Toward High-Fidelity Haptic Interaction with Virtual Materials: A Robotic Material Scanning, Modelling, and Display System

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Abstract—We present a robotic setup for the acquisition of object surface material properties. Our setup is able to collect selected kinesthetic characteristics, such as the surface structure and weight, as well as tactile properties like the friction coefficient and the fine roughness characteristics of the object surface. Additionally, the setup captures the visual appearances of the object. The recorded multimodal sensor data provide all relevant information required to form a haptic model of a material sample. We then use this representation in a standard haptic rendering framework and display the virtual materials using an augmented Phantom Omni device. We conducted a subjective experiment which shows that its participants perceived and rated the rendered virtual materials as similar to the corresponding real materials in a direct comparison test where the users interact simultaneously with the real and the virtual material samples. An overall user rating of 4.3 out of 5.0 is achieved during the subjective experiment.

I. INTRODUCTION

Visual and auditory information are predominant in modern multimedia systems. The acquisition, storage, transmission and display of these modalities have reached a quality level which is typically referred to as high definition (HD). For example, video cameras capture HD or UHD content, modern video codecs achieve remarkable compression factors, and high-resolution monitors enable impressive visual experiences. Similar HD technology for audio is also available.

Technical solutions addressing the sense of touch, in contrast, have not yet reached the same level of sophistication. In the context of haptic interaction, kinesthetic and tactile interactions are typically considered separately, as different perceptual mechanisms are involved. A high-fidelity haptic recording and display system is supposed to extract and recreate kinesthetic as well as tactile properties of a material sample, such as the shape, the weight, the fine roughness, and other relevant haptic impressions. To the best of our knowledge, a system that scans an object and extracts a complete haptic (both tactile and kinesthetic) representation which is displayed using common haptic devices has not been reported by now. As a step toward this objective, our paper presents a material analysis-to-display pipeline which adapts the six manual human material exploratory procedures reported in [1]. We aim to transform real materials into a parametric representation and to display these virtual material models using a commonly available haptic device.

A. Contributions

The following list summarizes the contributions of this paper.

- We present a robotic material scanning device which is able to extract both kinesthetic as well as tactile material properties. A short video describing the system can be found on our website [2].
- We extract kinesthetic and tactile material properties for 16 material samples and calculate tactile and kinesthetic parameters representing the materials.
- We use the extracted parametric representation to artificially recreate the feel of the scanned materials using the Chai3D haptic rendering framework. We use a Phantom Omni device, augmented with a Peltier element and a Voice Coil Actuator (VCA), to display material properties like thermal conductivity, roughness, friction, stiffness, and contour information.
- We ask ten subjects to compare the virtually displayed material samples to their real counterparts in terms of the six manual human material exploratory procedures reported in [1] and show the results of this experiment.

B. Background

The human haptic perception system relies on both kinesthetic and tactile sensory information during the interaction with object surfaces. Humans typically perform six exploration patterns, as described in [1], to identify unknown objects. Visual observations reveal spatial information about the shape of the object and its contour properties. Subsequent to pure visual analysis, humans lift objects to identify their weight. In parallel, static touch is used to identify thermal conductance. Pressing on the material enables assessment about its stiffness. Eventually, arbitrary sliding motions allow for the identification of the fine contour, but also to feel the fine roughness and the friction properties of the object surface.

Current technical systems which aim to identify tactile properties mainly concentrate on the acquisition and display of vibrotactile signals using acceleration sensors during tool-mediated material interactions [3], [4], [5]. These tactile signals are either used to recreate the feel of real object surfaces using voice coil actuators, or, to recognize material surfaces using robots [6], [7] or during human freehand movements [8], [9], [10]. The work presented in [3] started a line of research, denoted as haptography, to set up a tactile pipeline focusing on the analysis and synthesis of tactile signals. The most recent work in [11] uses a Phantom Omni haptic device (Geomagic Touch) equipped with...
a haptuator (Tactile Labs) to additionally render friction, hardness and microscopic roughness during unconstrained human surface material exploration. In this paper, we build upon their reported setup but improve the acquisition of the tactile material properties by adapting the sensing capabilities reported in our previous work in [10]. We specifically aim to imitate the aforementioned six exploratory steps performed by humans when interacting with objects. Moreover, we extract kinesthetic features from the scanned materials, such as the object weight. Note that the object stiffness is considered as a kinesthetic as well as tactile material property. In this paper we use cubic material samples for which the shapes and dimensions are trivial to determine. In future work, we plan to extend the approach to arbitrarily-shaped objects.

II. ROBOTIC MATERIAL SCANNING SETUP

We use the notation \( \mathbf{x} = \sum_{i=1}^{N} x_i \) to calculate the mean value of a one-dimensional array \( \mathbf{x} = \{x_1, x_2, \ldots, x_N\} \) containing \( N \) elements throughout this work. Additionally, \( I \) denotes a two-dimensional grayscale image, or, a RGB color image.

The robotic setup and the sensor head, which we denote as uTexplor (uArm Texplorer) is motivated by our device in [10] and shown in Fig. 1. We use a uArm Swift Pro robot because it has a precise position resolution while moving and we measured only negligible accelerations during the tasks performed in this work. We use the uArm Studio module Blockly to control the uArm robot. Absolute position values and rotations in world coordinates can be sent to the robot in sequences to reproduce human-like exploration patterns like sliding over or pressing on a material. We measure the height between the uArm ground zero position and the material surface with the sensor head using a height gauge to reproduce similar absolute height values \( h \) for different materials. Note that the height gauge is also used to horizontally align the materials to the ground.

A USB Data Acquisition Card (NI USB-6002) attached to a Windows 7 workstation (i7-4770 CPU at 3.4 GHz, 16 GB RAM) collects the multimodal sensor data with the maximum sampling rate of the DAQ (2850 Hz). The sensor head is 3D-printed and embeds a three-axis acceleration sensor ADXL335 (Adafruit) with a range of \( \pm 3 \) g. The acceleration signals are band-limited between 10 Hz and 1 kHz. We combine the three acceleration signal components into one using the DFT321 algorithm from [12] as used in [3] and denote the resulting one-dimensional acceleration signal as tactile signal \( \mathbf{t} \). Note that in our setup the acceleration sensor printed circuit board (PCB) is in direct contact with the materials. Different to previous single-point of interaction approaches [3], [4], [5], [10], we slide the 19-mm-long edge (red line in Fig. 1) of the ADXL335 over the materials to collect multipoint high-frequency tactile information during the sliding interaction. Similar to a human finger, this step enables the accelerometer to capture spatially distributed tactile information of the underlying material during a slide. Moreover, we use a gear motor (see rotation motor in Fig. 1, right schematic) to rotate the attached material and to collect stationary acceleration signals \( \mathbf{t}_{\text{stat}} \) over adjustable time lengths. The different material samples are placed on an electronic scale (Smart Weight, 0.1 g - 2 kg) to measure their weight.

We place a microphone (omni-directional capacitive Blumart Lavalier Clip) on the uTexplorer to capture sound signals \( \mathbf{s} \) in a frequency range of 10 Hz - 7.5 kHz with a sampling rate of 44100 Hz. These sound signals are recorded in parallel to the acceleration signals.

<table>
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Previous work in [13] and [14] used infrared reflective (IR) scans to extract height-related material properties. We use a comparable IR sensor (EXP-R15-696), consisting of an emitter, a detector, and a 10 kΩ resistor in a voltage divider circuit, to measure a one-dimensional reflectance signal, denoted as \( r \). The IR sensor has a constant distance \( d_2 \) to the material surface.

We use two electric conductive tissues as electrodes \( E_1 \) and \( E_2 \) during the static contact with a material to identify metals. This procedure leads to an inverted binary array \( m' \in \{ 5V, 0V \} \), which we map to the values \( m \in \{-1, 1\} \). Only electrically conductive materials, e.g., metals, pull down the DAQ input to ground (0 V) during scan time, leading to a \( m = 1 \) array. We set a binary value \( metal = 1 \) if \( m > 0 \).

Thermal conductivity properties further aid during the discrimination of different object surfaces [1]. All surfaces obtain ambient temperature after an indefinite time, however, differently conduct heat from the human skin during bare-finger touch. The work in [15] uses a laser to heat up a material sample and measures the thermal decay, or cooling, using infrared sensing. In this work, we follow a similar approach to infer thermal properties of the used materials, shown in Fig. 2. We actively heat up the material surface and measure the subsequent thermal cooling rate \( r \). We heat up a Peltier element for about 3 seconds while pressing it on the material sample. Subsequently, we let the uArm move 2 cm in \( X_3 \) direction to measure the thermal cooling rate using an Infrared temperature sensor (Melexis MLX90614) for about 14 seconds and denote the recorded temperature data as \( T(t) \).

Two Force Sensing Resistors (FSR400, Interlink) are used to determine the exerted normal force and the tangentially exerted friction force during the movement. The acceleration sensor is movable in \( Z_3 \)-direction (sensor head coordinates). While sliding over a material, it presses on a bolt which is in contact with the FSR measuring the friction force. The contact of the accelerometer with the material generates a voltage value \( f \) in logarithmically with increasing pressure. We convert each \( f \) according to the inverse force-voltage relation diagram (Interlink FSR integration guide), leading to the normal and friction force arrays \( f_N \) and \( f_R \).

Visual information is relevant to convey material properties [16] beside haptic impressions. The uArm is moved to a viewing distance approximately 10 cm above the material samples to capture the images \( I_{disp} \) for visual display information. In this work, we initially examine cuboid object material samples, e.g., a granite tile. More complex shapes require, e.g., a point-cloud-based approach which we target in future work using commonly available depth scanners. The images of the materials, denoted as \( I_{disp} \), are captured using a USB camera (Mini USB endoscope DBPOWER HD, 2 MP) with a resolution of 640 x 480 pixels.

All required sensing components are inexpensive and their prices are shown in Table I. We consider this as an important contribution and hope that the low costs motivate other researchers to reproduce such scanning setups to provide large datasets of all possible materials available.

### III. OBJECT PROPERTY EXTRACTION FROM EXPLORATORY PROCEDURES

We use a set of 16 materials, shown in Fig. 4, as material database in this work. We extract a parametric material description from the recorded sensor data for each material sample. The corresponding model parameters are presented in Table II with their corresponding units of measurements.

**Enclosure - Volume and Global Shape:** We use the material surface images as the visual representation of all used materials in this work. In our current setup, we use plain tiles which have the shape of cuboids. Hence, we manually can measure the length, width and thickness of each material. In future work, we intend to use a depth scanner in a point-cloud-based approach to be able to determine any volume and shape.

As further relevant material properties, we determine the diffuse and specular reflection intensities \( I_{diff} \) and \( I_{spec} \) (introduced in [17]) from the reflectance and metal detection signals, respectively. The mean value of the reflectance signal indicates the diffuse lighting characteristics of the material (Lambert model [17]), and hence, we set \( I_{diff} = \max(1, r) \).

Additionally, specular reflections usually occur for metals, and we use our binary \( metal \) indication to set \( k_{spec} = metal \) in \( I_{spec} = k_{spec} (\hat{R} \cdot \hat{V})^n \) as object property while assuming a specular reflection coefficient \( n \) of 1. By moving the camera position through the Virtual Environment (VE) and considering a fixed light vector \( \hat{L} \), the resulting reflectance vector \( \hat{R} \) and the moving observer vector \( \hat{V} \) generate different reflectance impressions of the metallic material.

**Unsupported Holding - Weight and Density:** We determine the weight manually using the electronic scale. In combination with the volume \( V = l \cdot w \cdot t \), using the cuboid dimensions from Table II, we can infer the material-specific density \( \rho_{mat} = m/V \) of each object.
**Static Contact - Thermal Properties**: The ambient temperature is typically lower than the skin temperature of 33° [1], and consequently, thermal energy flows from the human finger to the material sample. Observations in [18] show that we can assume a model of heat dispersion for materials. According to the law of cooling by Newton, heated-up material surfaces cool down following the expression:

\[ \frac{\partial T(t)}{\partial t} = -\frac{\lambda}{\rho c_m} \cdot \nabla^2 T(t) \]

with \( T_{\text{amb}} \) being the ambient temperature. This differential equation can be solved as:

\[ T(t) = T_{\text{amb}} + (T_0 - T_{\text{amb}}) \cdot e^{-rt} \]

assuming that surfaces cool down to ambient temperature after an indefinite amount of time. Note that \( r \) is an object-specific constant containing the mass \( m \), the touch area \( A \), the thermal conductivity \( \lambda \) and the thermal capacity \( c \)

\[ r = \frac{\lambda \cdot A}{c \cdot m} \]
During the pressing procedure, we use the normalized normal force $f'_{N}$ to infer the stiffness of each material according to Hooke’s law. We tap and press on each material with decreasing sensor head target position (in world coordinates), and hence, increasing normal force. As a result, three material-dependent increases in the normal force can be observed which are proportional to the material stiffness. Softer materials have lower differences in these increases than harder materials. We use the mean value $f'_{N} = f_{N}$ of each of the three segments to calculate the scalar values $f'_{N,1}$, $f'_{N,2}$ and $f'_{N,3}$, shown in Fig. 6. The material-dependent spring constant $k_{mdl}$ is calculated as

$$k_{mdl} = \frac{\Delta F}{\Delta x} = \frac{f'_{N,3} - f'_{N,1}}{0.002 \, m}$$

with $\Delta x$ being 2 mm, determined by the step width of the uArm robot while advancing downward. The spring constant values are shown in Table II and range between 80 N/m to 1300 N/m. As initially evaluated in [19], the perception of stiffness requires the rendering of dynamic high-frequency tapping impulses, too. As in [11], we record such tapping impulses using the maximum velocity of approximately 60 mm/s of the uArm Swift Pro robot and linearly adjust the amplitude to the user velocity in the tactile rendering Section IV.

**Lateral Motion - Texture**: The uTexplorer sensor head is positioned in an initial mid-air position which results in a no-contact indicating infrared reflective sensor maximum distance value of 5 V before a sliding motion is started. After the initial contact, the IR sensor data determine the beginning and the end times of the sliding motion. We consider IR values below this threshold and use the corresponding indices to extract the relevant material sliding information from the acceleration sensor recordings which we denote as $t_{slide}$ and for the microphone sound recordings as $s_{slide}$. We also include recordings of arbitrary length $t_{stat}$ using the rotation motor and a fixed distance between the rotational center and the accelerometer contact line if, for any case, longer recordings are desired.

**Roughness**: The tactile signals resulting from the accelerometer recordings provide the high-frequency roughness information of a scanned material. We extract $t_{slide}$ during the sliding motion, which we manually post-process using an audio file manipulation program (Audacity). We smoothen the beginnings and endings of the short acceleration signals, repeat them until they approximately have a duration of 3 seconds and denote the resulting signal as $s_{mdl}$. This duration is an approximation of how long humans explore a material surface at maximum.

Audible sensor-surface interactions play another important role in human material identification. We repeat our sound signals $s_{slide}$ to the length of 3 seconds, and denote the resulting array as $s_{mdl}$. The tactile and audio signals mainly cover different frequency ranges in their spectra, however, overlapping frequencies can be observed. Tactile signals range from 1 Hz - 1000 Hz and audible signals from 20 Hz - 20000 Hz. We combine both signals into the audio-tactile signal $a_{mdl}$. We remove the frequency components below 1000 Hz of $s_{mdl}$ and add the spectrum of the tactile component. Intuitively, audible and tactile cues jointly enhance the perceived material realism if the virtual tool is slided over the virtual material during haptic rendering.
Additionally, we calculate the Tactile Signal Amplitude $TSA = \overline{r}_{mdl}$ with $t_{mdl}$ as the average amplitude of the upper 1% maximum values in each tactile signal, shown in Table II as percentages of the maximum possible output amplitude. In our setup, we display these tactile signals over the sound card which is limited to the range between -1 V and 1 V. We use the TSA as gain factor during the haptic rendering of the objects.

**Friction Coefficient:** We use the typical definition of the dynamic friction coefficient $\mu_d$ as the ratio of the friction force to the normal force (Coulomb Friction). Our dynamic friction coefficient $\mu_{d,mdl}$ is calculated as

$$\mu_{d,mdl} = \frac{\overline{r}_{R}}{\overline{r}_{N}}$$

(7)

We compute the static friction coefficient from the dynamic friction using the approximation $\mu_{s,mdl} = 1.1 \cdot \mu_{d,mdl}$ being 10% larger than the dynamic coefficient. This constitutes a rough approximation of the steady-state friction force of the LuGre model [20].

**Lateral Motion - Contour:** We use the reflectance signals to determine the contour of each material surface. We calculate the 100-point-moving-average signal of $r$ and denote it as $r_{avg}^{(100)}$. Adapted from [10], we use the standard deviation of the difference of $r$ and $r_{avg}^{(100)}$ to calculate the Macroscopic Roughness Strength (MRS) as

$$MRS = \max(100 \cdot c \cdot \sigma(r - r_{avg}^{(100)}))$$

(8)

with $c$ being a scaling coefficient to normalize this value to a percentage between 0% and 100%.

![Fig. 7: Normal map generation from the grayscale-converted display images shown for the materials $M_5$ and $M_{10}$. We use the MRS value which defines the strength of the contour to set the intensity of the normal map image $I_{normal}$.](image)

The grayscale-converted display images are passed to a normal map image generator (e.g. using Photoshop CC 2014.1) to provide $I_{normal}$, shown for the two materials $M_5$ and $M_{10}$ in Fig 7, which are used by Chai3D to render coarse texture information. The MRS values adjust the global intensity of $I_{normal}$. For example, the normal-mapped image of $M_{10}$ contains an intensity value $MRS(M_{10}) = 56\%$, and hence, a more noticeable surface structure needs to be rendered compared to $M_5$ with $MRS(M_5) = 22\%$.

IV. HAPTIC RENDERING

We use the Chai3D framework in Visual Studio 2013 on a Windows 7 workstation to run a display application for material interaction in a Virtual Environment. We use a Phantom Omni device which is enhanced with a Voice Coil Actuator (NCM02-05-005-4JB, H2W Technologies). We adapt the approach in [11], [21] which renders objects with haptic properties like friction or stiffness. Additionally, we include our extracted parameter set from the previous section which is necessary to render an object with all required attributes by Chai3D and, furthermore, we drive our added Peltier element to display thermal effects depending on the material sample.

**Enclosure - Volume and Global Shape:** Since the Phantom Omni device has only single-point interaction capabilities, it cannot fully provide a kinesthetic enclosing haptic experience. However, we visibly display the cuboid object by width $w$, length $l$ and thickness $t$ properties to provide a user in the VE with a visible volume representation of each object. Also, the diffuse and specular lighting parameters are passed to the Chai3D lighting model for each object and the global illumination.

**Unsupported Holding - Weight and Density:** If the haptic interaction point (HIP) comes close enough to a material, we let the user feel the weight of the object by pressing a key on the keyboard and lift the object with the Phantom Omni. We change the currently selected material position with the Phantom Omni position. We use the weight values from Table II to render a weight force $F_{weight}$ in negative z-direction of $F_{z,weight} = m * 9.81 N/kg$. All other interaction forces are set to zero during the lifting procedure.

**Static Contact - Thermal Properties:** We use an M4-H5 relay, attached to a micro-controller (Arduino Micro), to periodically turn a Peltier element on and off. The Arduino Micro is connected over serial communication (baudrate 115200, one stop bit, no parity) with the rendering application. If the virtual tool gets in contact with a material and the condition $r_{mdl} > 0.20$ /s is fulfilled for this material sample, its thermal cooling rate $r_{mdl}$ changes the on-off timing period of a 1 Hz pwm signal as

$$t_{on}(r_{mdl}) = \max(1.0, \frac{r_{mdl}}{r_{max}})$$

(9)

with $r_{max} = 0.52$ /s being the thermal cooling rate of $M_{13}$ (Stainless Steel) the best thermal conductor in this work. In case of $r_{mdl} = r_{max}$, the Peltier element is constantly turned on. The turned-off time period $t_{off}$ is calculated as $t_{off} = 1 - t_{on}$. Better thermal conductors, e.g., copper or silver, can be simulated by increasing the overall voltage on the Peltier element, which is currently limited to 1.0 V.

**Pressure - Stiffness Properties:** We use the Axis-Aligned Bounding Box (AABB) collision detection and haptic rendering implementations from Chai3D. According to the Phantom Omni device specifications, we render a stiffness up to 1020 N/m in z-direction. Hence, we clamp all stiffness values larger than this upper limit from Table II to the maximum device stiffness of 1020 N/m. Additionally, we use the acceleration tapping impulses to provide tactile feedback if the user impacts on the surface of an object. Chai3D provides an audio impact buffer which loads the corresponding acceleration tapping impulses in advance. We
linearly scale the amplitude according to the user impact velocity toward the material between extreme limits of 2 mm/s and 460 mm/s as proposed in [11].

**Lateral Motion - Texture:** Chai3D uses the OpenAL library to drive the sound card output. Our VCA is attached to the amplifier (Velleman PMK190) and controlled over the sound card output. Internally, an audio buffer is set to the combined audio-tactile signals $a_{ndl}$, resulting from the combination of $t_{ndl}$ and $s_{ndl}$ described in Section III. The maximum gain is set to the TSA values from Table II. The Chai3D implementation linearly adjusts the output intensity of the signals according to the haptic device velocity.

As for the friction rendering, we use the Chai3D implementation of the friction cone algorithm based on [22] to render static and dynamic friction forces.

**Lateral Motion - Contour:** The authors in [23] initially used the bump mapping technique, adapted from computer graphics, to perturb the magnitude and direction of surface normals as a function of height field gradients based on, e.g., grayscale images. Low-frequency vibrations and noticeable height differences can be rendered on the material surface. We use the corresponding Chai3D normal mapping implementation `computeAllNormals()` to enable such coarse structure rendering based on our normal-mapped images $t_{normal}$.

### V. Evaluation

We conducted a subjective experiment to evaluate the system capabilities to display the six exploratory patterns described in [1].

#### A. Setup

Ten subjects, 4 females and 6 males aged between 21 and 31, participated in this study, with no subject being author of this paper. Five subjects had previous experience with haptic devices. None of the participants reported any known touch sense disabilities. The total time of the experiment for each participant did not exceed 20 minutes.

The 16 materials were randomly placed on virtual tables in our VE application, shown in Fig. 8. We place an armrest to ease the usage of the Phantom Omni device handle and to avoid haptic fatigue. The subjects were able to freely move around by using the keyboard. If the haptic interface point (HIP) was close to a material, a key enabled the material to be lifted using the Phantom Omni device. We showed the subjects the depictions of the six manual exploratory patterns from [1] to ensure a consistent understanding of the relevant movement patterns.

#### B. Procedure

Initially, each subject was allowed to freely move around the VE and try all virtual materials to learn about the experimental setup and the kinesthetic and tactile rendering capabilities of the system. This training step took not longer than 5 minutes for all subjects. During the main part of the experiment, each subject moved from virtual table to table to interact with the material samples. The initial positions of the materials were permuted for each experimental run to avoid bias. The experimental supervisor handed the subject the real material samples, once she or he encloses the corresponding virtual material representation in the VE to interact with it. The subjects put the real material in their left hand and the modified Phantom Omni device handle in their right hand to compare the material properties. The subjects spoke out their ratings for all the six exploratory patterns as well as an overall impression rating of the virtual material representation.

#### C. Results and Discussion

![Fig. 8: Experimental Setup. We let subjects perform and rate the six common exploratory patterns proposed in [1].](image)

The Mean Opinion Scores (MOS) across all ten subjects for each real and virtual surface material were computed. Table III shows the MOS for each exploratory movement pattern. The last column shows the averaged results of each exploratory procedure and the overall perception rating of the materials.

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</table>

TABLE III: Mean Opinion Scores (MOS) across all subjects resulting from the real-virtual material ratings from 1 (not similar) to 5 (similar). $C_i$ denotes a comparison between a real material and its virtual representation. The last column shows the averaged results of each exploratory procedure and the overall perception rating of the materials.
denoting a comparison between the real material and its virtual representation in the VE. The average value of all overall comparison ratings is 4.3, leading to our conclusion that the virtual material representations successfully can convey most of the impressions of real materials, especially in terms of visual representation (enclosure), pressure and static contact. Note that the perception of enclosure is generally limited to single-point of interaction with current haptic devices. Several further exceptions exist which decrease the perceived realism for a couple of materials. We observe that the rendering of contours can create spurious vibrations if the material is rendered with a large stiffness coefficient. Hence, we decided to decrease the overall stiffness to avoid unrealistic vibrations, but at the cost of softer stiffness rendering. Additionally, we observe that VCAs perform less convincing for rendering soft material microscopic roughness impressions, such as for $M_2$ (Fabric). Also, materials like $M_2$ (Coarse Foam), which induce very strong roughness impressions, were evaluated not to convey the same tactile signal strength as their real material counterpart. We assume that holding a tool-like handle always comes with the limitation that soft virtual objects appear stiffer than their real material counterpart, and hence, reduce the total perceived realism. Moreover, the representation of soft materials would benefit from a graphical deformation while pressing the HIP on the virtual surface.

Another limitation using a single-point of interaction haptic device like the Phantom Omni is about human-like enclosure object interactions, such as grasping and pinching. In the future, devices like the Sigma 7 (Force Dimensions) with 7 degrees-of-freedom can be used to provide such necessary actuation to recreate pinching or grasping actions. The same actuators as introduced in this work need to be attached to provide a complete haptic object interaction experience.

The current thermal property estimation approach will be embedded into the main uTexplorer in future work. An additional linear actuator may be required to lift up the thermal measurement unit to avoid being in contact with the material surface during the sliding phase.

VI. CONCLUSION

This study presents a material property recording, analysis, and display setup and pipeline. We show that real material samples can be scanned semi-automatically, represented and displayed using a common haptic display device. A subjective study was performed to show that typical human exploratory patterns, such as lifting or sliding over the material, can be reproduced using an augmented tactile and kinesthetic setup inspired from [11]. In future work, we intend to scan arbitrarily-shaped objects and represent them in a VE for increased audio-visual-haptic immersion.

ACKNOWLEDGMENT

This work has been supported by the German Research Foundation (DFG) under the project STE 1093/6-1.

REFERENCES