Signal Generation for Vibrotactile Display by Generative Adversarial Network

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Abstract. Various methods have been proposed for collecting vibrotactile information. However, the collection procedure requires manual scanning of texture, collection of vast information may be difficult. Owing to the fast progress of machine learning technologies, even with little information, there is a possibility to generate further virtual data from existing collected data by using Generative Advisory Network (GAN). In this paper, we proposed a generation model of vibrotactile information by Deep Convolutional GAN (DCGAN) from the collected acceleration data. We generated various vibrotactile information by using the proposed DCGAN, and compared the tactile stimulation based on the generated data with the actual texture.

Keywords: Vibrotactile information· Acceleration · DCGAN

1 Introduction

To collect many vibrotactile information, several methods have been proposed. However, the collection procedure requires manual scanning of texture depending on the condition of the touch, collection of vast information may be difficult. Owing to fast progress of machine learning technologies, even with smaller information, there is a possibility to generate further virtual data from existing collected data by using Generative Advisory Network (GAN) [1]. If such generation method is realized, it may be possible to reduce the collecting conditions and the collection cost of vibrotactile data In this paper, as a first step for realizing the proposed method, we generated vibrotactile information by using Deep Convolutional GAN [2]. In addition, we held an experiment to compare the similarity of generated virtual stimulation with actual texture.

2 Systems

In this section, we described the GAN, which is used for the generation of virtual stimulation, and our vibrotactile display, which is used to display vibrotactile information to the user during the experiments.

GAN is one of the many existing machine learning method, which is mainly used for virtual image generation. It is composed of two models: generator and discriminator. The generator generates data from the learned result, whereas the discriminator evaluates the data generated by generator. In this paper, we used DCGAN. Our generator and discriminator have six convolution layers. The input data for the generator are random vectors; the output of the generator is 3-axis vibration data. The input data of the discriminator is the 3-axis vibration data. whereas the output data is the probability of whether input data is generated data or not.

By employing the generated data, we held an experiment to evaluate the similarity of the virtual stimulus. We used the display method proposed by Saga et al. [3]. The display employs the tension of the thread to generate shearing force to the user's fingertip. Using this shearing force the display reproduce the texture feelings on a flat touchscreen.

3 Experiment

We held an experiment to evaluate the reality of tactile stimulation using the generated virtual information. By comparing the stimulation between the virtual information and the actual one, the participants evaluated the rate of reality between 1 and 5.

One participant (male, 22 years old) wore an accelerometer on his finger and collected acceleration data by tracing five types of textures with the finger. By using the collected vibrotactile information, the generator learned the model, and generated the virtual vibrotactile information using DCGAN model. In this experiment, two dimensional vibrotactile stimulation was generated during the user's free movement on the touchscreen. The virtual tactile stimulation and the actual one were given to four participants (male, 20s), and they were asked to evaluate the rate of reality, i.e. how much the virtual stimulation reproduces the actual texture, using a 5-point rating (5 being the maximum).

Fig.1 shows the textures used in this experimental and the experimental results of rating. The tile texture obtained the highest rate. On the other hand, the artificial grass obtained the lowest rate. In the case of touching actual tile texture, the participants induced stick-slip movement on the flat surface. When collecting acceleration from tile, the participant also induced stick-slip movement. Thus the difference of sticky region and un-sticky region is clear compared to other textures. From this result, it was found that such clear difference between regions induced higher rate of reality compared to harsh and random textures. It is assumed that our DCGAN model learned this feature and generated tile vibrations with higher reality.

4 Conclusion

In this paper, we generated the virtual vibrotactile information using DCGAN. We held a reality rating experiment using virtual information and actual infor-

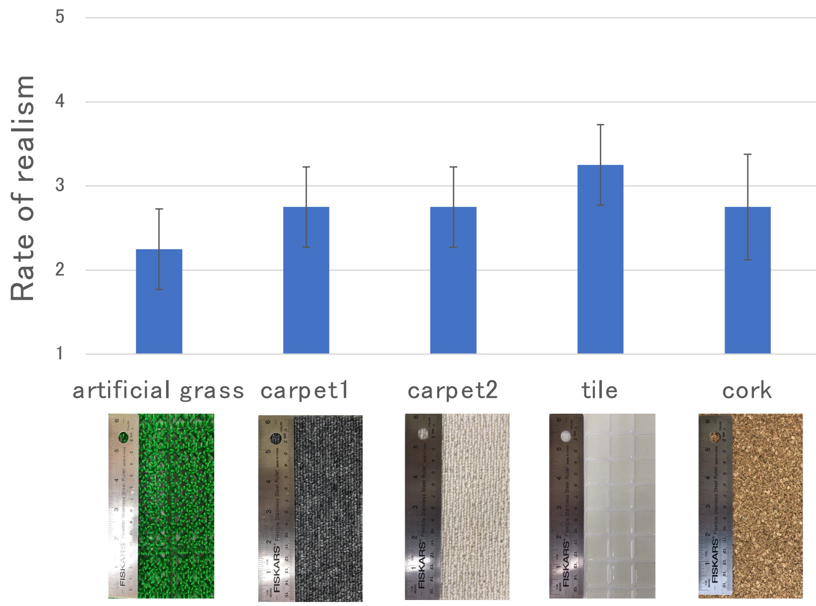

Fig. 1. Experiment result and textures. The bar graph shows the average of the obtained rates. The black line on the bar graph shows the range of the obtained rates.

mation, and evaluated how much realistic information could be generated with the virtual one. Based on the result of the experiment, it was found that the proposed method can present vibration with higher reality when the method reproduces flat surface texture. That is because our DCGAN model can learn stick-slip movement on the flat surface. In the future, we improve the DCGAN to generate more realistic information.

Acknowledgement

This work was partly supported by JSPS KAKENHI Grant Number 16K00265 (Grant-in-Aid for Scientific Research (C)), 16H0285301 and 16H02853 (Grant-in-Aid for Scientific Research (B)).

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