Learning an Action-Conditional Model for Haptic Texture Generation

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Abstract—Rich haptic sensory feedback in response to user interactions is desirable for an effective, immersive virtual reality or teleoperation system. However, this feedback depends on material properties and user interactions in a complex, non-linear manner. Therefore, it is challenging to model the mapping from material and user interactions to haptic feedback in a way that generalizes over many variations of the user's input. Current methodologies are typically conditioned on user interactions, but require a separate model for each material. In this paper, we present a learned action-conditional model that uses data from a vision-based tactile sensor (GelSight) and user's action as input. This model predicts an induced acceleration that could be used to provide haptic vibration feedback to a user. We trained our proposed model on a publicly available dataset (Penn Haptic Texture Toolkit) that we augmented with GelSight measurements of the different materials. We show that a unified model over all materials outperforms previous methods and generalizes to new actions and new instances of the material categories in the dataset.

I. INTRODUCTION

Realistic virtual reality (VR) environments benefit from rich multi-modal sensory feedback, including the visual, haptic, and auditory signals that humans normally receive during real-life manipulation tasks. Humans are conditioned to expect the sense of weight, hardness, deformability, texture, and slipperiness when interacting with an object [1, 2, 3, 4], an experience that does not fully exist in commercially available VR systems. To this end, several researchers have rendered textures by varying the magnitude and direction of the force imposed on the user using a force feedback device [5, 6, 7], by varying local surface friction using a surface haptic display [8], or by using a voice coil motor to induce controlled acceleration signals in a hand-held pen [9, 10]. These approaches develop a separate model for each texture, which makes it hard to scale them to the unlimited variety of textures in the world. There are approaches that learn a joint latent representation for different textures who show generalization to novel inputs. However, they focus on texture classification or property estimation and not on generating haptic feedback [11, 12, 13, 14].

In this paper, we focus on data-driven modeling of the vibratory feedback that different textures induce in a probe as it is moved over a surface. This vibration is linked to humans’ perceptual impression of texture and is a function of the probe’s action as well as the texture [3]. This form of haptics was selected for study because of the availability of public datasets in this area. We propose a novel learning-based method for haptic texture generation using an action-conditional model. This model takes as input (i) an image from the GelSight tactile sensor [15, 16] while pressed on a texture, and (ii) force and speed of the user on that texture during a tool-mediated interaction over a horizon of 1 ms. Given this input, we train a model that predicts the magnitude of the discrete fast Fourier transform of the generated acceleration in the hand-held probe within the next 0.1 s. We predict the spectral content instead of the temporal signal because there is evidence that human texture sensation is invariant to phase shifts [17].

We train our model using supervised learning data from the Penn Haptic Texture Toolkit (HaTT) [9]. We show that our novel methodology for generating haptic textures learns a unified model for several textures and generalizes to new force and speed interactions. The learned latent representation of different textures places materials that feel similar closer to each other. This opens the opportunity to generate haptic textures of new materials by locating them within that latent space. In sum, this paper presents a new action-conditional model for generating haptic textures that is learned from data. The primary contributions are as follows:

1) By concatenating human actions with a feature representation of a GelSight image of the texture, our model can predict the vibratory feedback in a hand-held probe during user interactions.

2) Our proposed model is unified across different textures, reducing the need for developing a separate model for each texture instance.

3) Our model generalizes to previously unseen force and speed interactions as well as new instances of the modeled textures and outperforms prior work in terms of DFT prediction accuracy. Additionally, we have augmented the HaTT dataset with GelSight videos, which will be made publicly available upon publication.

II. RELATED WORK AND BACKGROUND

Materials respond to user interactions in a highly variant and non-linear fashion. This makes manual modelling of haptic feedback hard. Therefore, researchers have explored data-driven approaches. For data-driven voice-coil based texture rendering, there are approaches based on linear predictive coding (LPC) [10], auto-regressive moving-average (ARMA) [18] and piece-wise auto-regressive moving-average [9].
Fig. 1. Neural Network architecture for short horizon haptic signal generation. This model takes a GelSight image of the material as well as the force and speed imposed by the user over a 1 ms window on the material surface (action) and predicts the magnitude of the spectral content of acceleration in the next 100 ms induced in the material due to this interaction.

However, these approaches are challenging to scale to the unlimited number of textures around us because they learn a separate model for each texture and do not relate them to each other in a joint model. Thus, as the number of desired textures for rendering increases, the number of saved models linearly increases. Furthermore, this set of models cannot generalize to new textures as it is unclear how this new texture is similar or different from the textures instances in the training set.

There is work that learns a joint model of different textures which generalizes to novel textures. \cite{11, 12, 13} focus on using data collected during tool-mediated interactions to extract surface properties. As input, the proposed models use a variety of different modalities such as recorded acceleration, sound, normal force, friction, and RGB images – either individually or in combination. The output of the models are properties that are then used as a texture representation feature which helps to evaluate the similarity of different textures for texture classification. However, \cite{11, 12, 13} do not use this representation for generating haptic feedback. More recently, Takahashi and Tan \cite{14} have provided evidence that a network can be trained to estimate tactile properties of new surfaces using an RGB image as input and shown the value of a learned latent representation vector in estimating tactile properties, but the performance of their model on predicting temporal data is unclear.

Deep learning-based approaches can learn complex functions which are hard to model manually. They learn feature representations from data and can generalize to new data \cite{19, 20}. Inspired by this, we propose a learning-based approach that uses the image of a texture and the action of the user to generate haptic texture feedback. In our approach, we learn a joint model over many textures such that it can generalize to novel textures. Furthermore, the experienced sensation of a texture is not just a function of the material but also the imposed force and speed on that texture by the user. Therefore, we propose an action-conditional model.

III. GENERATIVE ACTION-CONDITIONAL MODEL

The inputs of this structure are a GelSight image, obtained by pressing the sensor on the material, as well as a user’s force and speed measurements during 1 ms of interaction with the texture. Our model outputs the magnitude of the discrete Fourier transform (DFT) of the induced acceleration for the next 100 ms. This acceleration corresponds to human’s perceptual impression of texture.

The goal of this model is to infer the relationship between a combination of a user’s action and texture’s representation with the corresponding induced acceleration. During a live demo, this model could be used in the following example application. First, we collect a GelSight image of the material that would be encoded in a texture representation vector. Afterwards, the user’s force and speed are recorded as they move their hand in virtual reality. These readings are fed into our model to predict the magnitude of the short term DFT of the expected acceleration. This short term spectral prediction is then used to construct a temporal acceleration signal that can be displayed to the user through vibratory feedback in real time.

A. Neural Network Architecture

Fig. 1 shows the architecture that enables the short time DFT prediction of our model. This architecture encodes the GelSight image into a texture representation vector and combines it with the encoded action representation from the user’s force and speed to predict the desired DFT using an acceleration predictor module.

We use AlexNet \cite{21} with fine-tuned weights as image encoder with two additional CNN layers to further decrease the resolution of the input images (960x720x3). This encoder was chosen based on its optimal performance on the proxy task of classifying the GelSight images. The other encoders or layers in the model are fully connected (FC) with rectified linear layers in between.
The architecture is trained in two stages. First, we train the image encoder augmented with three fully connected layers for texture classification using a cross entropy loss. Afterwards, we freeze these pre-trained weights and use the output of the image encoder as input to the texture encoder. We then train the full architecture for predicting the DFT magnitude of the accelerations. The choice of freezing over fine-tuning was motivated by its better performance on the validation set. As loss we choose the Euclidean distance between the ground truth and predicted magnitude up to 1000 Hz.

B. Temporal Signal Construction

Rendering haptic textures require a long term temporal vibratory signal. To construct such signal from the predicted short term DFT magnitude of our model, we use Prusa's implementation of the Griffin and Lim Algorithm (GLA) in Matlab. To achieve faster convergence, we use a variation of GLA called fast GLA.

The caveat of using GLA is that it does not run in real time. However, similar algorithms that are capable of running online exist and can be explored in future work. To provide a basic proof of concept that our method can work in real-time, we also directly stitched the inverse Fourier transformed sequence (with random phase) and report the performance using this constructed long term temporal prediction in the experimental section.

IV. DATASET

Researchers in the computer vision community have studied and published purely image-based texture databases for several years. However, these datasets lack multi-modal sensory information such as haptic information. Only a few limited databases have been made publicly available in the haptics community. Specifically, the Penn Haptic Texture Toolkit (HaTT) and the LMT Haptic Texture Database are the two main publicly available haptic texture databases. The sensory data collected in the LMT haptic is suitable for texture classification but is unsuitable for our task as they lack positional tracking of the tool. Hence, our model was trained using HaTT.

HaTT includes raw data used to create haptic texture and friction models for one hundred different materials from diverse categories including paper, metal, carbon fiber, fabric, plastic, wood, stone, foam, tile, and carpet. The original data were collected by a sensorized pen providing 6 DoF force/torque readings, acceleration measurement, as well as positional and oriental tracking of the pen’s top. For each material, Culbertson et al. used this pen to measure a 10-second signal of a human’s unconstrained circular motion. The resulting dataset (HaTT) includes textural haptic information about a large variety of textures making it a suitable choice for evaluating our model.

We have augmented this dataset with GelSight images. GelSight is a vision-based high resolution tactile sensor made of a piece of clear elastomer coated with a reflecting membrane. A video-recording camera is attached to the other side of this elastomer and captures its deformation during contact. These deformations provide high resolution information about the geometry of the surface they are in contact with. Using this sensor, we have collected videos of 5 presses on 93 out of the 100 materials due to availability during data collection. The location of these presses (shown by white rectangles) as well as an example GelSight image is shown as the input of the image encoder in Fig. 1.

This addition provides the opportunity to explore research questions on the advantages of using GelSight over RGB in texture rendering or hardness estimation using a similar approach to that of Yuan et al. in future work.

Data Preprocessing

Force and speed measurements during interactions do not merely include the action of the user, but also oscillations generated by the texture. To mitigate the texture’s influence, we low-pass filtered the force and speed signals at 20 Hz before feeding them into the neural network.

To build the training, validation, and test sets, we divide each interaction sequence into 25 sections and re-group them. An example is shown in Fig. 2.

The test and validation sets are then chosen such that their force and speed regions overlap with those of the training set. This was imposed to increase the likelihood of the test and training data sharing similar sampling distributions. Out of the 5 collected GelSight videos (each containing a single press), 3 were used for training, 1 for validation, and 1 for testing. These videos were processed by extracting the frame that has the highest pixel value difference from the non-contact frame. This frame usually corresponds to when the sensor is making the largest contact force with the material. For the videos used in the training set, the adjacent frames of this peak frame were also used for a total of 12 images per video. For further augmentation, these images were rotated at multiples of 90 degrees and mirrored.

V. EXPERIMENTS

The primary goal of our experiments is to evaluate the performance of our model for the purpose of haptic texture acceleration signal generation. The experiments are driven by three main questions:
1) Can this model generate the induced haptic acceleration signal of a texture given the user’s actions?

2) Is there an advantage to learning a unified model for different textures based on their GelSight image as opposed to modeling each material separately?

3) Does the model generalize to: (i) new interactions by the user (ii) new GelSight images of training materials (iii) GelSight images of novel materials?

In all of our experiments, we conducted training on a Quadro P5000 GPU using Pytorch with Adam as the optimization algorithm. The t-SNE plots were generated using the implementation in Scikit-learn.

A. Evaluation Metrics

To evaluate the performance of our model, we directly compare the original signal with the output of our model for texture signal generation. Here, the term texture signal generation refers to predicting the induced acceleration due to the user’s action with a material (i.e. their force and speed) during a tool-mediated interaction. As previous evidence suggests that humans’ texture sensation is insensitive to phase shifts, we only take into account the magnitude of the discrete Fourier transform of this generated acceleration. Furthermore, as the variation of the user’s force and speed during interaction results in a non-stationary signal, we compare the spectral distance of the two signals in short time windows and average the results over a shifting window. In our evaluation, we used a window size of 0.1 sec (1000 data-points) with a step size of 100 data-points and an Euclidean distance measure. Furthermore, we only calculated the spectral distance for frequencies up to a 1000 Hz as the original acceleration signal in the dataset was low-pass filtered at that frequency.

Finally, as a qualitative metric, we gain insight regarding the texture encoder in our generative model by visualizing the high-dimensional texture representation vector in our model (the output of texture encoder in Fig. 1) in a 2D space using a dimension reduction technique called t-Distributed Stochastic Neighbor Embedding (t-SNE).

B. Baseline

We compare our model to the piece-wise auto-regressive model used in which is a state-of-art method for vibration-based texture rendering. For a direct comparison to our model, we refit only the training and validation sections of the data into a piece-wise AR model and use it to synthesize the acceleration for the test set. This approach fits a separate model for each of the materials and requires manual labeling to match a new instance of a material with existing models.

C. Generalization to New Interactions

For a direct comparison to the baseline, we first train one model per material by only feeding the action representation vector into the acceleration predictor module and removing the texture representation vector from the structure (since it is only one texture per model). Fig. 3 (top) shows the comparison of this trained model with the piece-wise AR model by showing the difference between the Euclidean errors of these two models on test set. Due to the randomness associated with the output of the piece-wise AR model, it was run 10 times on the test set and the average of the difference between all these runs was calculated. Our model outperforms the baseline model for 75 out of 93 materials on average. Error bars indicate 25 and 75 percent quartiles.

Afterwards, we trained a joint model for all the materials by adding the GelSight image as an input to the model. To assess the generalization capabilities of this unified model only in its capabilities to generalize to new actions we keep the GelSight image input the same as the ones included in the training set and use the force and speed in the test set as input. This would be similar to a scenario where the material’s label is known and one is trying to render it given a new action. The average results of the comparison of this model to the baseline as well as the 25 and 75 percent quartiles are shown in Fig. 3 (middle). This unified model outperforms the baseline model on 82 out of 93 materials on average which is an improvement on the model in Fig. 3 (top). Looking at the t-SNE visualization of the representation vector learned by the material encoder provides great insight on the source of such improvement. This method visualizes high-dimensional vectors (here of the size 256) in a lower-dimensional space (here 2D). Fig. 4 shows that our texture encoder has learned to place the materials that feel similar closer to each other. For example, our encoder has created approximate clusters for all carpets as well as artificial grass -which feels like carpet-, meshes, similar floor-tiles, stones, and similar sandpapers. Our hypothesis is that a unified model enables our network to share data between similar materials and cover a wider range of force and speed. Thereby, the unified model achieves an improved generalization performance.

D. Performance Evaluation of Constructed Temporal Signal

As described in detail in Section III-B the output predictions of our neural network structure on short horizons should be combined to create a temporal signal for haptic rendering. We found the Euclidean loss evaluation performance of such stitched signal using GLA on the short horizon output of our unified model to outperform the baseline on 85.6% of the materials. This value is close to that of the non-stitched signal (88.2%) suggesting that the temporal signal has kept its local spectral properties even after being stitched into a long horizon which is desired. Using the proof-of-concept real-time stitching approach explained in Section III-B, we found the model to still outperform the baseline on 55.9% of the materials. This can be even further improved by using existing optimization-based online phase retrieval and signal reconstruction algorithms in the future. Due to space constraints, the performance bar plots are not shown.

To provide context for these numerical values, Fig. 5 shows 4 sample signals in temporal as well as the spectral domain for the first 0.1 sec of the temporal signal constructed using GLA. It should be noted that for some materials even
though our method outperforms the previous method, on an absolute scale the prediction can still be far from the original signal. Floor tile 1 in Fig. 5 captures such incident. A possible cause for this can be the relatively small dataset. Furthermore, there are other factors such as the grip force of the user while holding the data collection pen that can affect the output and are not accounted for in our model. We believe collecting a larger automated dataset using a robot can further improve the performance in the future.

E. Generalization to New GelSight Images and Actions

Fig. 3 (bottom) shows the performance of our trained unified model on generalizing to new GelSight images (of the training material) as well as new actions. The baseline model requires manual labeling of the materials, so we report comparisons with respect to the baseline model’s performance on new actions only. Our model outperforms the baseline on 77 out of 93 models, without manual labeling.

F. Generalization to New Materials

We provide preliminary evidence regarding our model’s capability for generalizing to materials not in its training set by looking at the placement of the latent representation of these materials in the t-SNE space. The orange crosses in Fig. 4 represent 20 new materials. Materials with carpet-like textures were placed near other carpets. The new floor-tiles as well as floor-wood 3 were also placed close to the other floor-tiles. Metal foil, which had a very similar look and feel to whiteboard, has been placed close to it. Our method has also placed Balsa wood, Floorwood 2, and Floor wood 1,4 in the same region as wood and painted wood. Clear acrylic is also placed near other smooth plastics such as file portfolio and vinyl. Our method had difficulty generalizing for materials with significantly different texture than those in the dataset such as nylon strap, woodstraw mat, a uniquely patterned foam, and package foam.

VI. CONCLUSION AND FUTURE WORK

In this paper, we model the vibratory signal that different textures induce in a hand-held tool moved over a surface. The action-conditional model takes as input a GelSight image of the texture as well as the force and speed the user applies to the texture, and outputs the desired acceleration for haptic texture generation. Furthermore, we augmented the HaTT dataset with GelSight images. In the future, we will evaluate our model during haptic rendering in a human user study and collect data from a wider range of materials with an autonomous robot to reduce human effort. We also plan to investigate the effects of replacing GelSight images with RGB images. Furthermore, one can investigate the effects of using other loss measures for evaluating the performance of a model for haptic texture rendering.
Fig. 4. t-SNE of the learned latent representation for GelSight images in the training, validation, and test set as well as the encoding for new materials not in the training set. This 2D visualization of the high dimensional representation of the materials in the training set suggests that the neural network has learned to associate materials that feel and look similar in its latent space. Furthermore, the crosses showing the results for new materials not in the training set provide preliminary evidence that our approach has the potential to generalize to new materials (in italics) only using their GelSight image specially for those with distinct textural features (e.g. carpets).

Fig. 5. Comparison of the generated vibration by our model to ground truth and that of the Piece-wise AR model for four sample materials on test set.
ACKNOWLEDGEMENT

The authors thank Katherine Kuchenbecker and Yasemin Vardar for giving us access to the textures used in the Penn Haptic Texture Toolkit (HaTT) and hosting N. Heravi at the Max Planck Institute for Intelligent Systems (MPI-IS) during data collection. We also thank Shaoxiong Wang for his technical support with the GelSight sensor, and Heather Culbertson for answering our questions regarding HaTT. N. Heravi was supported by the NSF Graduate Research Fellowship. This work has been partially supported by Amazon.com, Inc. through an Amazon Research Award. This article solely reflects the opinions and conclusions of its authors and not of Amazon or any entity associated with Amazon.com. This work has also been partially supported by the Stanford Institute for Human-Centered Artificial Intelligence (HAI).

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