Interaction Design Using a Child Behavior-Geometry Database

Hiroyuki Kakara[1,2], Yoshifumi Nishida[1], and Hiroshi Mizoguchi[1,2]

[1] Digital Human Research Center, National Institute of Advanced Industrial Science and Technology, 2-3-26 Aomi, Koto-ku, Tokyo 135-0064, Japan
[2] Department of Mechanical Engineering, Faculty of Science and Technology, Tokyo University of Science, 2641 Yamazaki, Noda-shi, Chiba 278-8510, Japan

Abstract. Unintentional injuries, that is, injuries due to accidents, account for a large share of the cause of death in children. Some accidents can be prevented by designing products that are based on an understanding of the interaction between children and the object. Improving products to prevent injuries requires a system that helps product designers predict the behavior that the object induces in children. In this paper, we developed a behavior-geometry database that consists of 1) data on children's behavior with common objects, 2) for various objects, data from 3D shape models for which the feature vectors are calculated by a 3D discrete Fourier transform, and 3) two kinds of models for using a 3D shape-feature vector to predict the induced behavior, the barycentric behavior model and the multiple linear regression model. We also developed the following behavior-symmetry-search functions that use the database: a) a shape-similarity search, b) an induced-behavior search, which is a function for predicting the behaviors induced by an object's 3D shape, and c) a behavior-symmetry search, which is a function for finding objects that induce behaviors similar to those induced by the shape of a target object. The third function is useful for finding shapes that are similar in terms of inducing child behavior. In this study, we evaluated the effectiveness of the implemented system using data from 275 accidents and 3D shape data from 45 objects.

Keywords: Injury prevention, interaction design, safety, 3D object retrieval.

1 Introduction

Unintentional injuries, that is, injuries due to accidents, account for a large share of the cause of death in children. According to the National Vital Statistics Reports 2012[1], in 2009 unintentional injuries accounted for more than 30% of the deaths of children aged 1-14 years, as shown in Fig. 1. This trend is a serious problem worldwide, and the number of unintentional injuries needs to be reduced.

The number of unintentional injuries can be reduced by designing products that are based on an understanding of the interaction between the child and the shape of the objects. In the field of product safety, technology is strongly

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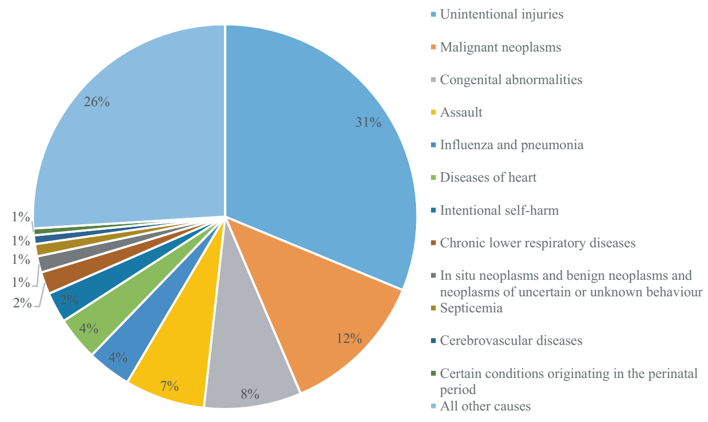

Fig. 1. Cause of Death, 1-14 years old (Source: National Vital Statistics Reports 2012)

needed that can predict a child's behavior with common objects. Childrenfs unforeseen interaction with an object often leads to accidents (e.g., climbing on an air conditioner compressor unit and then falling from a balcony). Product designers must consider the actual use of the target object and design products that do not induce children to engage in high-risk behaviors.

There are some systems that enable product designers to search actual accident data associated with an object. For example, an object-feature-based searching system has been developed[3]. This system enables users to retrieve data on actual accidents that were caused by not only the same category of object as the target object, but also objects in other categories that have features similar to those of the target object. With this system, users can predict behaviors even if there is no accident data associated with the target object. However, conventional systems support only a text-based search, namely, they can only search by literal information, making it impossible to determine behaviors and accidents induced by the shape of a target object.

We live in the real 3D world. Therefore, it is essentially important to consider 3D shape information. We therefore need to be able to search a shape-feature-based system in addition to a text-based system. Recently, technology for 3D shape processing has been developed, and many algorithms are available[2]. This technology allows us to develop a new system for supporting the design of safe products. If a shape-feature-based system becomes available, we will be able to predict the behaviors that may be induced by a 3D shape by associating the 3D shape of the object with behavior data. Without such a system, we overlook data on accidents that are associated with objects belonging to a different category or objects having different features, and are thus unable to take measures to prevent those accidents. Furthermore, we believe that this system allows a new approach to behavior science or interaction science by using accident information to reveal scientific knowledge about the relationship between an object's shape and the behaviors that are induced.

The objective of this study is to develop a database that allows users to predict the behaviors that can be induced by a object's shape (shape-to-behavior prediction), and to develop a method for retrieving shapes that can induce behaviors similar to the behaviors induced by the shape of a target object. This shape-to-shape prediction function is useful for understanding the shape features of objects that induce similar behaviors in children. We will refer to this database as the "behavior-geometry database."

2 Development of the Behavior-Geometry Database

The behavior-geometry database consists of 1) children's behavior with common objects, 2) data for an object's 3D shape model and its shape-feature vectors, and 3) two kinds of models for predicting the induced behavior by using the 3D shape-feature vector, the barycentric behavior model and the multiple linear regression model. Figure 2 shows a conceptual diagram of the behavior-geometry database.

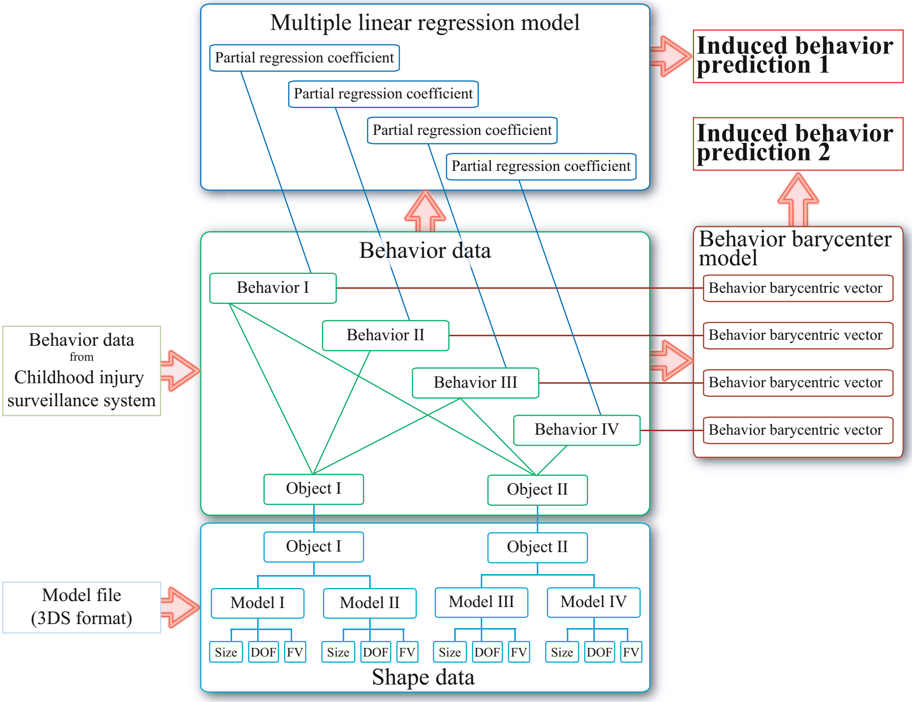

Fig. 2. Conceptual Diagram of Behavior-Geometry Database

2.1 Accumulation of Child Behavior Data

We extracted data on children's behavior and related objects from the Accident Database of the Injury Surveillance System[4,5] developed by the National Institute of Advanced Industrial Science and Technology. The database includes text that describes information such as the accident situation, any related objects, the place, and a summary of each accident. The behavior data consists of the behaviors before and during the accidents. Since we needed to collect behaviors that can trigger accidents, we used the database instead of conducting experiments to observe behavior. We have accumulated data on the behavior related to 275 accidents involving tables or chairs.

2.2 Implementation of 3D Object Retrieval Technology and Behavior Prediction Model

We used 3D model data to register the 3D shape of each kind of object. Also, for each kind of object, such as a dining table or a highchair, we collected more than two models in order to reduce the noise due to the artificial selection of the model. When entering the models, we also entered information on the model's size, direction, and movability. The direction information indicated which aspect is face up and which faces front, from a functional viewpoint. For movability, we mean the model's mechanistic movability; for example, some chairs swivel around the vertical axis (we denoted this swivel by "RZ") and move across a horizontal surface (we denoted this movement by "DXY"). For a swivel chair, we thus indicated that the model had mechanistic movability in RZ and DXY.

Next, we converted the 3D shape models to shape-feature vectors, in order to develop a shape-based behavior prediction model by associating shape information with behavior data. To do so, we implemented the 3D object retrieval method introduced by Vranić and Saupe[6]. This allowed us to extract a feature vector for the whole shape of the input model. The retrieval method voxelizes the 3D polygon model and then calculates a feature vector by using a 3D discrete Fourier transform. Using this method, our system converts a 3D shape model into a 172-dimension shape-feature vector. We have thus far accumulated 45 models into the database, as shown in Fig. 3.

The basic concept of the barycentric behavior vector lies in the idea that the feature vectors of objects that induce the same behavior are similar to each other. The barycentric behavior vector is a weighted mean of the feature vectors of the 3D shape groups. Each 3D shape group consists of feature vectors that describe the objects that induce a target behavior. Our system calculates the barycentric vector for each behavior, as follows.

Figure 4 shows a conceptual diagram of the barycentric behavior vector for sitting. First, for each object, the system calculates the mean feature vector of the models as

$$\mathbb{F}_{i,mean} = \frac{1}{M_i} \sum_{j=1}^{M_i} \mathbb{F}_{i,j}, \tag{1}$$

Object name	Number
Dining chair	4
Table (<400 [mm])	4
Table (400-700 [mm])	4
Table (700-1000 [mm])	10
Table (>1000 [mm])	3
High chair	3
Bench	3
Low chair	3
Swivel chair	3
School chair	3
Folding chair	2
Bench with backrest	3

Fig. 3. Number of Models for Each Object

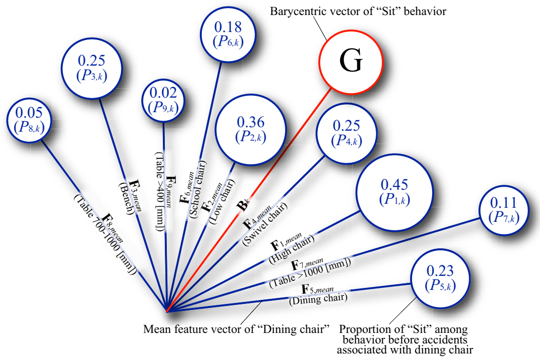

Fig. 4. Conceptual Diagram of Barycentric Behavior Vector

where $\mathbb{F}_{i,j}$ indicates the feature vector of the model$_j$ that describes object$_i$, and M_i indicates the total number of models that describe object$_i$. Next, the system calculates the barycentric vector of behavior$_k$ as

$$\mathbb{B}_k = \sum_{i=1}^{O} P_{i,k} \cdot \mathbb{F}_{i,mean}, \tag{2}$$

where O indicates the total number of object categories accumulated in the database, and $P_{i,k}$ (the occurrence proportion) indicates the proportion of the occurrence of behavior$_k$ among all behaviors associated with the object$_i$. Thus, there exists the following relation:

$$\sum_{k=1}^{K} P_{i,k} = 1.0, \tag{3}$$

where K indicates the total number of behavior categories.

Behavior Prediction Model using Multiple Linear Regression Analysis. We also developed another prediction model using the multiple linear regression analysis. Our system creates cross tables for each behavior, as shown in Table 1. In Table 1, for example, Object (ID=6) is a swivel chair, and since it has movability in DXY and RZ, they both equal 1. We removed the 172nd element of the feature vectors because all vectors had the same value. The rightmost column indicates the occurrence proportion of the behavior of standing on the object. For example, the value "0.223" in the top cell of the red area indicates that in 22.3% of the accidents related to Object (ID=1), standing on the object was the behavior that preceded the accident. We created a linear regression model for each behavior by using the cross table and the following variables:

Table 1. Example of the FV-Behavior Table (standing on the object)

Object ID	Model ID	Model size x	y	z	Movability DXY	RZ	Feature vector (FV) 1	2	3	…	170	171	Behavior Stand on
1	1-1	50.1	46.9	88.5	0	0	4.39E-03	2.74E-03	1.13E-02	…	4.42E-02	3.77E-02	0.223
	1-2	55.9	44.3	95.4	0	0	2.68E-03	1.54E-03	9.20E-03	…	2.25E-02	3.21E-02	0.223
	1-3	40.3	46.5	95.8	0	0	2.80E-03	5.79E-03	6.43E-03	…	1.52E-02	3.15E-02	0.223
2	2-1	142.8	81.6	59.5	0	0	1.85E-04	5.61E-04	1.38E-03	…	5.85E-02	6.25E-02	0.216
	2-2	100.0	100.0	45.6	0	0	1.13E-03	1.02E-03	2.70E-03	…	6.45E-02	6.62E-02	0.216
	2-3	120.0	120.0	63.1	0	0	1.46E-03	5.16E-04	2.99E-03	…	5.60E-02	4.49E-02	0.216
3	3-1	155.3	81.6	71.6	0	0	4.33E-04	2.91E-04	1.53E-03	…	5.89E-02	6.24E-02	0.093
	3-2	160.0	90.0	73.0	0	0	4.55E-04	8.34E-04	9.37E-04	…	5.83E-02	6.34E-02	0.093
	3-3	149.8	79.8	75.0	0	0	1.13E-03	7.95E-04	4.34E-03	…	4.37E-02	5.06E-02	0.093
4	4-1	110.0	92.1	37.7	0	0	5.84E-04	1.60E-03	2.49E-03	…	4.42E-02	5.97E-02	0.116
	4-2	101.8	101.8	38.2	0	0	2.87E-03	2.83E-03	2.96E-03	…	6.13E-02	6.51E-02	0.116
	4-3	148.4	86.9	40.0	0	0	6.07E-04	6.31E-04	6.00E-04	…	5.80E-02	6.53E-02	0.116
5	5-1	42.6	44.8	45.0	0	0	2.13E-03	8.08E-04	2.70E-03	…	1.25E-02	2.24E-02	0.375
	5-2	55.4	39.1	52.9	0	0	2.20E-05	1.10E-04	3.16E-04	…	1.97E-02	4.19E-02	0.375
	5-3	41.8	41.8	67.4	0	0	6.74E-04	1.56E-03	3.20E-03	…	2.61E-02	3.15E-02	0.375
6	6-1	60.5	61.0	93.0	1	1	1.79E-03	8.45E-04	2.08E-03	…	2.53E-02	2.30E-02	0.000
	6-2	66.5	61.0	120.4	1	1	1.50E-03	4.36E-03	5.14E-04	…	1.33E-02	2.16E-02	0.000
	6-3	62.1	61.0	114.4	1	1	2.18E-03	2.04E-03	3.71E-03	…	2.63E-02	1.92E-02	0.000
7	7-1	65.0	98.6	75.0	0	0	2.35E-03	2.68E-03	6.37E-03	…	1.82E-02	4.36E-02	0.500
	7-2	64.6	100.6	75.0	0	0	1.66E-04	9.41E-04	3.06E-03	…	2.49E-02	4.22E-02	0.500
	7-3	59.1	87.4	75.0	0	0	1.03E-03	1.31E-03	2.02E-03	…	2.07E-02	3.44E-02	0.500
8	8-1	67.3	67.3	110.0	0	0	8.73E-03	3.30E-03	1.25E-02	…	5.38E-02	3.65E-02	0.333
	8-2	64.6	64.6	110.0	0	0	5.16E-03	8.80E-03	9.99E-03	…	4.68E-02	4.19E-02	0.333
	8-3	79.7	79.3	110.0	0	0	1.16E-03	1.98E-03	4.92E-03	…	3.56E-02	3.66E-02	0.333
…	…	…	…	…	…	…	…	…	…	…	…	…	…

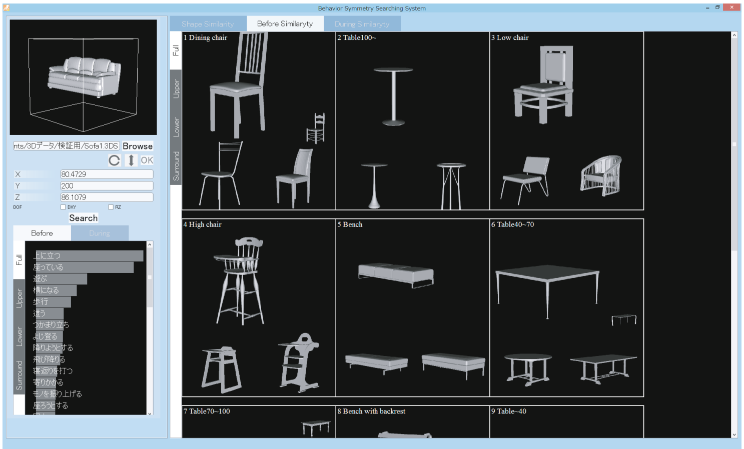

Fig. 5. Browser for the Behavior-Geometry Function

– Objective variable: the occurrence proportion of each behavior (red area in Table 1).
– Explanatory variables: the models' shape-feature vectors, size, and movability.

3 Development of the Behavior-Symmetry Search System

We developed a browser for the child behavior-geometry database and implemented the behavior-symmetry search functions in the browser. By behavior symmetry, we mean that an object induces the same or similar behavior as that induced by another object. The unique characteristic of our system lies in the fact that the system allows us not only to retrieve objects that are similar in terms of shape but also to retrieve behavior-symmetric objects. To operate our system, the user enters a query model that provides information, including the shape and the actual size. The system then produces a feature vector of the 3D shape model, which allows the user to conduct a behavior-symmetry search. This consists of 1) a shape-similarity search, 2) an induced-behavior search, and 3) a behavior-symmetry search that ranks the similarity.

3.1 Shape-Similarity Search

The system uses the inner product to calculate the similarity (S') between the feature vector of the 3D shape query and the feature vectors of the accumulated 3D shape models. Then, the system calculates the similarity $S = f(d_{max}) \cdot S'$ in order to consider information on both size and shape. $f(d_{max})$ expresses the similarity of the size and is defined as

$$f(d_{max}) = \exp\left(-\frac{d_{max}^2}{2\sigma^2}\right), \tag{4}$$

where d_{max} indicates the maximum value of the differences between models in the lengths of each side (x,y,z) of a bounding box, and σ is a controlling parameter. If the sizes of the bounding boxes are the same, $f(d_{max})$ becomes 1.0. σ is given. We selected $\sigma = 13.97$.

3.2 Induced-Behavior Search

In the case of using the barycentric model, for each behavior, the system uses the inner product to calculate the similarity between the feature vector of the 3D shape query and the barycentric behavior vectors. They are then sorted to create a ranking of the behaviors that can be induced by the object's shape query. When using the multiple linear regression model, the system calculates the occurrence probability of each behavior by using the model and the entered information (feature vector, size, movability). Figure 6 shows an example of an induced-behavior search result for the case where the user entered the dining chair model shown in Fig. 7 as a 3D shape query, and the system conducted a search using the multiple linear regression model. This search function enables product designers to predict the behaviors that will be induced by a target object based on its shape, instead of taking an intuitive approach or using literal accident information.

3.3 Behavior-Symmetry Search

Each object accumulated in the behavior-geometry database has ranking information for the occurrence proportion for each behavior. This ranking has the same format as the induced-behavior prediction. Thus we treated those rankings

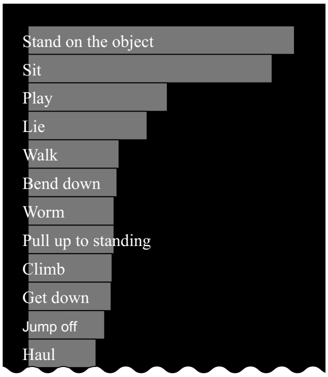

Fig. 6. Prediction Results for Induced Behavior

Fig. 7. 3D Model of Dining Chair

as vectors and used the inner product to calculate their similarity. In this way, we can calculate which object is more similar, in the sense of inducing behavior, to a shape given as a query. Figure 8 shows an example of the behavior-symmetry search result when using the dining chair shown in Fig. 7 as a shape query. The behavior-symmetry search function enables users to retrieve shapes that can induce behaviors similar to those induced by a query, even if the shapes are quite different.

Fig. 8. Example of Behavior-Symmetry Search Result

4 Behavior-Symmetry Search System Performance Evaluation

We evaluated the induced-behavior search by using the sofa models shown in Fig. 9. First, we prepared data on the behaviors related to sofas using the Accident Database that we used to accumulate the behavior data in Sect. 2.1. Next, we input 3D shape models of sofas and retrieved an induced-behavior ranking. We then calculated the following two measures to evaluate the induced behavior search performance: 1) f-measure and 2) average precision.

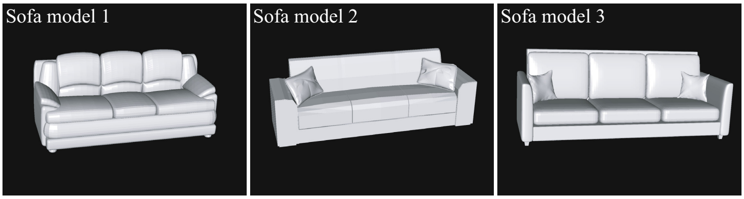

Fig. 9. Sofa Models

The F-measure is the weighted harmonic mean of precision and recall:

$$F - measure = \frac{2 \cdot precision \cdot recall}{(precision + recall)}. \tag{5}$$

The F-measure considers both precision and recall, and its best value is 1, while the worst value is 0. The average precision can consider the order of the resultant ranking by calculating the precision at each position:

$$precision(k) = \frac{1}{k} \sum_{i=0}^{k} r_i, \tag{6}$$

where k is the position in the ranking, and r_i equals one if the behavior at rank k is relevant, and is otherwise zero. Then average precision is calculated as

$$average\, precision = \frac{\sum_{k=1}^{N} r_k \cdot precision(k)}{number\ of\ relevant\ data}, \tag{7}$$

where N indicates the total number of data points that were retrieved.

Table 2 shows the result of the evaluation. We confirmed that a search using the multiple linear regression model performed better than the barycentric behavior model, and our system has a high retrieval performance.

Table 2. Result of Induced-Behavior Search Performance Evaluation

Prediction model	Model	F-measure	Average precision
Multiple linear regression model	Sofa model 1	0.688	0.78
	Sofa model 2	0.750	0.80
	Sofa model 3	0.688	0.79
	Average	0.708	0.79
Behavior barycenter model	Sofa model 1	0.500	0.69
	Sofa model 2	0.438	0.43
	Sofa model 3	0.625	0.80
	Average	0.521	0.64

5 Conclusion

In this study, we developed a child behavior-geometry database. The database consists of 1) 275 records of children's behavior with common objects, 2) for various objects, 3D shape model data and shape-feature vectors calculated by the 3D discrete Fourier transform, and 3) two kinds of behavior predicting models. We developed the barycentric behavior model and the multiple linear regression model as the prediction model. We implemented the behavior-symmetry search function in the database browser. This function allows a user to predict how a child may interact with an object, based on the 3D shape of the object, and to find objects that can induce similar behavior.

In the future, in cooperation with hospitals and fire departments, we will continue to accumulate both 3D shape data for objects related to childhood accidents and data on the interactions of children with those objects. Improving the shape-feature calculating method to process interaction with common objects more correctly is also an important area of future work.

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