A Novel Texture Rendering Approach for Electrostatic Displays

TAMARA FIEDLER*[1] AND YASEMIN VARDAR†[2,3]

[1]*DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING, TECHNICAL UNIVERSITY OF MUNICH*
[2]*HAPTIC INTELLIGENCE DEPARTMENT, MAX PLANCK INSTITUTE FOR INTELLIGENT SYSTEMS*
[3]*DEPARTMENT OF MECHANICAL ENGINEERING, KOÇ UNIVERSITY*

Generating realistic texture feelings on tactile displays using data-driven methods has attracted a lot of interest in the last decade. However, the need for large data storages and transmission rates complicates the use of these methods for the future commercial displays. In this paper, we propose a new texture rendering approach which can compress the texture data significantly for electrostatic displays. Using three sample surfaces, we first explain how to record, analyze and compress the texture data, and render them on a touchscreen. Then, through psychophysical experiments conducted with nineteen participants, we show that the textures can be reproduced by a significantly less number of frequency components than the ones in the original signal without inducing perceptual degradation. Moreover, our results indicate that the possible degree of compression is affected by the surface properties.

INTRODUCTION

Due to the popularity of touchscreens used in a wide variety of electronic devices, surface haptics has recently gained significant interest by scientific and industrial communities. In particular, the development of new techniques for rendering realistic textures on touchscreens is one of the active research topics in the haptics field. Electrovibration is one of the promising technologies which can be used to give various texture feelings on displays. This technology is based on the electrostatic forces that modulate frictional forces between the fingertip and the touchscreen. This phenomenon was first found by Mallinckrodt [16] and later implemented for generating tactile feedback on opaque electrodes by Strong and Troxel [27]. Recently, Bau et al. applied this method on large transparent surfaces in combination with a visual feedback, and showed the viability of using this method for texture rendering on commercial displays [1].

The first attempt to reproduce natural textures on electrostatic displays has been made by Wu et al. [33]. They proposed an image-based rendering method which establishes a mapping model based on gradients of image-textures using the Roberts filter. They used this mapping model to synthesize frequency and amplitude information of the textures by electrovibration. Later, Vardar et al. followed a different approach, and generated textures by modulating low-frequency unipolar pulse waves in different waveforms and spacing with high-frequency carrier signal on an electrostatic display [31]. They showed that roughness perception of virtual textures can be controlled by changing input waveform and spatial frequency. Ilkhani et al. followed another approach and presented a data-driven texture rendering method [12]. They used the texture models in the Penn Haptic Toolkit [6] as the input signals for the electrostatic display. They conducted psychophysical experiments and analyzed the results using multi-dimensional scaling method. They showed that virtual and real textures had similar perceptual dimension. Similarly, Jiao et al. proposed another data-driven rendering approach which uses the contact frictional forces [13]. Nonetheless, Osgouei et al. [20], proposed an inverse NARX neural network model to generate PRBS-like actuation signals to mimic real textures on an electrovibration display. They trained the networks based on the lateral forces collected from the surface of the display as a result of applying a full band PRBS. Recently, Schultz et al. demonstrated the possibility of making audio-tactile displays by modulating the recorded contact vibrations with using high carrier frequencies [24].

Although data-driven techniques are promising for displaying a wide variety of textures on future displays, their need for large data storages and transmission rates hinder online streaming. Therefore, developing tactile codecs that use the properties and conceptual limitations of tactile information is essential for future applications [19, 25, 25]. For that reason, several efforts have been made by different groups. The first tactile compression method was suggested by Okamoto and Yamada [19]. They described a frequency-domain texture compression method that considers the human vibrotactile perceptual limitations. In their work, they recorded surface profiles using a laser scanner. Then, they transformed these profiles to the frequency domain using the Discrete Cosine Transform (DCT). They set the DCT coefficients below human perceptual detection thresholds to zero. Afterwards, they quantized the remaining coefficients with step-sizes determined from perceptual detection thresholds. Their subjective experimental results showed that this method can reduce the tactile data to 10-20% of their original size without perceptual degradation. Later, Chaudhariu et al. proposed another approach by inspiring from speech signal coding techniques [4, 3]. They reported that their method can compress texture data to 12.5 % of its original size, and provide an output bit rate to as low as 2.3 kbps. Following an approach that is different from others, Culbertson et al. modeled data-driven textures using a low-order auto-regressive moving average (ARMA) [7]. Their method significantly reduced the model storage space requirements by more than 90% and lowered the computational complexity of real-time texture synthesis compared to an earlier work in which linear predictive coding was used for texture modeling [21].

In this paper, we introduced a texture rendering approach, which can reduce the homogeneous texture data significantly for electrostatic displays. We first collected contact acceleration data from three different surfaces to obtain their tactile properties. Then, we analyzed these acceleration data in the frequency domain, compressed and re-synthesized them. Finally, we rendered them on an electrostatic display. This paper explains the recording, compression, re-synthesizing, and rendering methodologies used in detail.

Our compression approach is somewhat similar to the one presented by [19]. They quantized and truncated the data beneath a shifted perception threshold. However, in this study we quantize the spectrum with frequency bands determined from perceptual difference thresholds measured by [1]. Also, we selectively display the main frequency compo-

*tamara.fiedler@tum.de
†yvardar@is.mpg.de

nents, not the entire spectrum. Therefore, the texture data can be compressed by a large amount (down to 9-10 frequency components in total) without inducing perceptual degradation.

METHODS

Texture Data Recording

Previous studies provided evidence that contact acceleration data can store surface properties [22, 26, 8, 17]. Inspired from these studies, we recorded accelerations which occur while sliding a thin steel tooltip over three surfaces: aluminum grid, sandpaper 150, and paper cardboard (see Fig. 1). These surfaces were selected based on their varying periodicity. The accelerometer (ADXL335, Analog Devices) was mounted on a 3D-printed head which was connected directly to the handle of a force feedback device (Falcon, Novint Technologies). The device was programmed to scan surfaces horizontally with a constant velocity of 80 mm/s and a normal force of 1 N with a duration of 1 second. The acceleration data is collected with a data acquisition board (PCI-6221, NI) with a sampling frequency of 10 kHz. This recording system (Fig. 2) enabled to collect small topographical details in a controlled way.

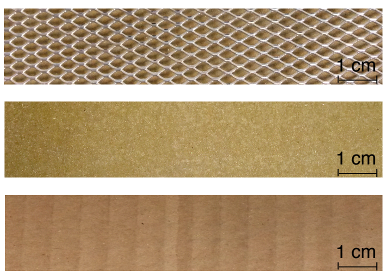

Figure 1: Surfaces that were scanned with the recording system. From top to bottom: aluminium grid, then sandpaper 150, and cardboard.

Figure 2: The data recording system. An accelerometer on a tool tip that is mounted on the force feedback device scans surfaces horizontally with a constant velocity of 80 mm/s.

Texture Reproduction

The recorded acceleration signals in the normal direction were first filtered with a bandpass filter with cut-off frequencies 10 and 1000 Hz. Then, they were cut into a 0.2-second segment which represented the constant sliding of the tooltip. Afterwards, the FFT (Fast Fourier Transform) of each signal was obtained. Then, the peak frequencies were selected with a JND (just noticeable difference) of 12%. This value was chosen based on a previously reported experimental result conducted on an electrostatic display [1]. This procedure was applied to reduce the number of peak frequencies without inducing perceptual deficiencies. Then the signals were reproduced based on the following formula:

$$V_s(t)^* = A_1 sin(2\pi f_1 t) + A_2 sin(2\pi f_2 t) + ... \quad (1)$$

A_1 : Amplitude of the highest peak,
A_2 : Amplitude of the second highest peak,
f_1 : Frequency of the highest peak,
f_2 : Frequency of the second highest peak.

Finally, each reproduced signal for the same surface, $V_s(t)^*$, was normalized to the same signal power:

$$V_s(t) = K(A_1 sin(2\pi f_1 t) + A_2 sin(2\pi f_2 t) + ...), \quad (2)$$

where $V_s(t)$ is the final reproduced surface signal and K is an arbitrary constant. The procedure of reproducing textures from acceleration data is summarized in Fig. 3.

In addition to these signals, we also weighted the FFT of the acceleration signals with the inverse human sensitivity curve using the method presented in [28, 29]. This procedure was tested to reduce the number of necessary frequency components to represent surfaces on a touchscreen. Afterwards, the same peak analysis method described above was applied. Fig. 4 shows the collected acceleration signals from each surface, their synthesized signals using 10 frequency peaks with and without weighting with human sensitivity curve, and resultant FFT of each signal.

Texture Rendering on Electrostatic Displays

On electrostatic displays, the friction forces are modulated using electrostatic actuation. If an alternating voltage is applied to the conductive layer of a touch screen, an attraction force is generated between the finger and its surface. This force changes the friction between the surface and the skin of the finger moving on it, and induces different tactile sensations. The relationship between input voltage signal, $V(t)$, and the resultant electrostatic force, $F_e(t)$, is nonlinear $(F_e(t) \propto V(t)^2)$ [14, 18]. Due to this relationship, when a voltage input containing a single frequency component is applied to a touchscreen, the frequency of output force is doubled [29, 30, 28]. To eliminate the distortions on the output electrostatic force due to this doubling effect, we shifted the reproduced signal to the positive axis by adding proper DC voltage [15], and then took the square root of it:

$$V(t) = \sqrt{V_s(t) + min(V_s(t))}. \quad (3)$$

The input voltage signals obtained from original acceleration signals of each surface and their FFT can be found in Fig. 5.

Psychophysical Experiments

To evaluate the feasibility of our rendering method, we conducted psychophysical experiments. In particular, we wanted to determine the minimum number of frequency peaks needed to render a texture signal using our method. Nineteen (ten female and nine male) participants having an average age of 29 (SD:2) participated in the experiments. None of the participants had previous experience with electrostatic displays. All procedures were approved by Koç University Ethical Council.

During the experiments, the participants sat in front of a touchscreen (3M Microtouch). The touchscreen was placed on a LCD display for visual feedback. On top of the touchscreen, an IR frame was placed to track the participants' finger position and speed. The voltage signals were generated by a data acquisition board (PCI-6221, NI), and amplified by an amplifier (E413 PZT, PI Inc.) before sending to the touchscreen. The participants were grounded with a wristband. They were asked to

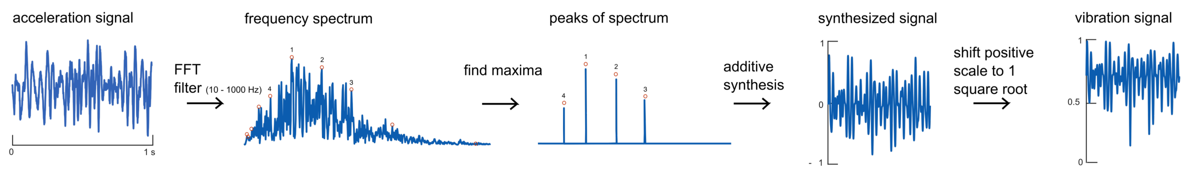

Figure 3: The procedure of reproducing textures from the acceleration data. In the first step, the acceleration data is filtered, and cut as a 0.2 second segment. Then, the peak frequency components with JND of 12% are extracted from its FFT. With these components sinusoidal signals are added to reproduce the new signal. In the last step, the signals are adapted using Eq. 2 to obtain the necessary input voltage signal.

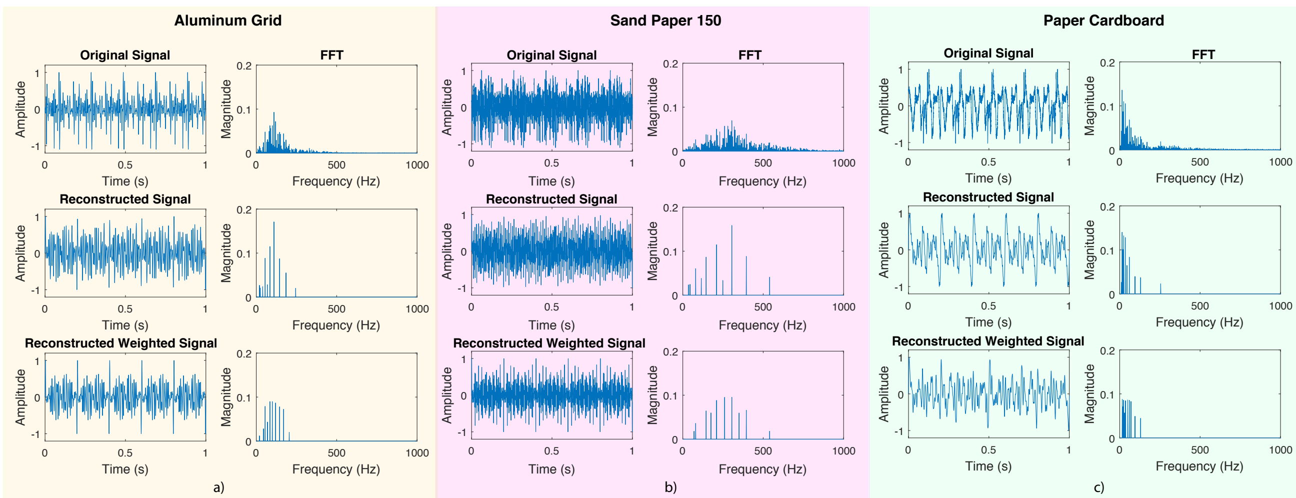

Figure 4: The recorded acceleration signal of three surfaces and their frequency spectrum. The second row shows the reproduced spectrum with ten frequencies. At the bottom, the original frequency spectrum was fitted to the human sensitivity and then ten highest peaks were extracted to reproduce a texture signal. All signals' power were equalized to the same level.

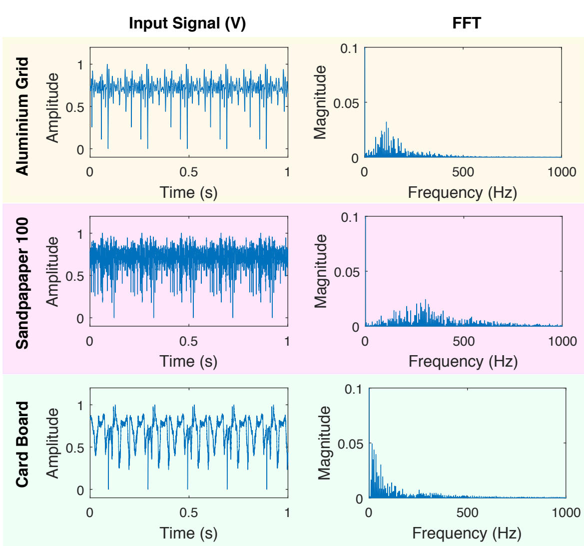

Figure 5: The input voltage signals sent to the electrostatic display representing three surfaces and their FFTs. Each voltage signal was obtained by processing the original acceleration signals based on Eq. 3.

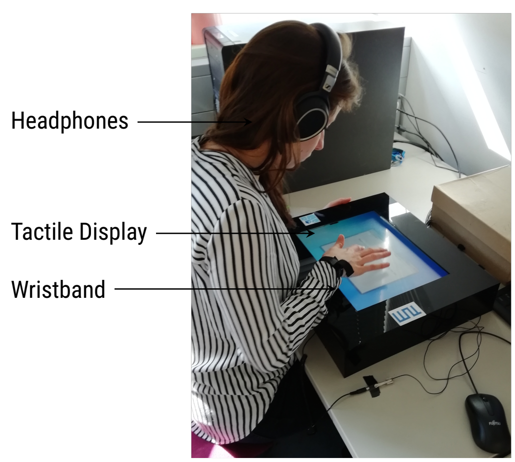

Figure 6: Setup with participants conducting the experiment. The setup is composed of an electrostatic display, an IR touch panel and an LCD display. The subject is wearing a wristband to be grounded to the system and headphones playing white noise to suppress noises.

wear headphones displaying white noise during the experiments for isolation of the background noises (see Fig. 6).

Before the experiments, each participant washed her/his hands with water and soap. Also, the touchscreen was cleaned with alcohol before each experiment. Before starting the experiment, the participants were given instructions about the experiment and asked to complete a training session. This training session enabled subjects to get familiar with the electrostatic actuation.

The stimuli for the experiments were the original and reproduced signals of the surfaces. Before each experiment, participants adjusted the voltage amplitude to a comfortable level for each original surface signal. Due to the security reasons, the maximum selectable input voltage level was 150 V peak to peak.

The experimental procedure was based on the three-interval forced-choice method. The stimuli were displayed in three temporal intervals, which were signaled to participants as yellow, blue, and green using a graphical user interface (GUI) designed in Matlab. Each interval lasted for two seconds. Between each time interval, there was a gap of three seconds. Participants were instructed to hold their finger at an initial point when the yellow signal appeared on the screen. They were asked to move their fingers in tangential direction while synchronizing their finger movements with the motion of a moving cursor for two seconds. The speed of the cursor was 80 mm/s. When they finished one stroke, they were asked to raise their finger and bring it back to the initial point. Then, they repeated the same procedure for the blue and green intervals. After the green interval ended, participants were asked to make their choices as YELLOW, BLUE, or GREEN [30]. In these experiments, the task was to decide whether which stimulus was different than the others. In two of these intervals, the original surface signal was displayed. However, in one of them, its reproduced signal was shown. The location of each signal was randomized in each trial.

The number of frequency peaks contained in the reproduced signal was adapted based on the answer of the participant with two-up-one-down staircase procedure [1, 29]. If the participant gave the correct response twice in a row, the number of frequency components is increased by 5 frequencies. If the participant gave the wrong response, the number of frequency components was decreased by 5 frequencies. A change from increasing number of frequency components to decreasing and vice versa was called reversal. After the first three reversals, the step size was decreased from 5 to 1 frequency, that guaranteed faster convergence. The procedure was carried out until 12 reversals. The discrimination threshold for the number of frequency components was determined by the average of the last 12 reversals. An illustration of the method is presented in Fig. 7.

Each participant conducted the experiment for at least one surface for 2 approaches with and without weighting with the human sensitivity curve. In total, the experiments were completed in 60 sessions (3 surfaces x 2 approaches x 10 repetitions). The duration of each session was about 15-20 minutes.

RESULTS

The average discrimination thresholds for the number of frequency components of reproduced signals for each surface (aluminum grid, sandpaper 150, cardboard) and two methods (unweighted, weighted) are shown in Fig. 8. Pairwise t-test results showed that, for each surface type and method, the average number of frequency components needed to reproduce a texture was significantly lower than the ones in the original signal ($p<0.01$).

The results were analyzed using a two-way analysis of variance (ANOVA) with repeated measures. The surface type was statically significant on the discrimination thresholds ($p<0.05$). However, weighing the FFT based on human sensitivity curve did not affect the number of frequency

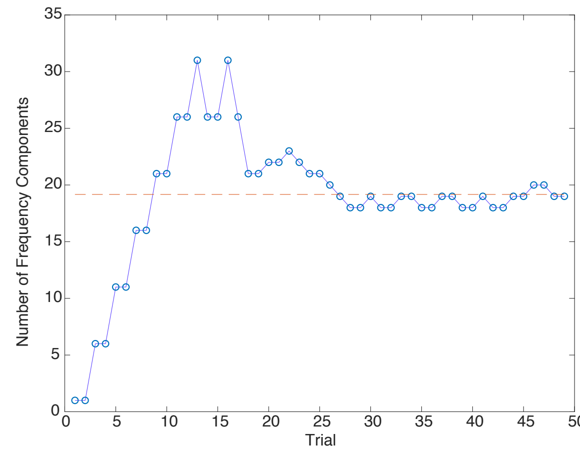

Figure 7: An example data set collected by one up-two down adaptive staircase method. The x-axis shows the number of trials and the y-axis shows the number of frequency components from which the texture signal is reproduced. When the user can distinguish original an reproduced signal, further frequency components are added to the reproduced signal.

components compared to unweighted one. Moreover, Bonferroni corrected paired-t-test results showed that cardboard and sandpaper were statistically different ($p<0.05$).

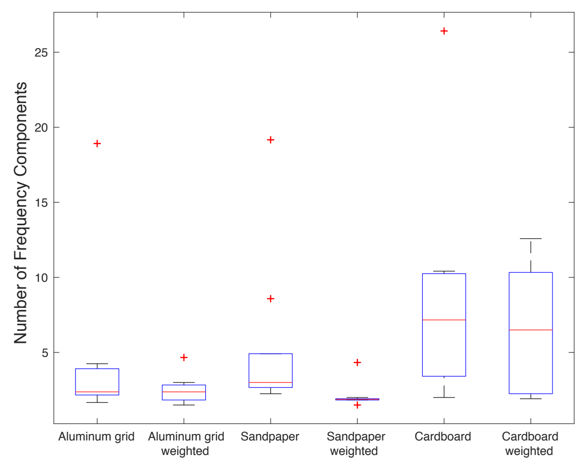

Figure 8: Box-whisker plot of the experimental results. The data show the discrimination threshold for the number of frequency components needed so that the original and the reproduced signal were still discriminable. ANOVA analysis showed that the texture type was significant for the number of frequency components. However, the type of the method (weighted or unweighed) had no significant influence.

DISCUSSION

The experimental results showed that our method can compress the texture data significantly without perceptual loss. The mean number of needed frequency components in the reconstructed signal was less than 10 for each surface and method, whereas the original signals contain at least 50 (compare Fig. 4 and Fig. 8). This result indicates that the texture data is reduced to less than 20% of the original signal. This compression amount is similar to the prior studies [19, 4]. To reach this high compression amount, we used the human inability to distinguish multi-frequencies. Previous literature also supports this methodology. Cholewiak et al. [5] analyzed the detection and discrimination threshold of haptic gratings in the frequency domain. They found that higher spatial frequencies were indistinguishable from the corresponding fundamental components until the third harmonics was added. Recently, Friesen et al. found that a sinusoidal texture with two frequency components can be perceived as one single pitch. Depending on the amplitude ratio, the pitch lied in-between both frequencies [10]. The results of both studies suggest that complex textures can be reduced to simpler representations.

We observed that the obtained compression amount is affected by the surface properties. Specifically, the number of frequency components needed to reproduce sandpaper were significantly less than those required for the cardboard. This is mainly because each texture-elicited vibration is texture-specific and dependent on the surface microgeometry [17]. As shown in Fig. 4 cardboard and sandpaper have different frequency spectrum: the first one has mainly low-frequency components, whereas the latter has components at much higher frequencies. As indicated in [32], the information about most natural textures is conveyed through precise temporal spiking patterns in afferent responses, driven by skin vibrations elicited during scanning. When these vibrations vary temporally, they will generate temporal spiking patterns which activate different mechanoreceptor populations in a varying manner [32, 2].

Our results indicated that weighting the frequency spectrum with the inverse of the human sensitivity curve did not affect the compression amount significantly. This might be caused by the fact that human sensitivity curve is only valid for the stimuli at the threshold levels [11]. In fact, most natural (supra-threshold) stimuli excite all afferents and most tactile percepts are shaped by multiple submodalities [32, 23]. The weighting function augmented the high-frequency components between 100-300 Hz while suppressing the low-frequency ones. For fine textures such as sandpaper, this can be an effective method to increase compression amount, not for textures that have mainly low-frequency components in their frequency spectrum like cardboard (see Fig. 4).

CONCLUSION

In this study, we proposed a new texture rendering approach which can compress tactile data significantly for electrostatic displays. For this approach, we firstly collected acceleration signals from three surfaces, and then analyzed them in the frequency domain. The frequency spectrum of these signals was simplified based on previously measured frequency discrimination thresholds (JND) [1]. Then, the texture signals were reproduced by adding each frequency component in this simplified spectrum and then rendered on an electrostatic display. Through psychophysical experiments conducted by nineteen participants, we showed that the number of frequency components required to reproduce a texture signal is much lower than the total number of frequencies contained in the original signal. Moreover, the texture type had a significant effect on the compression amount.

To the best of our knowledge, this is the first detailed texture rendering study for electrostatic displays which also considers the compression of tactile data. Engineers and designers can benefit from our method to generate realistic texture feelings on commercial displays. For the cases, in which finger scan speed is pre-determined, our method can provide small data storage and high data transmission rate by storing and rendering the reduced temporal spectrum of a texture. However, if the finger speed is not known beforehand, the spatial spectrum of the texture should be stored, and its reduced temporal spectrum should be calculated based on the finger scan speed in real time. In this case, our method still reduces the transmission rates, but it may not benefit from reduced data storages.

Although our method can provide high compression rates for the tactile data, it is only effective for homogeneous textures since it is based on the temporal aspects of reconstructed waveforms. However, for inhomogeneous textures, spatial information is also necessary [23]. The position of the finger should be observed in real-time and the input signal should be adjusted based on this information. During this process, the macro-details should be kept as original, but the micro-details can be compressed. The temporal information coming from the micro-details should be modulated by the spatial information [9].

Another limitation of our study is that we tested our method by exploring only three different textures by the same horizontal motion. In the future, we plan to extend our work by exploring more textures and motion patterns.

ACKNOWLEDGMENTS

The authors would like to thank Prof. Dr. Cagatay Basdogan and Prof. Dr. Eckehard Steinbach for providing necessary lab equipment and support during the project. Also, we thank Matti Strese and Johannes Ackermann for their comments. This work has been supported by the Technical University of Munich and The Scientific and Technological Research Council of Turkey (TUBITAK).

REFERENCES

[1] O. Bau, I. Poupyrev, A. Israr, and C. Harrison. TeslaTouch: electrovibration for touch surfaces. *Proceedings of UIST 2010*, pages 283–292, 2010.

[2] S. J. Bensmaïa and M. Hollins. The vibrations of texture. *Somatosens Mot Res*, 20:33–43, 2003.

[3] R. Chaudhari, B. Çizmeci, K. J. Kuchenbecker, S. Choi, and E. Steinbach. Low bitrate source-filter model based compression of vibrotactile texture signals in haptic teleoperation. In *Proc. ACM Multimedia*, pages 409–418, Nara, Japan, 2012.

[4] R. Chaudhariu, C. Schuwerk, M. Danaei, and E. Steinbach. Perceptual and bitrate-scalable coding of haptic surface texture signals. *IEEE Journal on Selected Topics in Signal Processing*, 9(3):462–473, 2015.

[5] S. A. Cholewiak, K. Kim, H. Z. Tan, and B. D. Adelstein. A frequency-domain analysis of haptic gratings. *IEEE Transactions on Haptics*, 3(1):3–14, 2010.

[6] H. Culbertson, J. J. López Delgado, and K. J. Kuchenbecker. One hundred data-driven haptic texture models and open-source methods for rendering on 3d objects. In *2014 IEEE Haptics Symposium (HAPTICS)*, pages 319–325, 2014.

[7] H. Culbertson, J. M. Romano, P. Castillo, M. Mintz, and K. J. Kuchenbecker. Refined methods for creating realistic haptic virtual textures from tool-mediated contact acceleration data. In *Proc. IEEE Haptics Symposium*, pages 385–391, Vancouver, Canada, Mar. 2012.

[8] H. Culbertson, J. Unwin, and K. J. Kuchenbecker. Modeling and rendering realistic textures from unconstrained tool-surface interactions. *IEEE Transactions on Haptics*, 7(3):381–393, 2014.

[9] T. Fiedler, Y. Vardar, M. Strese, E. Steinbach, and C. Basdogan. Reproduction of textures based on electrovibration. Hands-on Demonstration in IEEE World Haptics, 2017.

[10] R. F. Friesen, R. L. Klatzky, M. A. Peshkin, and J. E. Colgate. Single pitch perception of multi-frequency textures. *IEEE Haptics Symposium, HAPTICS*, 2018-March:290–295, 2018.

[11] G. A. Gescheider. *Psychophysics: The fundamentals*. Taylor and Francis Group, 1997.

[12] G. Ilkhani, M. Aziziaghdam, and E. Samur. Data-driven texture rendering on an electrostatic tactile display. *International Journal of Human Computer Interaction*, 33(9):756–770, 2017.

[13] J. Jiao, Y. Zhang, D. Wang, Y. Wisell, D. Cao, X. Guo, and X. Sun. Data-driven rendering of fabric textures on electrostatic tactile displays. In *2018 IEEE Haptics Symposium (HAPTICS)*, pages 169–174, 2018.

[14] K. Kaczmarek, K. Nammi, A. K. Agarwal, M. E. Tyler, S. J. Haase, and D. J. Beebe. Polarity effect in electrovibration for tactile display. *IEEE Transactions on Biomedical Engineering*, 53(10):2047–2054, 2006.

[15] J. Kang, H. Kim, S. Choi, K.-D. Kim, and J. Ryu. Investigation on Low Voltage Operation of Electrovibration Display. *IEEE Transactions on Haptics*, 10(3):371–381, 2017.

[16] E. Mallinckrodt, A. L. Hughes, and W. Sleator. Perception by the Skin of Electrically Induced Vibrations. *Science*, 118(3062):277–278, 1953.

[17] L. R. Manfredi, H. P. Saal, K. J. Brown, M. C. Zielinski, J. F. Dammann, V. S. Polashock, and S. J. Bensmaia. Natural scenes in tactile texture. *Journal of Neurophysiology*, 111(9):1792–1802, 2014.

[18] D. Mayer, M. Peshkin, and E. Colgate. Fingertip electrostatic modulation due to electrostatic attraction. In *Proc. IEEE World Haptics Conference (WHC'13)*, pages 43–48, Daejeon, South Korea, 2013.

[19] S. Okamoto and Y. Yamada. Lossy data compression of vibrotactile material-like textures. *IEEE Transactions on Haptics*, 6(1):69–80, 2013.

[20] R. H. Osgouei, S. Shin, J. R. Kim, and S. Choi. An inverse neural network model for data-driven texture rendering on electrovibration display. In *2018 IEEE Haptics Symposium (HAPTICS)*, pages 270–277, 2018.

[21] J. M. Romano and K. J. Kuchenbecker. Creating realistic virtual textures from contact acceleration data. *IEEE Transactions on Haptics*, 5(2):109–119, Apr. 2012.

[22] J. M. Romano and K. J. Kuchenbecker. Creating Realistic Virtual Textures from Contact Acceleration Data. *Mechanical Engineering*, 5(2):109–119, 2012.

[23] H. P. Saal and S. J. Bensmaia. Touch is a team effort: interplay of submodalities in cutaneous sensibility. *Trends in Neurosciences*, 37(12):689 – 697, 2014.

[24] C. Shultz, M. Peshkin, and J. E. Colgate. The application of tactile, audible, and ultrasonic forces to human fingertips using broadband electroadhesion. *IEEE Transactions on Haptics*, 11(2):279–290, 2018.

[25] E. Steinbach, M. Strese, M. Eid, X. Liu, A. Bhardwaj, Q. Liu, M. Al-Ja'afreh, T. Mahmoodi, R. Hassen, A. E. Saddik, and O. Holland. Haptic codecs for the tactile internet. *Proceedings of the IEEE*, pages 1–24, 2018.

[26] M. Strese, C. Schuwerk, A. Iepure, and E. Steinbach. Multimodal feature-based surface material classification. *IEEE Transactions on Haptics*, 10(2):226–239, 2017.

[27] R. M. Strong and D. E. Troxel. An Electrotactile Display. *IEEE Transactions on Man-Machine Systems*, 11(1):72–79, 1970.

[28] Y. Vardar, B. Güçlü, and C. Basdogan. Effect of Waveform in Haptic Perception of Electrovibration on Touchscreens. 9775:190–203, 2016.

[29] Y. Vardar, B. Güçlü, and C. Basdogan. Effect of waveform on tactile perception by electrovibration displayed on touch screens. *IEEE Transactions on Haptics*, 10(4):488–499, 2017.

[30] Y. Vardar, B. Güçlü, and C. Basdogan. Tactile masking by electrovibration. *IEEE Transactions on Haptics*, 2018.

[31] Y. Vardar, A. İşleyen, M. Saleem, and C. Basdogan. Roughness perception of virtual textures displayed by electrovibration on touch screens. In *Proc. of IEEE World Haptics Conference*, pages 263–268, 2017.

[32] A. I. Weber, H. P. Saal, J. D. Lieber, J.-W. Cheng, L. R. Manfredi, J. F. Dammann, and S. J. Bensmaia. Spatial and temporal codes mediate the tactile perception of natural textures. *Proceedings of the National Academy of Sciences*, 110(42):17107–17112, 2013.

[33] S. Wu, X. Sun, Q. Wang, and J. Chen. Tactile modeling and rendering image-textures based on electrovibration. *Visual Computer*, pages 1–10, 2016.