Haptic Invitation of Textures: An Estimation of Human Touch Motions

Hikaru Nagano, Shogo Okamoto, and Yoji Yamada

Department of Mechanical Science and Engineering, Graduate School of Engineering, Nagoya University, Japan

Abstract. Some textures invite human touch motions in daily life, but studies on the methodology of designing such textures have just been initiated [1,2,3]. However, there is still no method of identifying various touch motions invited by these textures. For example, some textures are likely to invite stroking, while others are likely to invite pushing. We developed a Bayesian network model that represents the probabilistic relationships between texture-invited touch motions and properties of textures. We interpreted the constructed model and confirmed that the model is potentially useful for the estimation of human motions.

Keywords: Bayesian Network, Stochastic Reasoning.

1 Introduction

Some textures appeal to human touch. Examples of such textures are smooth and comfortable surfaces such as silk, elastic sponges, and finely woven cloths. Occasionally, such textures invite human touch; that is, people feel compelled to touch them. These textures are potentially useful for designing products that invite human touch motion and interfaces that stimulate human interest. Nevertheless, such textures and human responses have rarely been investigated. Nagano et al. [1,2], who investigated properties of textures that appeal to human touch, revealed that the linear combination of physical factors of textures described the degrees of haptic invitation with accuracies of 70–80%. Although glossiness and surface shape types strongly affected the haptic invitation, surface colors barely affected them. Klatzky and Peck [3] also investigated relationships between objects' properties and their appeal to human touch and reported that simple objects invited human touch rather than complex objects, and that people wanted to touch moderate objects more than rough objects. Based on the continuity of these studies, the methodologies for determining the best combinations of physical factors in terms of appeal to human touch will be established.

The results of past studies mentioned above will enable us to design textures and objects that appeal to human touch. However, exactly how people touch these textures is still not known. For example, hard pushing and soft stroking are just two of many touch motions. The touch motion for elastic rubber may be different from that of smooth fur. Some researchers have analyzed hand motions

P. Isokoski and J. Springare (Eds.): EuroHaptics 2012, Part I, LNCS 7282, pp. 338–348, 2012.

of touch. For example, Lederman and Klatzky [4] investigated relationships between hand movements during haptic object exploration and desired properties of objects, such as heaviness and hardness, and Peine et al. [5] analyzed finger motions during surgical palpation. However, touch motions invited by textures have not yet been investigated. If the relationships between touch motions and properties of textures are revealed, we can design not only textures that appeal to human touch but also texture-invited touch motions. For example, we could design textures that are more likely to invite specific touch motions such as stroking or pushing.

The objective of this study was to develop a stochastic model that represents the relationships between texture-invited touch motions and properties of textures. We observed such human touch motions through experiments; thereafter, we developed a Bayesian network, which enabled us to estimate the properties of textures from observed touch motions and vice versa.

2 Experiments

We conducted two types of experiments. In Experiment 1, participants evaluated textures consecutively using a semantic differential (SD) method. Sensory properties of textures acquired here were used in constructing the stochastic model. In Experiment 2, participants touched textures that had a strong appeal to human touch. Human touch motions were measured using a camera and a six-axis dynamic force sensor. Features of touch motions were also applied to the stochastic model. The details of each experiment are described below:

2.1 Experiment 1: Sensory Properties of Textures

Participant Five laboratory students, excluding the authors, approximately twenty years of age participated in Experiment 1.

Task: Sensory Evaluation. The participants evaluated the textures using five-point scales in terms of five adjective pairs: “rough-smooth,” “uneven-flat,” “hard-soft,” “warm-cold,” and “sticky-slippery,” without touching them. The evaluation sheets provided both English and Japanese terms.

As shown in Fig. 1a, a large white plate with an 80 mm × 80 mm square window was placed on a texture so that participants could see only the surfaces and not the sides of the samples. The participants were instructed to keep their head positions fixed in order to retain the relative position between the head and textures. The textures and adjective pairs were presented to each participant in random order.

Stimuli. Preliminary experiments were conducted in order to measure the degrees of affinity for various textures. For details of measurement method of degrees, refer to our articles [1,2]. The textures whose degrees of haptic invitation varied significantly depending on individuals were eliminated through experiments. This process led to the final thirty textures used in Experiments 1 and 2.

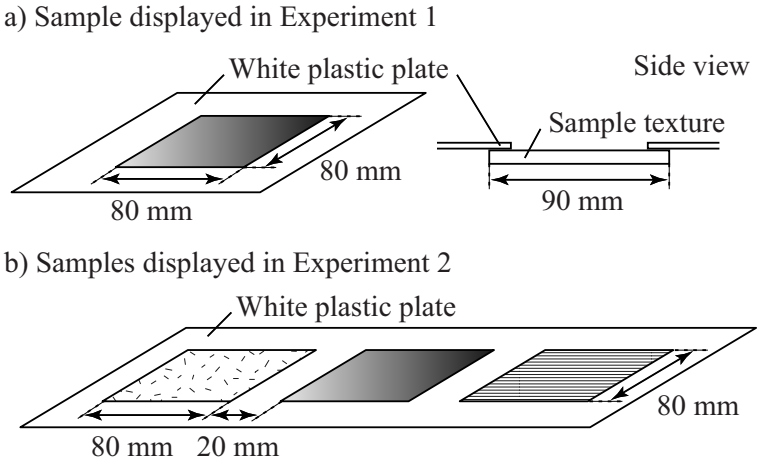

Fig. 1. Sample textures and presentation method

Table 1. List of textures

Group	Texture	Group	Texture	Group	Texture
Paper	Crumpled paper	Leather	Fake alligator hide	Cloth	Fine woven cotton
	Fine Japanese paper		Fake suede 1		Coarse woven cotton
	Coarse Japanese paper		Fake suede 2	Towel	Towel
	Embossed paper 1	Fur	Long hair fake fur	Felt	Felt
	Embossed paper 2		Short hair fake fur	Boa	Fake boa
	Fake paper		Soft fake fur	Artificial grass	Artificial grass
	Wall paper	Straw and rush grass	Fine woven straw	Metal	Woven wire mesh
Wood	Walnut wood		Coarse woven straw	Fiber	Coarse polyester fiber
	Cypress wood		Woven rush grass		
	Chestnut wood	Sponge	Soft sponge		
	Cork board		Hard sponge		

These textures, which are listed in Table 1 and shown in Fig. 2, include a fake fur with long hair and a flat Japanese paper. The textures were 90 mm × 90 mm squares. Flexible textures, such as cloths, were attached to a plastic plate with double-sided tape.

Analysis: Adjective Ratings for Thirty Textures. Ratings of 1 to 5 were assigned to the five-point adjective scales measured in Experiment 1. The rating of each adjective pair was normalized within a single participant to reduce the influence of individual differences in criteria for judgment. Ratings were then averaged across all the participants.

2.2 Experiment 2: Observation of Touch Motions to Textures

Participant. Another five laboratory students, excluding the authors, aged approximately twenty years, participated in Experiment 2.

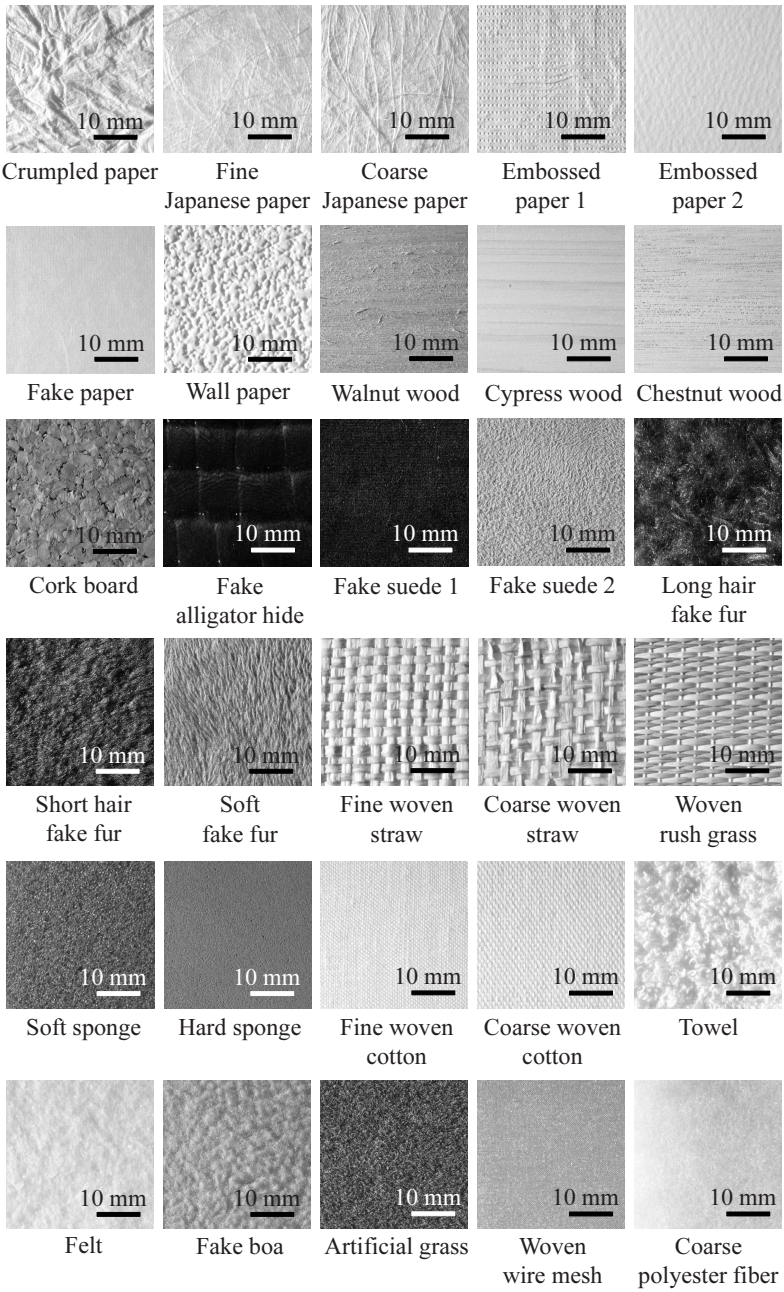

Fig. 2. Thirty textures used in experiments

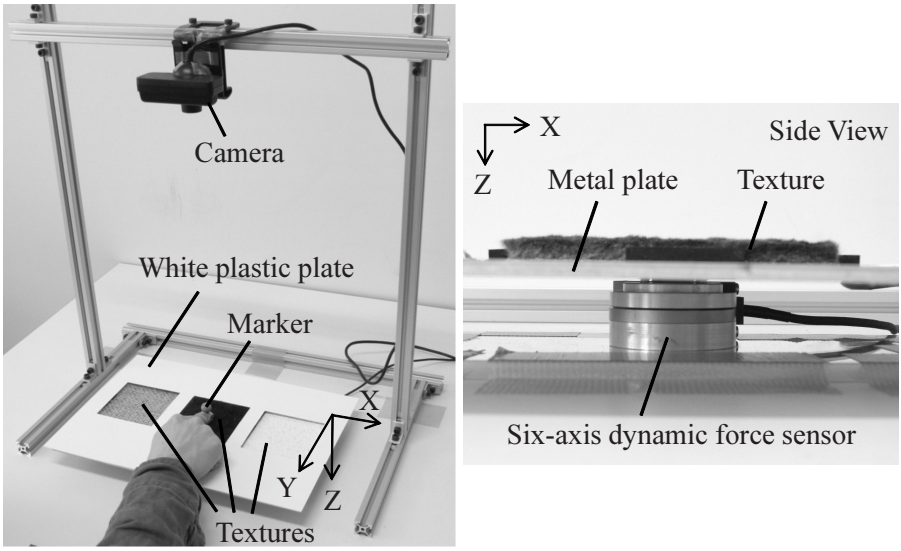

Fig. 3. Measurement of touch motions to textures

Task. In Experiment 2, participants touched one texture among three textures that most strongly appealed to them. These textures were placed under the white plastic plate, as shown in Fig. 1b. If only one texture was shown in the experiments, participants were forced to touch the texture. In order to avoid this unnatural situation, three textures were shown to the participants. Participants were instructed to keep their eyes closed until they heard a beep sound, and then they were free to touch one of three textures.

Stimuli. Three textures were selected through preliminary experiments that were described in Sec. 2.1. The preliminary experiments revealed the ranking of thirty textures in terms of measured degrees of haptic invitation. One of the three textures was selected from ten textures that exhibited the highest degrees of haptic invitation. Another texture was selected from the lowest ten textures, and the last was selected from the remaining ten textures. In total, ten combinations were presented to each participant in random order. Each texture was used only once, and each participant received a unique set of combinations.

Measurement Method for Touch Motions. Human touch motions to textures were measured in Experiment 2. Tip positions of the index finger were measured using a camera (Playstation Eye, Sony co., Tokyo, Japan), as depicted in Fig. 3. The position was detected using a red marker fixed on the nail of the index finger. The camera resolution was 320 × 240 pix, which corresponded to a position resolution of 1.03 mm, and the frame rate was 30 fps. Contact forces were measured by a six-axis dynamic force sensor (MINI 2/10, BL AUTOTEC. LTD., Kobe, Japan), as shown in Fig. 3. The sensor was fixed under a metal plate on which textures were placed. Contact force was recorded at a sampling frequency of 50 Hz.

3 Construction of Bayesian Network Model

In order to estimate touch motions from the properties of textures, we constructed a model that represents relationships among them. Considering that a certain texture frequently invites stroking while another may not, the probabilistic relationships are appropriate for representing connections. In addition, the causal connections are not previously established in relationships. Therefore, we adopted a Bayesian network to represent relationships between human touch motions and sensory properties of textures. Bayesian networks enable us to estimate unobserved states of variables using observed variables. In our case, we estimated properties of textures that are likely to invite specific touch motions.

First, we extracted feature variables that constituted a network from sensory properties of textures and measured touch motions. Second, a Bayesian network model was constructed using these variables as nodes. Finally, the constructed model was interpreted.

3.1 Feature Extraction

The feature variables that became nodes of the Bayesian network are described, and all nodes were discrete variables.

Material Type. Thirty textures were classified into thirteen groups on the basis of their materials, as shown in Table 1. As a result, the node representing material types was quantized into thirteen levels in the following manner:

Material Type: Paper, wood, leather, fur, straw and rush grass, sponge, cloth, towel, felt, boa, artificial grass, metal, or fiber.

Sensory Properties of Textures. We produced five nodes on the basis of adjective ratings "rough-smooth," "uneven-flat," "hard-soft," "warm-cold," and "sticky-slippery," which were acquired in Experiment 1. These ratings were quantized into two levels across their averages. For example, the standardized "rough-smooth" rating of short-hair fake fur was -1.8 (+: rough; -: smooth), which was lower than the average 0. Therefore, the *Micro Roughness* node of short-hair fake fur was labeled "smooth." On the other hand, the standardized "hard-soft" rating of walnut wood was 1.3 (+: hard; -: soft), which was higher than the average 0. Thus, the *Hardness* node of walnut wood was assigned the "hard" label. The five adjective ratings were quantized in the following manner:

Macro Roughness: Flat or bulky

Micro Roughness: Smooth or rough

Hardness: Soft or hard

Warmness: Cold or warm

Friction: Sticky or slippery

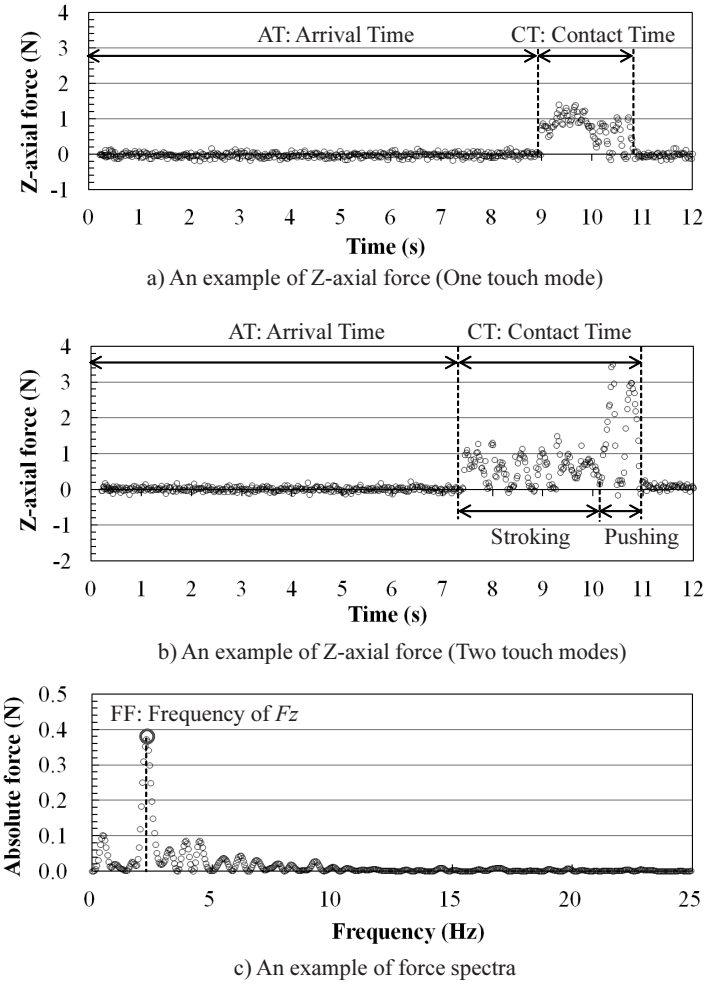

Fig. 4. Examples of Z-axial force and force spectra

Properties of Touch Motions. Human touch motions were measured using the camera and force sensor. From measured data, we produced eight feature variables. The ratings of each feature variable were normalized within a single participant and were then averaged across all participants. All nodes were discretized into two qualitative states across each average.

Two examples of Z-axial force and an example of force spectra are presented in Figs. 4a, b, and c, respectively. An example of distribution of fingertip position in a two-dimensional space (X-Y space) is depicted in Fig. 5. The following nodes were extracted from these force and position data:

Arrival Time: Short or long

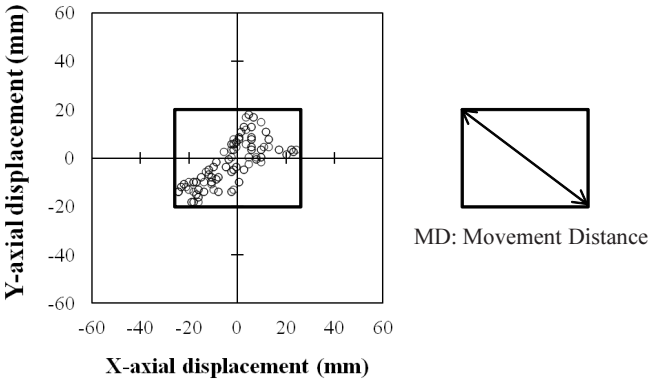

Fig. 5. An example of distribution of finger position

As depicted in Fig. 4a, the *Arrival Time* node was determined from a period between the starting time of the experiment ($t = 0$) at which a sound cue was presented to participants and the time at which the force signal began changing. The *Arrival Time* node was quantized into two levels across its average of normalized values 0. For example, the normalized value of *Arrival Time* for coarse Japanese paper was 2.0 (+: long; -: short), which was higher than zero. Therefore, the *Arrival Time* node of coarse Japanese paper was assigned the "long" label.

Contact Time: Short or long

As depicted in Fig. 4a, the *Contact Time* node was determined as the period during which the texture was touched. The time was quantized into two levels: long and short. For example, for cypress wood, the standardized contact time of -1.2 (+:long; -:short) was assigned the "short" label.

Average Z-axial Force: Weak or strong

The *Average Z-axial Force* node was determined from the average Z-axial force while in contact with the textures.

Maximum Z-axial Force: Weak or strong

The maximum Z-axial force during contact determined the *Maximum Z-axial Force* node.

Frequency of Z-axial Force: Low or high

The *Frequency of Z-axial Force* node was determined from a peak frequency of force spectra, as depicted in Fig. 4c.

Movement Distance: Short or long

As depicted in Fig. 5, we produced a minimum rectangle area surrounding a distribution of the fingertip position. The *Movement Distance* node was determined from a diagonal of the area.

Average Hand Velocity: Slow or fast

We calculated fingertip velocities from time series data of the fingertip position. The *Average Hand Velocity* node was determined from the average fingertip velocity while in contact with the textures.

Maximum Hand Velocity: Slow or fast

The maximum fingertip velocity while in contact with each texture determined the *Maximum Hand Velocity* node.

Mode of Touching Textures

Touch Mode: Soft touch, stroke, push, or scrub

We produced the *Touch Mode* node in order to quantize the modes of touch into four levels. This node was determined from combinations of the *Maximum Z-axial Force* and *Movement Distance* nodes. If the *Maximum Z-axial Force* node was strong and the *Movement Distance* node was long, we determined that the *Touch Mode* node was "scrub." Similarly, we determined three modes of touching: "push" (*Maximum Z-axial Force*: strong, *Movement Distance*: short), "stroke" (*Maximum Z-axial Force*: weak, *Movement Distance*: long), and "soft touch" (*Maximum Z-axial Force*: weak, *Movement Distance*: short).

Change in Touch Mode: Not changed or changed

As depicted in Fig. 4b, the touch mode changed during exploration for some textures and participants. We produced the *Change in Touch Mode* node in order to differentiate examples in which a touch mode changed from those in which the mode did not change. This node was quantized into two levels by the majority mode.

3.2 Structure Learning

We developed a Bayesian network model using the measured data in Experiments 1 and 2. For learning the network model, K2 algorithm and Bayesian information criteria were used. The constructed network is presented in Fig. 6.

3.3 Interpretation of Structure

We briefly interpreted the constructed network on the basis of some examples. The network that obtained the evidence of stroke touch mode estimated the probability of the *Friction* node. The probability of the *Friction* node being slippery was 0.75. The examples of corresponding textures are the short-hair fake fur and felt, which are likely to invite the stroking motion with weak *Maximum Z-axial Force* and long *Movement Distance*.

The network that obtained the *Touch Mode* node of "scrub" estimated that the probability of the *Micro Roughness* being rough was 0.88. The corresponding textures, such as coarse woven straw, are likely to invite the scrubbing motion with strong *Maximum Z-axial Force* and long *Movement Distance*.

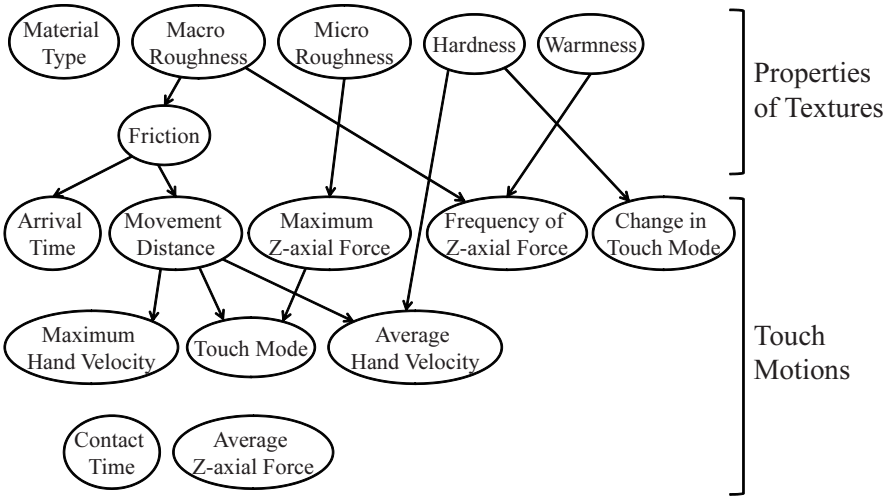

Fig. 6. Bayesian network model

The network that obtained the *Frequency of Z-axial Force* node of "high" estimated that the probability of the *Macro Roughness* being flat was 0.70. The walnut wood and fake suede 1 are examples of corresponding textures, which are likely to invite the high *Frequency of Z-axial Force*.

The network that obtained the *Maximum Hand Velocity* node of "fast" estimated that the probability of the *Macro Roughness* being flat was 0.69. The corresponding textures, such as cypress wood and artificial grass, are likely to invite the fast *Maximum Hand Velocity*.

When the network obtained the *Hardness* node of "soft" and the *Warmness* node of "cold," the probability of the *Touch Mode* being a soft touch mode was estimated to be 0.57. The crumpled paper is an example of a corresponding texture.

The above estimations suggested that the network is potentially useful for designing textures that invite specific human touch motions. However, a detailed validation of the networks is the next challenge.

In this constructed network, the *Material Type* node was isolated perhaps because the even textures belonging to the same material category are very different. For example, although the crumpled paper and embossed paper 2 are both in the paper category, their four sensory property nodes excluding the *Micro Roughness* node were very different. Further, the *Contact Time* and *Average Z-axial Force* nodes were not connected with the other nodes. These nodes have the potential to connect with the nodes we did not use in this study.

4 Conclusion

We investigated the stochastic relationships between touch motions and the properties of thirty textures that invite human touch. The sensory properties of

textures were measured through sensory evaluation, and the features of human touch motions were determined from experiments in which participants freely touched the textures they felt compelled to touch. The Bayesian network model was constructed using these features. A brief interpretation suggested that the network is potentially useful for designing textures that invite specific human touch motions, such as a stroke or push. A re-construction of networks with a sufficient number of data and a detailed validation of the networks are the next challenges.

References

1. Nagano, H., Okamoto, S., Yamada, Y.: Physical and sensory factors of textures that appeal to human touch. In: Proceedings of the 4th International Conference on Human System Interactions, pp. 324–329 (2011)
2. Nagano, H., Okamoto, S., Yamada, Y.: What appeals to human touch? effects of tactual factors and predictability of textures on affinity to textures. In: Proceedings of the IEEE 2011 World Haptics Conference, pp. 203–208 (2011)
3. Klatzky, R.L., Peck, J.: Please touch: Object properties that invite touch. IEEE Transactions on Haptics (to appear, 2012)
4. Lederman, S.J., Klatzky, R.L.: Hand movements: A window into haptic object recognition. Cognitive Psychology 19, 342–368 (1987)
5. Peine, W.J., Wellman, P.S., Howe, R.D.: Temporal bandwidth requirements for tactile shape displays. In: Proceedings of the IMECE Haptics Symposium, pp. 107–113 (1997)