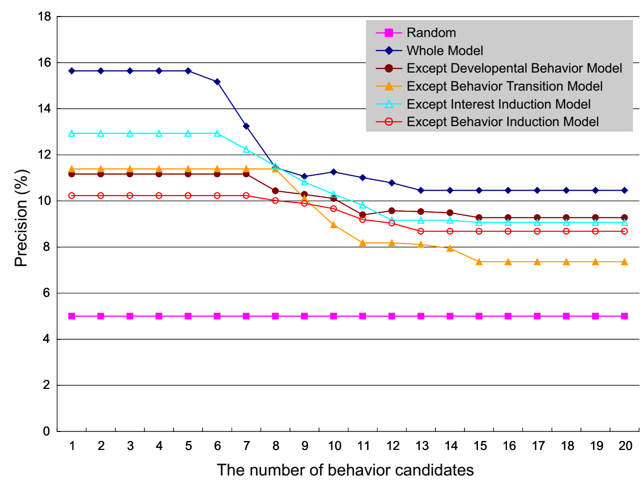

Fig. 21. Evaluation of precision in the case of an infant aged 26 months

- *Real-time monitoring of infants for the purpose of preventing accidents*
  Real-time monitoring of infants in order to prevent accidents will be possible by integrating the proposed simulator into a sensing system using the recently developed inexpensive sensors, sensor networking technology,

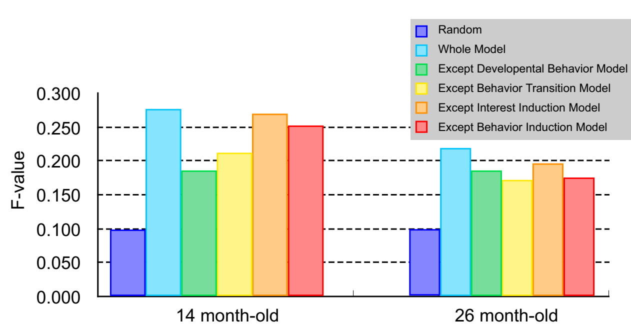

Fig. 22. Evaluation of F-values among different models

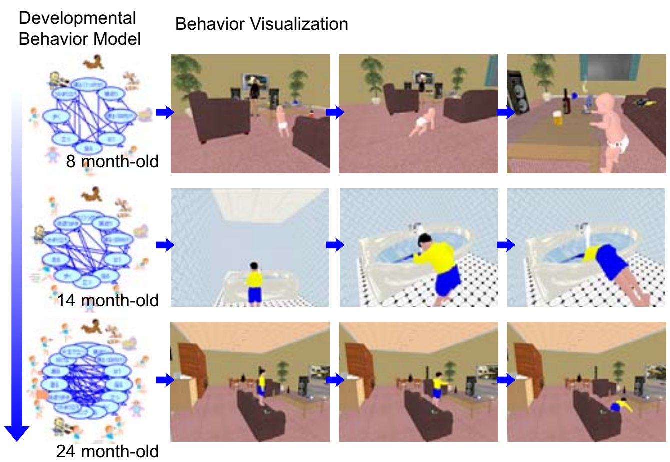

Fig. 23. Example of visualization of an infant-behavior-related accident

and ubiquitous computing technology.

- *Development of infant informatics*
  The proposed simulator contributes to the development of a new research area, which can be referred to as infant informatics or child informatics. Infant informatics attempts to comprehensively understand infant behavior by considering infant behavior from an informatics perspective.

VIII. Conclusions

The present paper described the necessity of a computational theory of infant behavior for scientific study of infant-related injury accidents. In addition, this research highlighted the significance of the computational approach as a method for addressing the problem of child safety in the home. As one possible approach, the authors proposed an infant behavior simulation system that enables the simulation of infant behavior in a virtual environment. To create a computational model of infant behavior for the simulator, the authors classified the determinant factors of infant behaviors as either internal or external factors. Internal factors were modeled using a developmental behavior model. This model describes behaviors displayed by an infant in relation to the infant's age. Behavioral capabilities are modeled using knowledge of the developmental behavior of infants. External factors were modeled using an environmental model that included the objects around the infant, as well as his or her position. The environmental model contains information on the behavior induced by the objects surrounding the infant. The infant behavior induced by the objects was selected using the data collected in an experimental behavior observation room developed by the authors. The performance of the developed simulator was evaluated by comparing the output of the simulator and the data measured in the infant observation room. Finally, the perspective of the infant behavior simulation was described.

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References

[1] A.L. Wallis, B.E. Cody, A.D. Mickalide, "Report to the Nation: Trends in Unintentional Childhood Injury Mortality, 1987-2000," National SAFE KIDS Campaign, 2003 (http://www.safekids.org/content_documents/nskw03_report.pdf)

[2] Victorian Injury Surveillance and Applied Research System http://www.monash.edu.au/muarc/VISAR/

[3] E.E. Birch, J. Gwiazda, R. Held, "Stereoacuity Development for Crossed and Uncrossed Disparities in Human Infants," *Vision Research*, Vol. 22, pp. 507-513, 1982

[4] R. Fox, R.N. Aslin, S.L. Shea, S.T. Dumais, "Stereopsis in Human Infants," Science, Vol. 207, pp. 323-324, 1980

[5] A. Yonus, C.E. Granrud, "Infants Distance Perception from Linear Perspective and Texture Gradients," *Infant Behavior & Development*, Vol. 9, pp. 247-256, 1986

[6] T. Wilcox, "Object Individuation: Infants' Use of Shape, Size, Pattern, and Color," *Cognition*, Vol. 72, pp. 125-166, 1999

[7] J. Kaufman, D. Mareschal, M.H. Johnson, "Graspability and Object Processing in Infants," *Infant Behavior & Development*, Vol. 26, pp. 516-528, 2003

[8] D. Marr, *Vision*, W. H. Freeman and Company, 1982

[9] U. Hansmann, L. Merk, M.S. Nicklous, T. Stober, *Pervasive Computing Handbook. The Mobile World*, Springer-Verlag Telos, 2001

[10] J. Fraden, *Handbook of Modern Sensors: Physics, Designs, and Applications*, AIP Press, 2003

[11] R. Baeza-Yates, *Modern Information Retrieval*, Addison Wesley, 1999

[12] W.K. Frankenburg, J. Dodds, P. Archer, et al., *The DENVER II Training Manual*, Denver, CO: Denver Developmental Materials, Inc., 1992

[13] The Japanese Society of Child Health, *Japanese Edition DENVER II*, The Japanese Child Medical Press, 2003

[14] J. J. Gibson, *The Senses Considered as Perceptual Systems*, Greenwood Press, 1966

[15] Y. Nishida, H. Aizawa, T. Hori, N.H. Hoffman, T. Kanade, M. Kakikura, "3D Ultrasonic Tagging System for Observing Human Activity, " *Proceedings of IEEE International Conference on Intelligent Robots and Systems (IROS2003)*, pp.785-791, October 2003

[16] Y. Nishida, K. Kitamura, T. Hori, A. Nishitani, T. Kanade, H. Mizoguchi, "Quick Realization of Function for Detecting Human Activity Events by Ultrasonic 3D Tag and Stereo Vision," *Proc. of 2nd IEEE International Conference on Pervasive Computing and Communications (PerCom 2004)*, pp. 43-54, 2004

[17] P. Martin, P. Bateson, *Measuring Behavior*, Cambridge University Press, 1990

[18] K. Järvelin, J. Kekäläinen, "IR evaluation methods for retrieving highly relevant documents," *Proceedings of the 23rd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp.41-48, New York, 2000.

[19] A. Simo, K. Kitamura, Y. Nishida, "Children Accidents' Simulation: Planning the Emergent Situations," Proc. of 4th International Conference on Interaction Design and Children," June 2005 (in press)

[20] http://www.virtools.com/