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Haptic Material Classification with a Multi-Channel Neural Network

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***Abstract*—We present a novel approach for haptic material classification based on an adaptation of human haptic exploratory procedures executed by a robot arm with an optical force sensor. A multi-channel neural architecture informed by findings from human haptic perception performs a spectral analysis on vibration and texture data gathered during material exploration and integrates this analysis with information gathered on material compliance. Experimental results show a high classification accuracy on a test set of 32 common household materials. Furthermore, we show that haptic material properties, relevant for robot grasping, can be classified with a simple haptic exploration while actual material classification requires more complex exploration and computation.**

I. Introduction

Embodied agents benefit from experience gained in the real world, as pointed out by Cangelosi et al. [1]. An implicit requirement for these experiences is suitable sensory capabilities. While visual and auditory perception is sufficient for many tasks, some challenges require haptic perception like the discrimination of materials with similar visual features.

Robotic haptic perception enables a more intuitive human-robot interaction in natural environments, as robots develop an embodied understanding of concepts frequently used by their human interaction partners. A human might, for instance, request *a soft towel*. Though a robot might be able to learn that the *blue* towel is the *soft* one, it will not be able to generalize the concept of softness to novel objects without haptic perception.

Aside from human-robot interaction, material classification is also relevant for robot grasping. Surface friction, compliance, and fragility of an object influence the minimal and maximal forces that need to be applied to an object during grasping to avoid slipping or damage.

Existing approaches for robot haptic perception use either proprietary [2], [3] or very complex, expensive, and maintenance-intensive sensors [4], [5]. We extend the state-of-the-art in robot haptic perception by presenting a novel approach for haptic material classification with a single optical force sensor mounted on a robot arm. The one-point force interaction of the sensor is used to perform multiple exploration procedures which yield different information about the explored material. We utilize a multi-channel neural network architecture to integrate information from different explorations to reach a high classification accuracy. Furthermore, we show that 1D-convolutional neural networks can learn to extract spectral features from haptic vibration and texture information without domain-specific preprocessing. Moreover, the proposed method for haptic material classification is robust with regards to its requirements on the motor control of the robot. The haptic exploratory procedures (HEPs), adapted from human haptic exploration strategies, are designed to compensate for the motoric inaccuracy of a robotic arm, thus requiring less complex robotic hardware and controllers.

The presented approach was evaluated on a collection of 32 materials including common household materials like metal, glass, paper, fabric, wood, etc. Data was collected using two different HEPs. The classification accuracy, as well as the recognition of two general haptic properties (compliance and texture of the material), were evaluated based on each single exploratory procedure and the combination of both procedures. Furthermore, we experimentally decreased the accuracy of the more complex lateral motion exploratory procedure to evaluate the benefit from the integration of different exploratory procedures by the multi-channel neural network architecture.

II. Related Work

This section summarises research on the human haptic perception that informed the development of our haptic exploratory procedures (HEPs), related approaches for robotic haptic material classification, findings from neuroscience regarding the haptic perception that motivate the design of our multi-channel neural network architecture and related work in neural network architectures.

A. Human Haptic Perception

Human haptic perception is based on multiple types of sensory receptors in the epidermis, that react to different frequencies of vibration as well as deformation of the skin and temperature. Additionally, information about the strain on muscles and tendons as well as knowledge about motoric actions complement this sensory system [6].

The integration of the sensory and motor system is necessary, as human haptic perception is active: Lederman and Klatzky [7] identified a set of haptic exploratory procedures (HEPs) that humans utilize to gain different information about an explored object. The exploratory procedures used by humans are lateral motion (sliding or rubbing over a surface) for gaining information about texture, pressing down an object for information about hardness, static contact to learn about an object's temperature, lifting up an object to judge weight as well as enclosing an object or tracing its contours for global and detailed information about its shape.

According to Klatzky et al. [8], some of these procedures play a prominent role when using haptic perception as a substitution for visual perception, like contour tracing to gain information about an object's shape. When identifying material properties, on the other hand, lateral motion and pressure are most often utilized. Therefore, we focus on adapting these two exploratory procedures for haptic material classification with a force sensor.

In humans, the haptic sensory signals are processed in the somatosensory system, where information about the surface contact, skin deformation, vibration, body movement, temperature, and also pain are integrated [9]. Therefore, haptic perception can be seen as a special case of crossmodal sensory integration. Though the sensory information stems from just one sensory modality, the information that is integrated is vastly different. Johnson et al. [10] propose that the invariance of roughness perception against different velocities of lateral motions over a surface is the result of a central neural mechanism that combines information about skin deformation and motion speed.

According to Yau et al. [11], lateral motion creates mechanical oscillations due to the fine texture features of the surface and friction between skin and object. There is evidence that spectral analysis plays a significant role in texture perception [12]. It is hypothesized that this spectral analysis is performed within the auditory cortex, a subsystem of the brain that is specialized in spectral analysis. Hackett et al. [13] showed that the caudomedial auditory belt area, which was assumed to be responsible exclusively for audio processing, also receives input from the somatosensory system.

These findings motivate the usage of artificial neural networks for haptic material classification, as neural networks can integrate multi-sensory information [14], [15] as well as perform spectral analysis [16].

B. Robotic Haptic Perception

Existing approaches for robotic haptic material classification vary regarding the employed haptic sensors, the haptic exploration, the material samples and the algorithmic approach used for classification. We organized the related work by sensor technology as this influences the type of the neural classification problem.

Complex, skin-like haptic sensors with a spatial resolution are used by Takamuku et al. [17], who utilize a robotic hand with 18 degrees of freedom to perform haptic exploration by squeezing and tapping objects placed into the palm of the robotic hand. The haptic sensors, developed by Tada et al. [5], are based on polyvinylidene fluoride (PVDF) films and strain gauges. The sensors are distributed on the fingertips and palm. A set of seven materials is explored, and the resulting data are used to train a self-organized map (SOM) [18], which can cluster materials according to haptic properties like softness. The same type of sensor is used by Jamali and Sammut [19], who employ a naive Bayes classifier to distinguish a set of seven different materials. The materials are explored with an artificial finger outfitted with strain gauges and Polyvinylidene Fluoride (PVDF) films embedded in silicone. Fourier coefficients of the recorded data are used to train the classifiers.

The even more complex SynTouch biomimetic tactile sensor (BioTac) [4] mimics the sensory capabilities of a human finger. It records low- and high-frequency vibrations, fluid pressure, temperature and deformation in the artificial finger surface. Fishel and Loeb [20] use Bayesian exploration to classify a set of 117 material samples that are recorded with a BioTac sensor mounted on a small robot arm that can press the finger onto a linear stage. This setup enables lateral motion with different speeds and contact forces. The parameters are chosen algorithmically based on previous explorations. Gao et al. [15] use a deep neural network to predict a set of 24 haptic adjectives from visual and haptic input from the BioTac sensor. The classification is done on the Penn Haptic Adjective Corpus 2 (PHAC-2), collected by Chu et al. [21]. The PHAC-2 dataset contains haptic recordings from 53 household objects. Four different haptic explorations were carried out (squeeze, hold, slow slide, and fast slide) using a BioTac sensor mounted on the PR2 robot.

Finally, one-point interaction-based approaches create vibrations by moving the sensor over the material sample to gain information about friction properties and texture. The optical force sensor used in our approach falls into this category. Jikvo Sinapov et al. [2] use a k-nearest neighbours algorithm (k-NN) and a support vector machine (SVM) to classify a set of 20 materials based on scratching exploratory procedures. An artificial fingernail is scratched over a material surface. From the resulting vibrations, features like magnitude and frequency components are extracted. Romano and Kuchenbecker [3] use One-Class Support Vector Machines to classify a set of 15 materials with a robot-held recording tool that features a vibration measuring accelerometer and a force sensor. The pen-like recording tool is moved over material surfaces by a PR2 robot.

While some of the presented approaches for highly complex sensors combine multiple exploration procedures, this has not yet been realized for one-point interaction-based sensors, which is the topic of our approach. Furthermore, for this type of sensors, neural network based classification has not been evaluated.

C. Neural Architectures for Cross-modal Integration and Spectral Analysis

From the perceptual haptic approaches, we see that neural structures exist that can (a) integrate sensory information

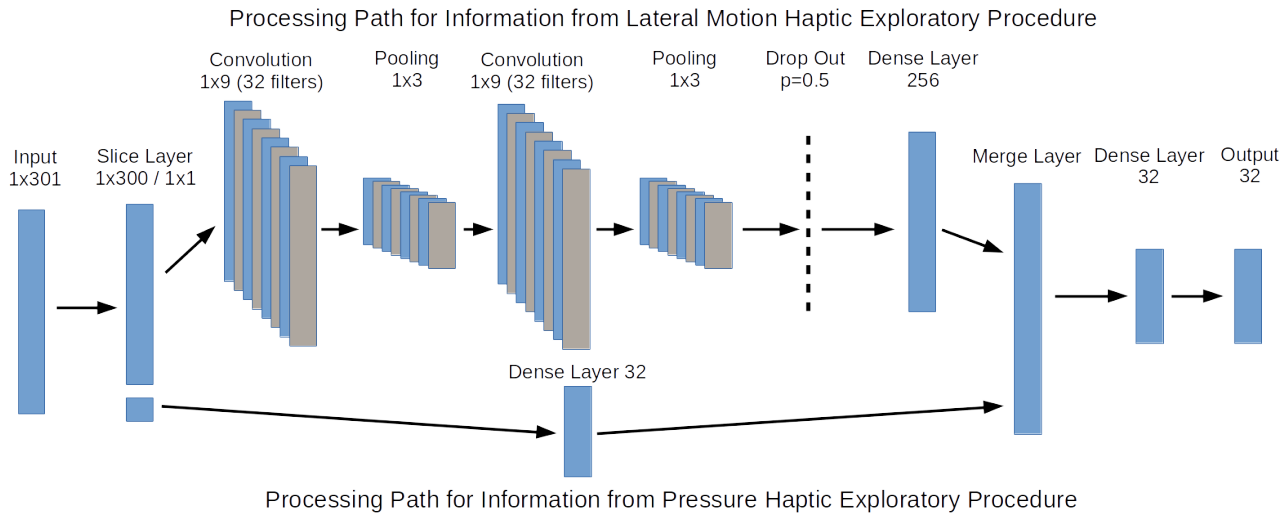

Fig. 1. Multi-channel neural network architecture for haptic material classification. The upper path processes vibration and texture information from the lateral motion HEP with a convolutional network. The lower feedforward path processes the compliance information gained during the pressure HEP.

from various sources and (b) perform spectral analysis of 1D-signals. Artificial neural network architectures with multiple channels based on convolution [22] use interleaved layers of convolutional filters and pooling layers that extract features from the input data. The convolution filters move over the whole input space to extract local feature maps that are then reduced in their dimensionality by the pooling layers, which also achieve a robustness against translational variance. Finally, the extracted features are joined by fully connected layers.

There is evidence that convolutional neural networks may well support sensory integration and spectral analysis. For instance, Hinton et al. [16] stress the recent success of neural network approaches for speech recognition, a complex task that encompasses spectral analysis. Lee et al. [23] use convolutional deep belief networks to learn audio feature representations for speech data. Abdel-Hamid et al. [24] use a similar approach where they apply interleaved convolutional layers and pooling layers to analyze the frequency domain of speech signals. It is also known that artificial neural network architectures are well suited for integrating input from multiple modalities as well as multiple inputs from the same modality. In the visual modality, Barros and Wermter [14] use multi-channel convolutional neural networks to classify emotions from facial expression and body posture. Gao et al. [15] use a similar architecture that features two convolutional network paths that are joined by a dense layer to integrate haptic and visual information. Wang et al. [25] show that varying granularity in different paths of a network can be beneficial. They propose a three-channel neural architecture for image similarity classification where one deep convolution channel is augmented by two shallow, low-resolution convolution channels.

In summary, the literature indicates that a multi-channel neural network architecture can integrate different sensory input while a convolutional neural network is able to extract spectral features from 1D-signals.

III. Multi Channel Network Architecture for Haptic Material Classification

Our deep neural network architecture for materials classification is motivated both by biological findings, [II-A], and known properties of deep convolutional networks, [II-C]. We utilize a multi-channel convolutional neural network architecture to classify materials based on data gathered during two haptic exploratory procedures (HEPs). A convolutional processing path extracts spectral features of sensory data gathered from the lateral motion HEP. This processing path is joined with a feedforward path for processing the compliance information gained during the pressure exploration procedure.

Figure 1 shows the architecture of the network. The input to the network is 300 samples from the lateral motion HEP and the compliance as computed from the pressure HEP. A slice layer splits the input into two processing streams. The samples from the lateral motion are processed by two sets of interleaving convolution and pooling layers. Both convolution layers have a dimension of 1x9 and are convolved over the input with a stride of 1. Each convolution is followed by a max-pooling operation with a receptive field of 1x3. The last pooling layer is connected to a dropout layer that randomly drops input with a probability of p=0.5. Dropout layers prevent interdependence of feature detectors and overfitting [26]. The dropout layer is followed by a fully connected dense layer with 256 units.

In contrast, the sample from the pressure HEP is passed through one fully connected dense layer with 32 units before both processing streams are integrated with a merge layer that concatenates the last dense layer of each respective processing stream. The merged information from both streams is passed to a 32 unit dense layer and then to an output layer of the same size. The meta-parameters of the network were

empirically determined; a set of parameters that performed best on the average of all experimental conditions was chosen. The rectified linear activation function introduced by Hahnloser et al. [27] is used for all units in the network as it addresses the vanishing gradient problem in deep networks. All layers use the Glorot Uniform initialization, also known as Xavier initialization [28]. This initialization stabilizes the strength of the input signal throughout the deep network and automatically adapts to changes in input and output connectivity of a layer, which is beneficial when performing separate evaluations of the two processing paths.

IV. Robot Arm Setup, Sensors, and Haptic Exploratory Procedures

The haptic exploratory procedures (HEPs) most relevant for material classification, pressure, and lateral motion [7], were adapted for a novel haptic force sensor and a small robotic arm. The exploratory procedures were used to collect a haptic material corpus from 32 common household materials.

A. Haptic Sensor

For recording haptic data, we use an OptoForce 3-Axis optical force sensor[1]. The dome-shaped sensor with a diameter of 11 mm and a weight of 23 grams (including cable) can easily be installed on different platforms. Its shape mimics a (small) human fingertip. The sensor uses an infrared emitter inside the semispherical rubber dome that has an intermediate stiffness property. Inside the sensor, a reflective layer is responsible for reflecting the infrared rays to the sensing element. The sensor can measure surface deformations and computes the applied force in three dimensions with an accuracy of 2.5 mN. The sensor is remarkably robust, the rubber is not permanently deformable and has a nominal pressure capacity of 10 N with an overloading capacity of 300% in the perpendicular direction and a capacity of 5 N on the X and Y-axes with an overloading capacity of 200%. During development and recording of data in estimated 5000 trials no wear and tear on the sensor was detected.

B. Robot Arm Setup

A robotic arm was developed for executing exploratory procedures on material samples. Four degrees of freedom allow the arm to perform the pressure HEP and the lateral motions HEP with speed comparable to that of a human hand. The robotic arm is constructed from Dynamixel servo motors: The first motor is responsible for the circular-horizontal movement of the whole arm. The second motor and third motor together control the radius of the semi-circular motion and thus the horizontal location of the sensor on the material surface. Also, the second motor is used to change the height of the sensor, therefore, controlling the pressure between sensor and surface. The fourth motor is used to adjust the orientation of the haptic sensor to ensure a perpendicular orientation towards the explored surface during movement. Figure 2 depicts the robotic arm with the attached sensor. The motors are controlled using PyPot[2], a library for controlling Dynamixel motors.

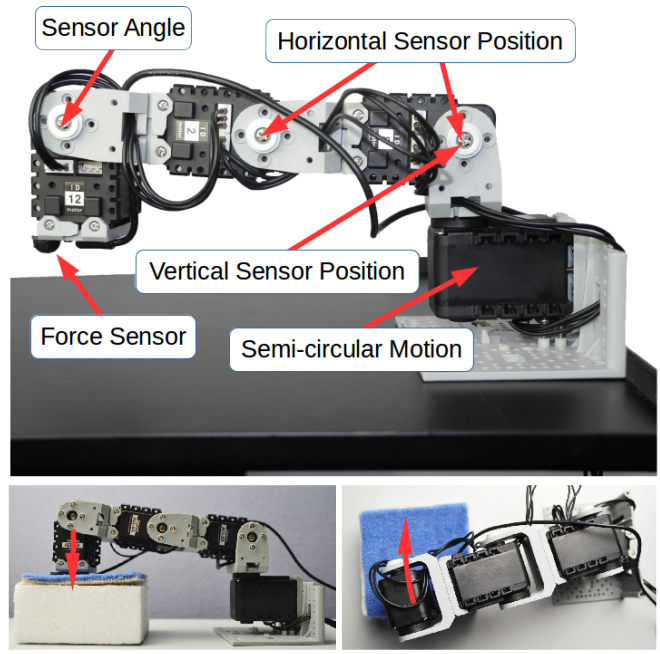

Fig. 2. Top: Robotic arm constructed with Robotis Dynamixel motors. At the tip of the arm, an optical OptoForce 3-axis force sensor is attached. The arm can perform haptic exploratory procedures on material samples placed below the sensor. Bottom left: During the pressure HEP, the sensor is gradually lowered onto the sample until a force threshold has been reached. Bottom right: During the lateral motion HEP, the sensor is moved across the sample to register vibrations and texture information.

C. Haptic Exploratory Procedures

Two exploratory procedures for material classification were implemented based on human exploration observed by Lederman and Klatzky [7]. During the pressure HEP, the sensor is slowly pressed down onto the material sample to gain information about the compliance of the material. During the lateral motion, the sensor is moved in a semi-circular trajectory over the material surface to gain information about its texture and friction properties. Figure 2 depicts the motion trajectories of both haptic exploration procedures.

The contribution of these exploratory procedures lies in the usage of real-time haptic feedback from the sensor to adjust the motion during the sampling process. The exploratory procedures were developed to mimic human haptic exploration, both regarding recorded sensory information and requirements to the motoric complexity and accuracy. The exploratory procedures rely on reasonably accurate Dynamixel motors that are widely used in robotic research, see [29], [30] for examples of robots based on these motors. Also, the sampling procedures are non-destructive to the sensor, the robot arm, and the material sample. This is achieved by using haptic feedback to avoid excess forces.

[1] http://optoforce.com/3dsensor/

[2] https://poppy-project.github.io/pypot/

1) Pressure Haptic Exploratory Procedure: The pressure HEP measures the compliance of an object, i.e. how well the explored material can be deformed. Humans execute this exploratory procedure by slowly pressing a finger onto a material sample. During this procedure, sensory information about deformation of the fingertip, the strain on tendons and muscles, and information about the executed motoric actions are integrated to judge the compliance of the explored object.

To adapt this exploratory procedure to a robotic arm with a force sensor, these values have to be formalized. The compliance of a material is the inverse of its stiffness, which is defined by Baumgart [31] as load divided by deformation. Load, i.e. the force exerted on the material sample, can be measured directly from the haptic force sensor. Material deformation, however, can only be computed indirectly from information about the performed movement in combination with the haptic sensor: the sensor is placed above the material sample and moves downward at a slow speed. The initial contact of the haptic sensor with the surface is recorded. The downward movement is continued at a linear speed until a force threshold ($\sim$0.625 N) is reached. We use the time between initial contact and reaching the force threshold as an indicator for the deformation of the explored material sample and compute the compliance of the object as the quotient of the force difference (0 - 0.625 N) and the time difference.

2) Lateral Motion Haptic Exploratory Procedure: The lateral motion HEP measures coarse and fine texture information as well as friction properties of an explored material. When humans perform this exploratory procedure, they move the tip of their fingers over a material [7]. Friction between skin and material as well as the surface structure of the material cause vibrations and skin deformation that are picked up by different sensory cells in the epidermis.

Our robot arm can execute a similar movement by moving the sensor in a wide semi-circular motion over the material surface. During the motion, force values are continuously sampled at a rate of 100 Hz for three seconds, yielding 300 samples. In contrast to the pressure HEP, which generated a force perpendicular to the surface, the lateral motion creates forces along all three axes. Like Sinappov et al. [2], we use the Euclidean vector norm, the square root of the sum of the squared forces of all three axes, to reduce the dimensionality of the recorded sensor data and to compensate for the semi-circular trajectory.

The main challenge for the development of this exploratory procedure is the reproducibility of the recorded data. The vibrations that are picked up by the haptic force sensor are caused by friction between sensor and material. The friction, in turn, is dependent on the force between sensor and material. Initial trials have shown that motor control with fixed vertical positioning instead of haptic feedback for initiating the lateral motion yields great differences in recorded data, see Figure 3 (top). Slight asperities in the material sample cause relevant differences in the forces between sensor and materials depending on the initial contact point.

Aiming at a bio-inspired approach, we looked at human haptic strategies: Klatzky at al. [32] report that humans execute hybrid exploratory procedures, especially applying pressure during lateral motion. This finding was adopted to the robotic lateral motion HEP. Like in the pressure HEP, the sensor is gradually lowered onto the material until a force threshold is reached, thus allowing to control the initial contact force. It ensures that lateral forces during movement caused by material properties like friction are always based on the same vertical force. This approach yields significantly more reproducible data, as indicated in the comparison in Figure 3.

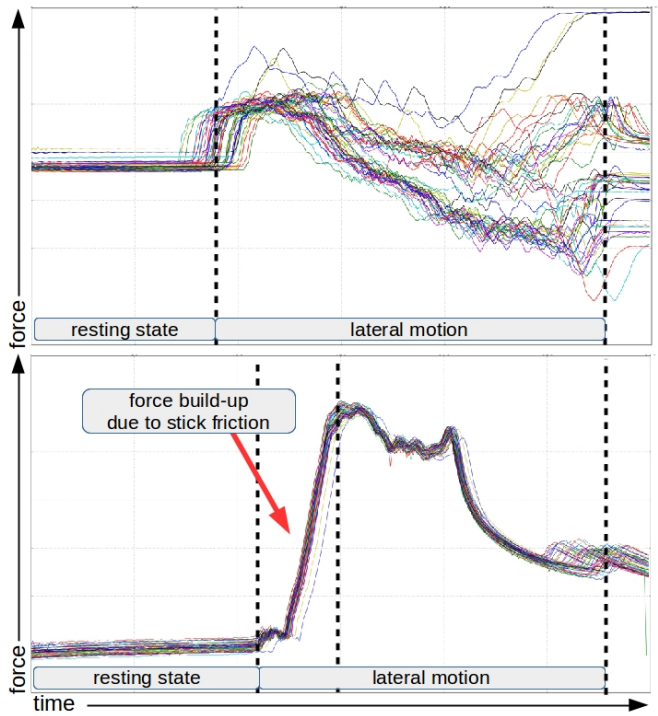

Fig. 3. Fifty recorded lateral motion explorations over a material sample (ID-3, hard plastic). Top: Without haptic feedback, the exploration yields unreliable data. Bottom: With haptic feedback, the exploration yields reproducible results. Initial stick friction lets the force between sensor and material rise until the sensor starts to slide over the material creating a unique haptic signature.

D. Material Samples

A set of 32 material samples was collected from common materials found in homes, see Figure 4. The materials were cut into squares with an edge length of ten cm and fixed on top of styrofoam bases of four cm height. The styrofoam provides an even surface. More importantly, it is slightly compliant, thus if a soft material is placed on top of the foam base, the sensor can slightly deform the sample material by pressing it down. This mimics the human exploration action of rubbing a material between fingers or placing it into the palm of the hand to provide a compliant substrate [17].

Each material is labelled with an ID. The materials were rated with regard to two haptic properties: softness and texture; see Table I. Softness refers to the deformability of the material and was rated as *low*, *medium* or *high*. Texture

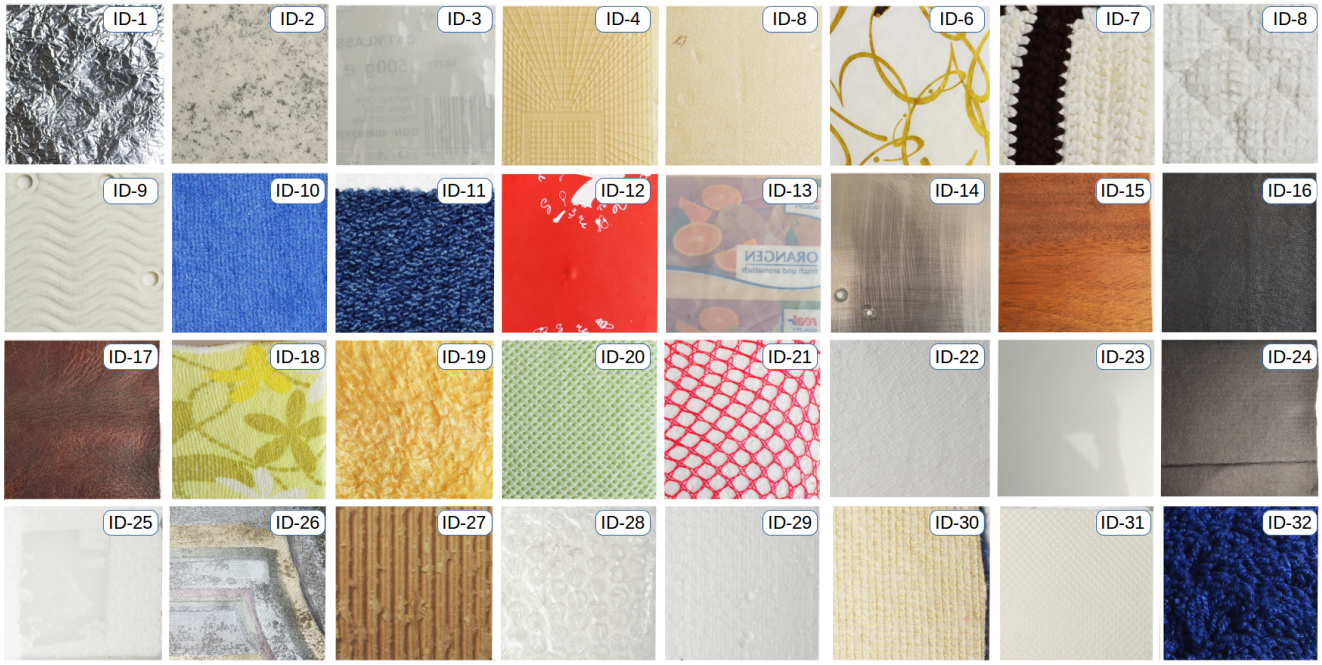

Fig. 4. Set of 32 common household materials. All materials are fixed onto a styrofoam substrate to provide an even and slightly compliant surface. See Table I for details on the different material samples.

describes the surface structure of the material and was rated as *smooth*, *fine* or *coarse*.

V. Experimental Results and Discussion

The presented approach was evaluated on a set of 32 material samples. Each material was explored 100 times with the pressure and lateral motion HEP. All samples were normalized during preprocessing to the range of -1 to 1. Three sets of experiments were performed on the recorded data. All experiments were performed with 400 training epochs using stochastic gradient descent with Nesterov momentum [33] (learning rate = 0.01, momentum = 0.9) and a batch size of 40. Categorical cross-entropy was used as a loss-function. For all experiments the available samples (32 materials with 100 samples each, equalling 3200 samples) were randomly split into 80% training data, 10% validation data and 10% test data. Each experiment was repeated ten times to compensate the influence of randomization.

A. Experiments on Haptic Property Classification

In the first set of experiments the classification of two general haptic properties, compliance and texture, was evaluated. The network was trained to classify materials according to three levels of compliance and texture, see Table I. Evaluation results (Figure 5) show that the full network, as well as the path for processing lateral motion on its own, performed with a very high accuracy ($\sim$99%). The path for processing the pressure HEP classified compliance with an accuracy of over 62% while it classified texture with an accuracy of over 48%. Though the pressure HEP is not suited to gain information about texture [7], the above chance level classification of texture was most likely enabled by the dependencies between texture and compliance in our material set, e.g. no smooth material had a high softness.

B. Experiments on Material Classification

Based on the promising results for haptic property classification, we evaluated the ability of the network for individual material discrimination. The network was trained to recognize the specific material that a sample was taken from, using only the pressure HEP, only the lateral motion HEP or both HEPs. The results, as depicted in Figure 5, show that the full network, and the network path for processing information from the lateral motion alone, achieved both a classification accuracy of over 98%. The processing path that only relies on information from the pressure HEP achieved an accuracy of $\sim$23%.

C. Experiments on Material Classification with Noise

The third set of experiments focussed on the performance of the network when the recorded data during the lateral motion is distorted by noise. This could happen due to external influences, oscillations in the motor control or factors that make it hard to maintain a steady force between sensor and sample. The last problem arises when exploring non-flat surfaces.

To simulate the influence of noise, the experiment for material classification was repeated with added Gaussian noise ($\mu = 1$, $\sigma = 1$) to all data points of the lateral motion data after the normalization during preprocessing. The results show that this negatively influenced the classification accuracy of the full network and the lateral motion processing path by lowering the classification accuracy by over 30%, see Figure 5. The accuracy of the compliance processing path

TABLE I
MATERIAL SAMPLES AND HAPTIC PROPERTIES.

ID	Material	Compliance	Texture
ID-1	Folded tinfoil	medium	fine
ID-2	PVC mat	medium	fine
ID-3	Smooth, hard plastic	low	smooth
ID-4	Patterned foam paper	medium	coarse
ID-5	Non-patterned foam paper	medium	smooth
ID-6	Smooth, soft cardboard	medium	smooth
ID-7	Knitted oven cloth	high	coarse
ID-8	Cotton oven cloth	high	coarse
ID-9	Textured rubber mat	medium	coarse
ID-10	Soft carpet	high	fine
ID-11	Rough carpet	high	fine
ID-12	Balloon (rubber)	medium	smooth
ID-13	Plastic foil	medium	smooth
ID-14	Steel plate	low	smooth
ID-15	Hard wood	low	smooth
ID-16	Fine leather	medium	smooth
ID-17	Coarse leather	medium	fine
ID-18	Microfibre cloth	high	fine
ID-19	Furry cloth	high	fine
ID-20	Spongy cloth	high	coarse
ID-21	Coarse net	medium	coarse
ID-22	Fine net	medium	fine
ID-23	Ceramic tile	low	smooth
ID-24	Smooth cardboard	low	smooth
ID-25	Glass	low	smooth
ID-26	Wallpaper	medium	fine
ID-27	Ribbed cardboard	low	coarse
ID-28	Bubble Wrap	medium	coarse
ID-29	Styrofoam	medium	fine
ID-30	Carpet backing fabric	medium	coarse
ID-31	Textured PVC mat	medium	fine
ID-32	Shaggy carpet	high	coarse

was not affected as was expected. The benefit of integrating the two processing paths was relatively small (2.75%). We hypothesize that this is due to the relatively low classification accuracy of the pressure HEP.

D. Discussion

We have shown that our multi-channel neural network architecture achieved a high accuracy for haptic material classification as long as undistorted information from the lateral motion HEP was provided. The processing path for lateral motion information, based on a convolutional neural network, could learn to extract spectral features that are unique to different materials. While it was expected that materials with distinct, coarse texture features would be distinguishable, our approach also performed well on materials with a smooth surface and similar (high) hardness like hard plastic, steel, ceramic tile, and glass. These materials can be discriminated on the basis of vibrations caused by friction between sensor and surface. These vibrations show a distinct pattern over many explorations due to the lateral motion HEP based on haptic feedback. We argue that the high accuracy

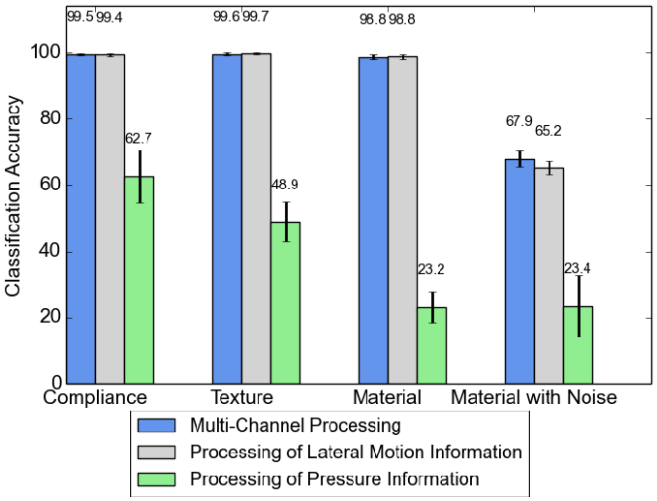

Fig. 5. Classification accuracy of full network and separate paths for processing only information from lateral motion and pressure HEP for material classification, material classification with noise, and compliance and texture classification.

was partly enabled by the laboratory conditions of having material samples of adequate size and an even surface. The results show that under these conditions the pressure HEP did not benefit the overall classification process as the lateral motion already provided enough information for accurate classification.

The integration of information from different HEPs, facilitated by our multi-channel neural network architecture, benefited the classification results slightly if the sensor data recorded during lateral motion became distorted by noise.

The result that robotic pressure HEP is faster to perform than the lateral motion HEP, which relies on pressure adjustment but in turn provides more accurate information about the material, is in line with findings of human haptic perception [7]. A robot can choose the pressure HEP for fast but less accurate material classification. This can be used in the preparation of grasping or manipulating an object, where information about the compliance of the object can help to select a suitable grasp. The lateral motion HEP, on the other hand, takes more time to execute but offers more accurate material classification. It can, for instance, be used to distinguish visually similar objects through more thorough haptic inspection.

VI. CONCLUSION

We introduced a method for haptic material classification based on two haptic exploratory procedures (HEPs) that utilize haptic feedback to improve the information gained from explorations with a novel optical force sensor mounted to a small robotic arm.

The physical one-point interaction between the sensor and the explored material is suitable to gain information about the material compliance by pressing down, and information about friction and texture by sliding the sensor over the material. We presented a multi-channel neural network architecture that learns to extract relevant spectral features from the

vibrations caused by friction and texture and integrates them with information about compliance. A high accuracy on experiments for haptic material classification with a set of 32 common household materials was achieved. This accuracy is difficult to compare with state-of-the-art approaches due to different sensor technology and material sets. The results are promising and show that the robust one-point interaction force sensors used in our approach can accomplish relevant haptic perception tasks e.g. for robot grasping.

For future work, we will extend our approach to more complex haptic classification tasks like the classification of uneven surfaces and 3D objects. Possibilities to increase the classification accuracy of the pressure HEP by recording and processing more haptic data will be explored. Also, we aim to adapt our approach to a full robotic arm with multiple fingers with force sensors for more complex explorations like contour tracing. These changes will, in turn, require adaptations in the neural network architecture. Finally, we will compare our results to the performance of blindfolded humans, which could enrich the understanding of human tactile perception.

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