Authoring New Haptic Textures Based on Interpolation of Real Textures in Affective Space

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***Abstract*—This paper presents a novel haptic texture authoring algorithm. The main goal of this algorithm is to synthesize new virtual textures by manipulating the affective properties of already existing real-life textures. To this end, two different spaces are established: two-dimensional (2-D) “affective space” built from a series of psychophysical experiments where real textures are arranged according to affective properties (hard-soft, rough-smooth) and 2-D “haptic model space” where real textures are placed based on features from tool-surface contact acceleration patterns (movement-velocity, normal-force). Another space, called “authoring space” is formed to merge the two spaces; correlating changes in affective properties of real-life textures to changes in actual haptic signals in haptic space. The authoring space is constructed such that features of the haptic model space that were highly correlated with affective space become axes of the space. As a result, new texture signals corresponding to any point in authoring space can be synthesized based on weighted interpolation of three nearest real surfaces in perceptually correct manner. The whole procedure including the selection of nearest surfaces, finding weights, and weighted interpolation of multiple texture signals are evaluated through a psychophysical experiment, demonstrating the competence of the approach. The results of evaluation experiment show an average normalized realism score of 94% for all authored textures.**

***Index Terms*—Feature selection, haptic texture, interpolation, perceptual space, rendering, texture authoring.**

I. Introduction

IMAGINE that you are designing multimedia contents of an immersive virtual reality (VR) based game where players can see, hear, and touch virtual objects. You assign a faded wooden image texture to a virtual prop used in the game play and try to create a realistic haptic texture (roughness) for it as well. One straightforward way is to find a real surface having haptic properties same as that you want to assign, measure/copy its haptic responses, and replay it during interaction (analogous to photos taken from real scenes used as image textures in three-dimensional (3-D) graphics). Furthermore, it would facilitate content generation if we could freely edit the perceptual property of the real measurement, e.g., creating a new haptic texture having a slightly increased roughness from a real surface, a new texture where the roughness value is inherited from one and hardness from another, and a texture that can be perceived as lying exactly in the middle of two real textures. Efficiently creating such textures from real textures is the goal of this paper, and we call this as haptic texture authoring.

In the contemporary world, the above examples are not quite possible yet, and this leads to a sub-standard level of realism and immersion for VR and augmented reality applications. This lack of realistic tactile contents is one of the major hindrances for haptics technology to become widely applicable. The main reason of this bottleneck is that haptic signals are relatively difficult to author compared to other modalities. They are usually based on very complex dynamics of very subtle physical characteristics of a surface, which usually need huge effort to measure, model, parameterize, and simulate in real time [1]. Data-driven approach, which reproduces haptic signals based on interpolations of premeasured data, can be an alternative, but this also has inherent drawbacks: the major one being lack of flexibility [2]. This naturally leads us to the need of an authoring tool that allows for creating rich and realistic tactile contents with little effort.

In general, successful authoring of sensory contents needs two technological prerequisites. First, final stimuli to be delivered to the user should be objectively describable. Stimulus that a content designer desires to create should be defined in a description space, so that it can be accurately replicable. The description space can be based on either physical dimensions, e.g., Red Green Blue (RGB) space in color, or perceptual dimension, e.g., decibel space in sound, but authoring needs a way of transforming one space to the other. Second, according to the given description of the desired sensation, its corresponding physical stimuli should be accurately synthesized. Synthesizing can be a combination of various processes: physical simulation of a signal, e.g., computer graphics and modifying/merging existing signals, e.g., sound synthesizer.

In this paper, we first select *surface haptic texture* as the subject of authoring among various haptic properties (e.g., stiffness, friction, and so on), as it is one of the perceptually important

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tactile properties of a surface. With regards to haptic texture, there are a few attempts at examining the first prerequisite, i.e., objective description of haptic texture. Unlike other properties that use physical dimensions for description, e.g., stiffness in N/m, color in RGB, most attempts for haptic texture use *perceptual* dimensions, since physical attributes involved in haptic texture perception are multidimensional, and the relationship between physical signals and their perception is not clearly revealed. Thus, many researchers have focused on the perceptual dimensions and affective properties of touch. Perceptual dimensions are the characteristics based on which humans are able to differentiate various textures. Affective properties of touch are the characteristics that quantify feeling of a given texture. Pioneering work in identifying perceptual texture dimensions was done by Yoshida [3]. They found out that the main dimensions of haptic textures were hard-soft, heavy-light, cold-warm, and rough-smooth. Others extended his work to tool–surface interaction. In [4], Lamotte showed that tool-based texture perception is highly related to the hard-soft dimension, whereas hollins *et al.* [5] showed that rough–smooth dimension is also of great importance. Similarly, various affective properties of texture were presented in [6]. Although these studies successfully identified the dimensions and affective properties of tactile perception, their goal was the dimension itself, and no further study was carried out to find the relationship between perceptual space and corresponding physical signal space, which is necessary for actual authoring, i.e., creation, manipulation, or control of tactile stimuli.

The second prerequisite has been extensively studied under the name of haptic texture modeling. Physics-based modeling [7], [8] and data-driven modeling [2], [9] are the two prominent ones, and both techniques come with their own advantages and limitations. The physics based method has been a common approach employed by various researchers to render haptic content, where the haptic responses due to tactile properties of a virtual surface are determined by coefficients of physics-based parametric models. For example, high-frequency textural vibrations were generated based on the simulation of contact dynamics of microscale geometry of surface made by parameterized cavity and bump models mapped into a surface [10], [11] or using stochastic surface geometry models [12], [13]. Although the designer usually has full control over all the parameters and aspects, such a method cannot replicate the complexity of real-life surfaces due to simplification in the models. In addition, the designer has to manually incorporate the delicacies and nuances of real surfaces into a synthetic surface, which is quite a demanding task.

In data-driven modeling, the vibrations originating from interaction with different surfaces are recorded and are subsequently used for rendering tactile contents. For instance, Culbertson *et al.* [2] were able to generate virtually perceptible textures based on the scanning velocity and normal force. Similarly, Abdulali and Jeon extended this idea to recreate more complex textures (anisotropic textures) by incorporating the direction of scan velocity into the equation [14]. Recently, a more robust and efficient technique has been employed where generative adversarial networks have been trained to create vibrotactile signals based on texture images or attributes albeit using predefined and constrained tool–surface interaction [15]. The upside of data-driven modeling is that the created contents are highly realistic and computationally simpler. However, the recorded model is an arbitrary signal having no physical meaning and is hard to modify meaningfully. This indicates that the number of feedbacks that a designer can generate are limited. In addition, it is impossible to create contents that are not physically available, and model building is a highly time-consuming process. In summary, on one hand, the physics-based models do not guarantee a high level of realism but can be controlled easily. On the other hand, data-driven models ensure higher realism with limited controllability and authoring power. Increasing realism of physics-based approaches generally come at a very high computational cost, which often make a system nonpractical. Instead, it seems that more feasible solution would be to keep the data-driven approach and to focus on improving controllability of data-driven models.

The goal of this paper is to provide an effective method for haptic texture authoring using data-driven haptic texture modeling. We achieve this goal through two contributions. We first established an *authoring space* where 25 data-driven texture models build from 25 fully featured real surfaces are placed according to their affective properties. The space is made in such a way that it maximizes the correspondence between affective properties of the 25 models and features in the physical signals of the models. Axes of the space are the affective properties, and this space plays a role as a perception-based descriptor of textures. Now, designers can freely select an arbitrary point in the space to author a texture, and then the system automatically synthesizes new texture signal corresponding to the selected affective properties. Our second contribution lies in this part. Our framework interpolates signals from adjacent data-driven models, so that two different haptic models are combined to form the new virtual texture. This step ensures that the new model inherits perceptual characteristics of the parent textures, allowing the aforementioned authoring scenarios. To the best of our knowledge, there is no such work that provides the approximation of physical properties across two different texture models.

The significance of this paper can be explained through an analogy from the field of vision. It is well-known that the RGB space can be used to create most of the colors perceivable to the human eye. Image editing tools often provide an RGB color table where a designer can easily select a color to be used. In a similar way, through this paper, we want to provide a unified haptic authoring tool comprising of the basic components or dimensions of haptic texture. Such a tool can be utilized by designers and researchers to create haptic models having arbitrary affective properties and would drastically reduce the time and effort required for haptic modeling.

II. System Overview

Fig. 1 presents a holistic view of the overall system, while Algorithm 1 provides the flow of the system. The methods used to approach our goal are detailed in the following sections.

The current study aims at providing a platform that can manipulate existing data-driven haptic textures in a perceptually meaningful manner. Since a data-driven model is just a recording

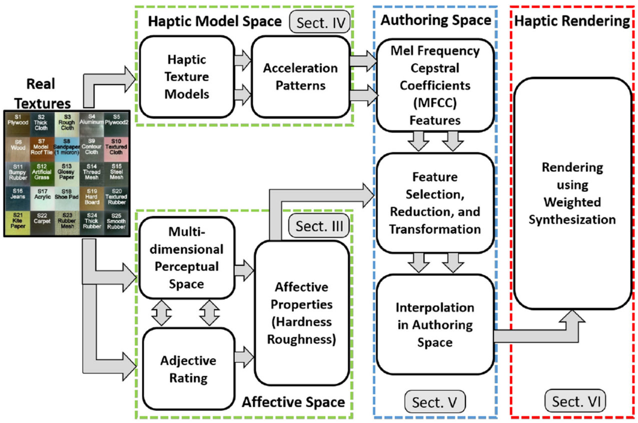


Fig. 1. Block diagram of the overall system.

Algorithm 1: Flow of the Overall System.

Input: Real textures and acceleration patterns from tool-surface interaction
Step 1: Affective Space
  Create Perceptual space from psychophysical experiment
  Establish adjective ratings for all textures
  Regress adjective ratings onto Perceptual space to form Affective space
Step 2: Haptic Model Space
  Create haptic models from interaction vibrations
  Approximate 25 uniquely spaced acceleration patterns
  Concatenate the 25 patterns to form raw features
Step 3: Authoring Space
  Calculate MFCC features from raw features
  Reduce features based on correlation with affective space
  Create new textures by Delaunay triangulation and interpolation in Authoring space
Step 4: Haptic Rendering
  Synthesize new textures using interpolation weights
  Render new textures
Finish

of haptic-related signals, it is not a trivial task to find a connection between a certain modification in signals and its perceptual result, and vice versa. This relationship is essential for our goal. The paper first tries to establish this relationship. To this end, we first build an affective space where 25 data-driven models are scattered in a two-dimensional (2-D) space defined by two perception-based affective properties (see Section III). Another space called haptic model space is built from the multidimensional features extracted from the acceleration signals of the same 25 data-driven models (see Section IV).

Now, the two spaces are merged based on the correlation between them, yielding an authoring space (see Section V). The main characteristic of the authoring space is that all textures are scattered in this space as a function of their affective properties while also maintaining their connection to the physical acceleration patterns. Each point in the affective space is linked with a corresponding acceleration pattern, and a change in affective values is instantly reflected in the acceleration patterns.

However, we only have acceleration patterns for a few points (the points where 25 real surfaces are located) in the authoring space. Therefore, interpolation is carried out to generate acceleration patterns for any arbitrary point within the convex hull of real surfaces in the authoring space (see Section VI). In order to do this in a perceptually correct manner, we did a time-domain acceleration signal interpolation based on distances to the nearest real samples. This results in a new virtual texture having arbitrary affective properties.

Finally, the newly authored virtual textures are evaluated using a psychophysical experiment (see Section VII).

III. Affective Space

Real-life textures used in this paper are scattered in the affective space as a function of their affective properties. Two psychophysical experiments are carried out to establish the affective space. The first one is a cluster sorting experiment to form a perceptual space and the second one an adjective rating experiment. The first experiment, with the help of multidimensional scaling (MDS), resulted in a 2-D perceptual space where textures are scattered based on differences in textural perception. The second experiment, called as adjective rating, is carried out to find affective properties that best describe the given textures. These affective properties are in the form of adjective pairs. The adjective pairs are regressed into a perceptual space to establish an affective space, and the perceptual space is projected onto each adjective pair.

Consequently, we are left with two affective axes (one from each adjective pair) where all surfaces are aligned according to one specific property. Furthermore, the two affective axes are combined to form the affective space.

A. Experiment 1: Perceptual Space

This experiment was performed using a set of 25 real-life textured surfaces. The variety of surfaces in this set was such that they encompassed a majority of the surfaces encountered in daily life haptic interactions. Details of all surfaces are shown in Fig. 2. Ten participants took part in this experiment. They were blindfolded and wore headphones playing white noise. The participants had little previous experience about haptics, and were paid for their participation.

The participants interacted with the surfaces using a pen-shaped aluminum tool with a solid plastic tip, as shown in Fig. 3. The length of the tool was 14 cm, whereas the diameter of the tip was 7 mm. The participants were asked to use free hand motion and to vary their hand velocity and penetration force during interaction. The vibrations emanating from the interaction propagate through the tool and help the users to identify various characteristics of texture. The main aim of using a tool was to emulate exactly the same situations encountered while interacting with a virtual texture, where interactions mostly occur through a stylus or other such media.

The experiment was a cluster sorting experiment similar to the one in [16] and [17]. Each participant carried out three

Fig. 2. Texture surfaces used to establish the perceptual space.

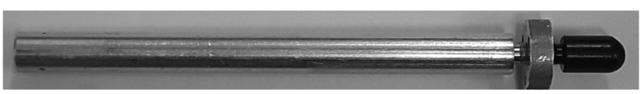


Fig. 3. Tool used for interaction during the psychophysical experiments.

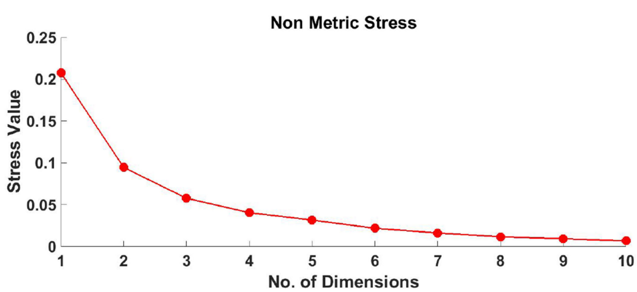


Fig. 4. Nonclassical (nonmetric) Kruskal stress values for the first ten dimensions of MDS.

trials where total number of groups were three, six, and nine. They interacted with surfaces using active touch and assigned perceptually similar surfaces to same groups.

Readers can refer to [16] and [17] for in-depth details of the experiment. Data from this experiment were in the form of a similarity matrix calculated by averaging the clustering data of all participants. A similarity score, equal to the total number of groups in the trial, was assigned to a pair of surfaces when grouped together in a trial. Similarity scores for all pairs of surfaces were added and scaled from 0 to 100. The similarity matrix was converted to a dissimilarity matrix and analyzed using the nonmetric MDS. Kruskal stress values for the first ten dimensions of MDS were calculated. The stress value of 0.09, at dimension 2 in Fig. 4, is considered as fair according to [18]. Hence, a 2-D perceptual space was established, shown in Fig. 5.

B. Experiment 2: Adjective Rating

Same participants took part in this experiment and interaction was through the same tool. A total of 20 adjectives were provided (provided in supplementary material) among which participants

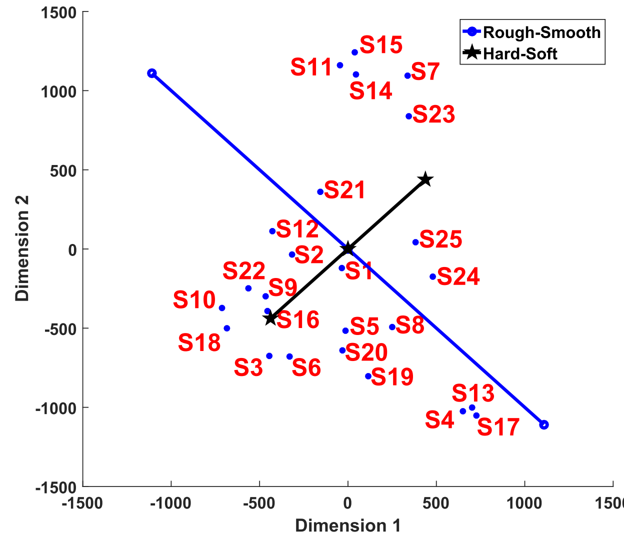


Fig. 5. 2-D MDS of the perceptual space. The lines show the regressed adjective pairs. The length of the line shows the goodness of fit for that adjective pair with the perceptual space.

TABLE I
CORRELATION VALUES OF DIFFERENT ADJECTIVE PAIRS WITH THE TWO DIMENSIONS OF THE PERCEPTUAL SPACE

Adjective Pair	Dimension 1	Dimension 2
Rough - Smooth	**-0.7565**	0.2603
Sticky - Slippery	-0.7286	0.0580
Hard - Soft	-0.0717	**-0.5906**
Irritating - Pleasant	-0.7220	0.0142

selected the ones that could be used to describe the surfaces in this experiment. The remaining adjectives were discarded. Within the selected adjectives, the ones having a corresponding adjective with an opposite meaning were paired together. As a result four pairs of adjectives were formed. Adjective pairs selected as a result of this experiment are given in Table I. Participants were asked to quantify affective attributes of the textured surfaces based on these adjective pairs. An unmarked scale was provided on a computer screen containing adjective pairs on opposite sides. Participants adjusted a slider on the scale to evaluate surfaces according to each of the adjective pairs. Slider values were scaled from 0 to 100 and averaged across of all participants. Detailed procedure of this experiment can be found in [19].

Correlation of adjective pairs with the dimensions of MDS was calculated to evaluate the correctness of these adjective pairs, given in Table I.

C. Regression and Projection

Multilinear regression is performed to interpret the adjective pairs according to the perceptual space. The adjective pairs are linearly regressed into the perceptual space, where the length of the line shows its goodness of fit, as shown in Fig. 5. For simplicity, we selected only the highest correlated adjective pair for each dimension.

After regressing the two adjective pairs, all the surfaces in the perceptual space are perpendicularly projected onto the given regressed lines. The main characteristic of projecting points onto the adjective pair line is that all points on the line are in an increasing or decreasing order of that particular adjective. Finally, we are left with two lines, i.e., hard–soft line and rough–smooth line. These lines are considered as independent axes and are combined to form the affective space, since angle between the lines is 90.01°.

IV. Haptic Model Space

The model space must be based on the characteristics of physical interaction with surfaces because the psychophysical experiments were also based on physical interaction. Since the model space will be mapped with the affective space, these physical characteristics must be the ones that are perceivable by humans. The most common source of haptic texture perception is the high-frequency vibrations (acceleration patterns) originated during interaction with a surface. Hence, we decided to use the acceleration patterns for the haptic model space establishment. Various scanning parameters were also taken into consideration while collecting the acceleration patterns, since different scanning parameters affect the spectral characteristics of the resultant vibration signal [20].

Since the aim of establishing the model space is to find a relationship between acceleration patterns and affective space, it is important to maintain a controlled environment while scanning textures. Same scanning parameters must be used across all texture models. There are two possible ways to collect such data; use a special machine for data collection; or simulate the signal using very sophisticated haptic modeling and rendering framework that accurately reflects real signals, e.g., data-driven haptic texture modeling and rendering. In [14], Abdulali and Jeon provided a haptic texture modeling algorithm, which showed reasonable performance. More importantly, the authors claim that their models are perceptually sound, therefore, it is decided to build haptic texture models based on [14] and use it to simulate the vibration output for a given combination of input parameters, by using the complementary rendering algorithm [21]. The data acquisition setup used for model building was similar to the one provided in [21].

The signal recording time for each texture is 40 s. Since all the textures in the current study are isotropic in nature, the directionality of the sample texture is deemed irrelevant. Therefore, the input space for the algorithm provided in [14] is reduced to two dimensions, i.e., velocity magnitude and normal force. Finally, 25 response signals are approximated using each texture model with a predefined input vector. The responses resulting from combining each value in the velocity vector (50, 100, 150, 200, 250) with each value in force vector (0.1, 0.2, 0.3, 0.4, 0.5) are approximated.

After calculating the responses, the 25 acceleration patterns are concatenated together to form a single feature vector for each texture. Employing such a strategy ensured that the signal preserves the delicacies induced due to varying scan parameters. This concatenated signal will be used for feature extraction in the next section.

V. Authoring Space

The main aim of this paper is texture authoring, which means that a change in the affective space should be replicated accordingly in the haptic model space. For this purpose, the authoring space is established by combining the two spaces. In the authoring space, surfaces are scattered based on their affective properties, while at the same time it carries information about physical properties of the surfaces.

Physical acceleration signals collected from the modeling of various surfaces carry redundant information in addition to useful haptic information. It is required to distill that information and to represent it in a meaningful and reusable way. Therefore, a feature extraction algorithm is used, called as Mel Frequency Cepstral Coefficients (MFCC) [22].

The MFCC features are used to predict the affective properties calculated in Section III. In order to find out which of the MFCC features can be useful for predicting the individual affective axes, further feature reduction and transformation algorithms were used. Sequential forward selection (SFS) [23] and parallel analysis (PA) [24] are performed to obtain the MFCC features that are highly correlated with the respective affective axes. Afterwards, principal component analysis (PCA) is applied to further reduce the feature dimension. As a result, we are left with a one-to-one correspondence between the features and affective axes, i.e., one feature representing one affective axis. These two features are combined to form a 2-D authoring space.

A. Mel Frequency Cepstral Coefficients

MFCC has been widely used in audio signal processing. It is fine tuned to be compatible with the human perception of audio. Therefore, it is a suitable choice to be used as the primary feature extraction technique. Additionally, Strese *et al.* [25] showed that MFCC provides a high level of accuracy in representing haptic perception data from tool-based interaction.

The overall signal is broken down into segments of 25 ms with an overlap of 10 ms. The higher and lower frequency thresholds are set at 500 and 10 Hz, respectively. A total of 13 MFCC coefficients are calculated from each segment. Afterwards, all the 13 MFCC coefficients for every sample are aligned in a single row to represent one instance, i.e., one given texture surface. At the end of this process, we are left with a matrix of 25 rows, which represented the texture surfaces and its columns representing the features.

B. Feature Reduction

The number of features after concatenating the MFCC coefficients is very large, therefore, SFS in combination with PA and PCA is used to reduce the size of feature vector. This reduction in size of the feature vector is carried out while keeping the affective space in perspective. The unnecessary features are removed while the ones that showed high correlation with the affective space are kept.

1) Sequential Forward Selection: The correlation between each feature and the individual axis of affective space is calculated. One axis of the affective space is considered at a time. SFS starts by selecting the most correlated feature and predicts the affective axis using linear regression. Afterwards, the next most correlated feature is combined with the first one and the affective axis is predicted. This process continues until a termination criterion is met. The termination criterion in this case is the prediction error of the linear regression model being significantly increased, i.e., $p \geqslant 0.01$.

As a result of SFS, we are left with 11 significant features for the rough–smooth axis and 16 significant features for the hard–soft axis. Since these features are selected based on correlations, it is possible that these correlations are achieved by chance. In order to prove that the correlations are significant, PA is carried out.

2) Parallel Analysis: PA compares the predictive ability of the significant features against random data. If the features are truly significant, correlation of features with affective axis will be higher as compared to the correlation between random data and affective axis. PA is carried out separately for both the affective axes using their respective features.

The features obtained as a result of SFS are divided into subsets of three features. Each subset is used to predict the associated affective axis. Correlation between the predicted values for the affective axis and the actual values of affective axis is calculated. Concurrently, a random data matrix having the same dimensionality as the feature vector is created and divided into subsets of three features. Similar to the significant features, the random features are used to predict the affective axis. The correlations between the predicted and actual values are calculated. In the next step, the correlation values from the significant features and random features are compared. Only those subsets are selected for further processing that show correlation values higher than the highest correlation value achieved by random features. After selecting these subsets, the features, which appear most frequently in these subsets, are selected as the most significant features. Seven features for the rough–smooth axis and six features for the hard–soft axis appeared most frequently in the significant subsets.

3) Principal Component Analysis: A cubic polynomial model is trained using the affective space as response, whereas features are used as predictors. This model is iteratively trained for all combinations of the features and it is found out that even a single feature can provide reasonable accuracy. Therefore, we further reduced the features obtained after PA. PCA is used to convert these features into just one feature to represent the associated affective axis. The affective axis is predicted using the cubic polynomial model to check the validity of this feature. Furthermore, five-fold cross validation is used to check the robustness in prediction when using a single feature. Five surfaces are used as test samples, while 20 surfaces are used as training samples. Average cross-validation root-mean-squared value for the rough–smooth axis is 91.59%, whereas that for the hard–soft axis is 92.49%. Average cross-validation correlation between the predicted and actual affective axes is 0.93 and 0.94 for the rough–smooth and hard–soft axes, respectively.

C. Establishing the Authoring Space

In the previous section, we calculated two features, which could predict the affective axes with a reasonable accuracy.

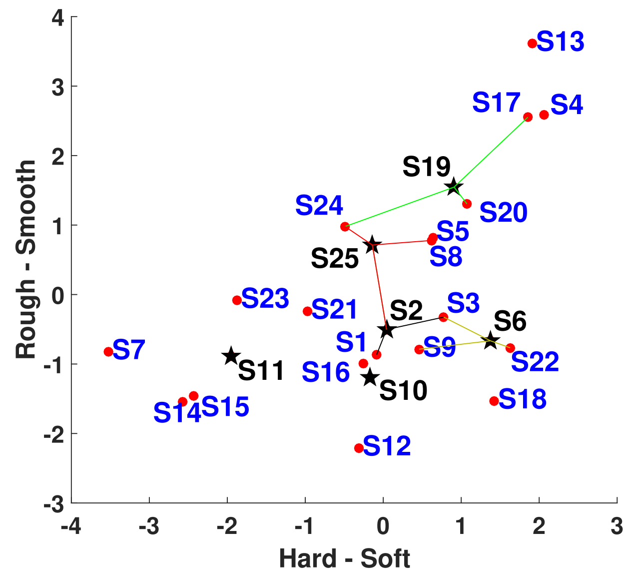


Fig. 6. 2-D authoring space established by combining the affective and haptic modeling spaces. The surfaces represented by black stars are the ones used in the evaluation section. The colored lines show the three samples, which are interpolated to render the authored texture at the location of black stars.

These two axes are combined to form a 2-D authoring space. Since the authoring space is established from both the spaces, it can be argued that it inherits the properties of both spaces. All textured surfaces are scattered into this 2-D space. The authoring space is shown in Fig. 6.

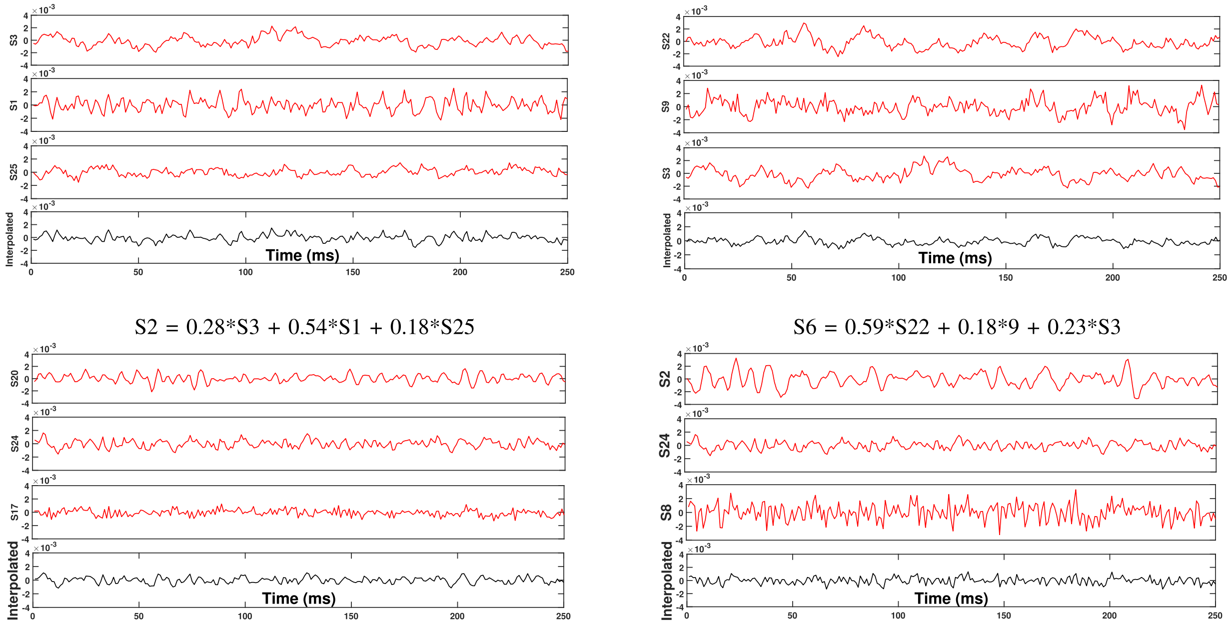
D. Interpolation in Authoring Space

Now, new virtual surfaces can be authored based on any given affective values from the authoring space. A point in the authoring space can be represented by a pair of rough–smooth and hard–soft values. Using these values, a new texture signal can be synthesized by interpolating neighboring real textures.

For instance, Fig. 6 shows the interpolation of a model at the location of S25. The three nearest neighbors from P25 are S2, S24, and S8, and we assume that a weighted interpolation among these three real models would yield a new texture model that properly represents the perceptual characteristic of the location of P25.

Finding nearest neighbors and calculating weight is done as follows. Any certain location can be enclosed by performing Delaunay triangulation. This gives us three nearest neighbors, and distances to them can be computed. These distances are used to assign weights to the three neighboring models using the inverse distance method. Using these weights, haptic models for the three surfaces are combined to render the virtual authored texture, which will be further discussed in Section VI.

It can be argued that perception is a nonlinear phenomenon, whereas the weights being used here are calculated linearly. It must be noted that the authoring space in itself is considered as a nonlinear entity and thus the interpolation weights being calculated in this space inherit the same nonlinearity.



S2 = 0.28*S3 + 0.54*S1 + 0.18*S25

S6 = 0.59*S22 + 0.18*9 + 0.23*S3

S19 = 0.70*S20 + 0.14*S24 + 0.16*S17

S25 = 0.18*S2 + 0.52*S24 + 0.30*S8

Fig. 7. First three plots in all sub-figures show the actual acceleration patterns for the real texture models, whereas the last plot shows the weighted synthesized acceleration pattern at the location of the new virtual texture. The authored signal is synthesized by adding the three original signals according to the weights given in the equation below each sub-figure.

VI. Haptic Rendering Using Weighted Synthesization

The three haptic models selected as a result of Delaunay triangulation in the authoring space are combined to author the new texture by weighted synthesization. The weights are calculated, using an inverse distance method, from the vertices of the Delaunay triangles (the vertices are the three nearest neighbors). The weighted synthesization is carried out in two steps. In the first step, under the given current interaction parameters (stroking velocity and normal force), three vibration waveforms from the three selected models are virtually generated using the rendering algorithm (see first three signals in all graphs in Fig. 7). Note that these signals are not physically rendered but only simulated internally. In the second step, these signals are added together in time domain using the weights associated with them (see the last signal in all graphs in Fig. 7). Finally, the synthesized signal is sent to a haptic interface to be rendered. It must be noted that in general such signal synthesization takes place as parametric interpolation in the frequency domain [2], [14]. Signal addition is usually carried out in the frequency domain since it breaks down the signal into individual frequencies and it is easy to keep track of these frequencies. However, weighted addition in time domain has the same effect on the signal according to [26], and the time-domain signal can easily be reconstructed from its Fourier transform. Additionally, superposition of time-domain signals was also carried out in [27] to study its effect on the neural system.

The rendering we used for simulating the signals is based on the algorithm in [21]. The original algorithm takes in a 3-D input, i.e., 2-D velocity and force to deal with dimensionality in texture. Since all the textures in the current study are assumed to have an isotropic texture, the original algorithm is modified to reduce the input dimensions from three to two, i.e., velocity magnitude and normal force.

In certain cases, adding two sinusoids having very similar frequency (but not exactly the same) can cause an interference pattern. Such an interference pattern is called as a *beat*, and it can positively or negatively affect the amplitude of the signal over time [28]. If we add two sinusoids having frequencies f_1 and f_2 , a beat frequency equal to the difference $|f_1 - f_2|$ of the two is generated. The beating effect becomes quite pronounced when we are adding two pure sinusoids. However, the amplitude of the beat frequency decreases as the number of sinusoids increase. Similarly, addition of noise can also dilute the effect of beating. Further details about this are provided in supplementary materials.

Theoretically, this phenomenon can occur in our system when we synthesize signals during rendering, since we are interpolating nearby models having similar characteristics, and it could destroy the haptic feeling of texture. However, it is very rare to encounter such a phenomenon in real life due to the complex nature of the stochastic signals generated during rendering. The signals used in this paper on average contain frequencies from 1 to 1000 in addition to being stochastic. Additionally, there is some mechanical noise added to the signals during the tool–surface interaction. These two factors effectively nullify the effect of any beating phenomenon that might occur. It has been shown that perceivable beats occur mostly in favorable conditions, i.e., high power beats can only be perceived in a specific noise band and through the superposition of a limited number of sinusoids [27], [29].

Furthermore, rendering of authored haptic textures, based on weighted synthesization, is perceptually evaluated in the next section.

VII. Evaluation

The overall texture authoring framework was evaluated using a psychophysical experiment. Some of the textured surfaces were removed (one at a time) from the authoring space and new textures were authored using the affective values of the removed textures. These affective values were located in the authoring space, and three nearest haptic models were selected based on Delaunay triangulation. Afterwards, new virtual haptic textures were synthesized with the given affective properties using the models selected in the authoring space. Finally, participants were asked to compare the authored textures against the associated removed textures. The details of the experiment are provided in the following sections.

A. Participants and Stimuli

A total of ten participants took part in the experiment. During the experiment, the participants were blindfolded and wore headphones to restrict visual and auditory cues.

A tablet PC (Microsoft Surface Pro 4) and a voice coil actuator (Haptuator Mark II; Tactile Labs) mounted on top of the Microsoft Surface Pen were used as a rendering device in this experiment. The experimental setup was same as the one provided in [21]. A total of six surfaces were removed (one at a time) from the authoring space. After removing a surface, a virtual texture was authored at its location. Thus, stimuli for the experiment was a total of six virtual textures, which were generated at the locations of the six removed textures. The removed surfaces were S2, S6, S10, S11, S19, and S25. These surfaces were randomly selected from different parts of the space. Comparisons between two extreme samples (S7 with S13) and two same samples located at extremes (S7 with S7, and S13 with S13) in the authoring space were also evaluated to provide reference for the dissimilarity scores. It should be noted that the virtual textures closer to a real texture should inherit a higher degree of its affective properties.

B. Procedure

The experiment was a pairwise comparison task using magnitude estimation without modulus. Every authored texture was compared against every removed (haptic model of real texture) texture. Thus, a total of 36 combinations were provided to the participants, one at a time. The participants were asked to rate the dissimilarities between two given textures at a time. A same pair of surfaces was presented to the participant two times. The order of stimuli presentation was randomized across participants and trials. The experiment took 30 min on average per participant.

C. Data Analysis

Data from the experiment are in the form of dissimilarity values. A value of zero means that two models are same, whereas a higher score shows a higher dissimilarity. Data are normalized (0–1) for each participant and averaged across all. Our hypothesis is that a pair of authored texture and its original haptic model should receive a dissimilarity score of zero.

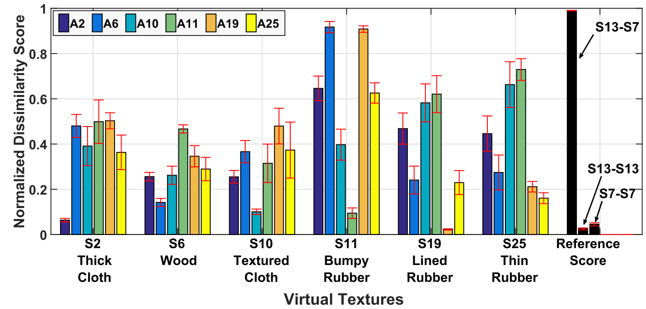


Fig. 8. *x*-axis shows the original haptic models of real-life textured surfaces, whereas the six bars against each one of them show the authored textures. The A in the legend stands for authored.

D. Results and Discussion

Fig. 8 shows the dissimilarity scores of the six authored textures against the six original haptic models of real-life textures. It can be seen that the participants rated each one of the authored textures as the most similar to its associated original haptic model, e.g., A2 and S2, A6 and S6, and so on. In case of the reference comparisons, the two farthest models received the highest dissimilarity score (0.99 for S13–S7), whereas the two same models received extremely low scores (0.025 for S13–S13, 0.045 for S7–S7). The dissimilarity scores for all the same real–real and authored–authored texture pairs (A1–A1, S1–S1, and so on) were also calculated, however, all the pairs showed values in the vicinity of zero (a value of zero means the two surfaces are exactly the same) and as such did not provide any further insights. This is also evident from the two same texture reference points provided in Fig. 8, which show extremely low dissimilarity values. Therefore, the scores for all similar texture comparisons (real–real and authored–authored) are not reported here.

From Fig. 8, it can be seen that haptic model of Bumpy Rubber (S11) received a very low dissimilarity score against its associated authored texture (A11), whereas all other authored textures (A2, A6, A10, A19, and A25) received significantly higher dissimilarity scores. This means that participants could easily associate them together. This can be due to the fact that S11 lies far away from the other surfaces in the authoring space, and its affective properties are significantly different from the other surfaces in the experiment.

The haptic models for the thick cloth (S2) and hard board (S19) also received very low dissimilarity scores with respect to their associated authored textures. However, the dissimilarity scores for most of the other authored textures were not as significantly large as that for the bumpy rubber. This is also a reflectance of the fact that the other authored textures are relatively closer to S2 and S19.

Normalized realism scores (NRS) for all the corresponding pairs of authored and original haptic textures were calculated to find out the perceptual authenticity of the authored textures.

TABLE II
NRS FOR THE CORRESPONDING PAIRS OF AUTHORED AND ORIGINAL HAPTIC TEXTURES

	A2-S2	A6-S6	A10-S10	
Normalized Realism Score	0.97	0.89	0.93	**Average**
	A11-S11	**A19-S19**	**A25-S25**	0.94
Normalized Realism Score	0.94	1.00	0.87	

These scores are provided in Table II. NRS were calculated by normalizing the dissimilarity values from Fig. 8 according to the reference values provided in the said figure. The two same reference textures (S7–S7, S13–S13) were averaged to obtain the lower bound, whereas the dissimilarity value of the extreme textures (S13–S7) was used as the upper bound. It can be seen that NRS for most pairs is around 90% or higher, and the average for all the six pairs is at 94%. Such a high value of NRS indicates that the perceived realism of the authored textures strongly matched that of the original textures, and the participants did not face much difficulty in identifying the correct match for all the authored textures.

Results of evaluation experiment validate that the proposed method of synthesizing textures produces perceptually correct authored textures. Results also show that we can readily author any haptic texture with predefined affective properties.

However, the range of the affective properties is limited to the convex hull of the authoring space. The current authoring space is established from 25 real-life textures. Increasing the number and variety of textures could expand the authoring space and more diverse haptic textures could be authored.

It must also be noted that new textures can be authored with any combination of the affective values. In the evaluation experiment, we selected these particular points so that authored textures could be compared to the original virtual textures, and authenticity of the algorithm could be evaluated. For this experiment, it was assumed that the haptic rendering algorithm provided perfect models of real-life textured surfaces.

VIII. CONCLUSION

In this paper, we provided a novel algorithm for haptic texture authoring. The affective properties of real-life textures were manipulated to create virtual textures exhibiting predefined affective properties by using contact acceleration patterns. This algorithm found great application in the realm of VR, where on demand textures are need of the hour. More specifically, it can provide virtual textures as a combination of various real-life textures.

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