

Textile identification using fingertip motion and 3D force sensors in an open-source gripper

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Abstract—We propose the use of a human-inspired exploratory motion in which a robot gripper’s fingertips are rubbed together, to obtain tactile information about and recognize a grasped textile. Our method not only recognizes different materials, but also distinguishes between one and multiple layers of the same material. The motion can be performed using an open-source, 3D printable gripper, without needing to move either the robot or the object. We also propose a set of features to extract from the proposed exploratory back-and-forth motion, which performs at over 94 % recognition rate when distinguishing 18 different materials with an easily-trained SVM. We compare the performance with frequency-based features as well as a deep-learning-based classifier.

Keywords—Grasping and Manipulation, Sensing, Biomimicking Robots/Systems

I. INTRODUCTION

The robotic manipulation of thin deformable objects and textiles¹ is a challenging issue at the base of both numerous household tasks, such as laundry, wrapping, and covering, as well as industrial assembly and manufacturing applications. When manipulating a textile object, it would be desirable to know if a robot has successfully grasped it as well as its identity. Tactile sensing is a promising avenue to obtain reliable information independent of illumination and configuration of the textile. Furthermore, it can be used for objects that are inside containers or otherwise inaccessible to computer vision approaches.

Lederman and Klatzky [1] observed that humans evaluate an object’s roughness by dragging their fingertips over its surface. We emulate this strategy with a back-and-forth finger motion that rubs the gripper’s fingertips together to extract tactile signals from the textile it has grasped. The motion is implemented on the NAIST OpenHand M2S², a gripper for textile manipulation we have introduced in previous work [2].

¹We use the term “textile” to include all thin, highly deformable objects with generally reversible deformation, such as plastic and aluminium foils.

²<https://github.com/naist-robotics/naist-openhand-m2s>

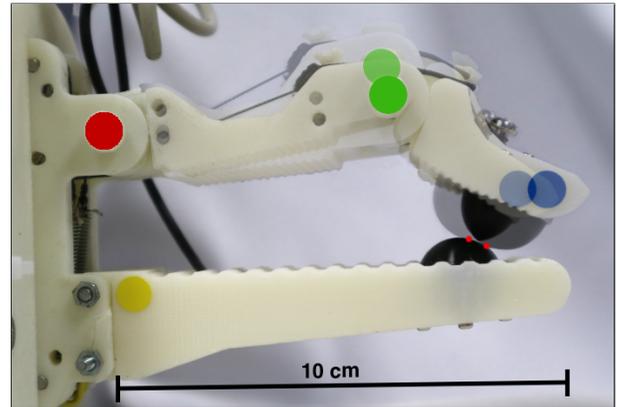


Fig. 1. The finger in the two extremal positions of the back-and-forth rubbing motion and the contact points between the sensors p_1 and p_2 , indicated in red.

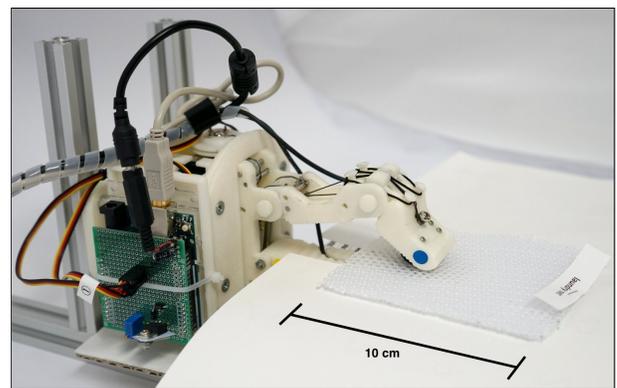


Fig. 2. The experiment setup, with a NAIST OpenHand M2S rubbing its index finger on a piece of textile to obtain tactile information. The white guard supports the textile so it does not slip away while the fingers are opened.

Human fingertips are highly complex and contain specialized cells to sense both low- and high-frequency vibrations, stress and temperature flow. Furthermore, the fingertip’s structured surface is involved in creating the vibrations sensed by

these cells. Under the assumption that all of these characteristics play a role in tactile sensing, complex biomimetic sensors such as the BioTac³ have been developed. However, dealing with the high-dimensional data delivered by these sensors can be challenging, and it is unclear if all of the sensor modalities are useful for a specific task.

We use a hemispherical 3D force sensor that extracts a 3-dimensional signal from the forces acting on its rubber surface, operating under the assumption that this signal is sufficient for the material recognition task at hand.

II. RELATED WORK

The number of tactile sensors that have been developed to measure textures is too large to cite in detail. We limit this overview to works using deformable tactile sensors that include friction in their tactile sensing approach, although we note that a significant body of work also exists on the measurement of surface acceleration data from textures, which is often performed using a material fixed to a flat surface and a hard sensor tip (such as a steel ball or artificial finger nail) with an accelerometer [3], [4].

The work of Fishel *et al.* [5] is notable for the large amount of textures measured (117 materials) under highly controlled conditions using a BioTac sensor. They propose the use of Bayesian exploration when classifying textures to minimize uncertainty and limit the number of exploratory motions required, and report an overall recognition rate of 95.6 %.

Kaboli *et al.* [6] use the same model of sensors as in this work, mounted on a Robotiq 3-finger gripper to detect slip and control the grasp when manipulating deformable objects with a varying center of mass. After lifting an object, they estimate the friction coefficient by slowly opening the gripper until the object starts to slip, which is detected by a sudden change in the tangential force. The friction coefficient is then used to regulate the grasping force on each of the three fingers. Their results support our assumption that this type of sensor yields sufficient information for slip detection and textile manipulation.

Another gripper for textile manipulation and recognition which contains a tactile sensor and can perform a rubbing motion has been developed in the CloPeMa project⁴. Le *et al.* [7] use its tangential force measurement to estimate an appropriate grasping force on their items of clothing. While Le *et al.* mention that this rubbing motion was intended for supporting the system's textile recognition, the authors were not able to locate a publication describing a method, the tactile signals, or textile features and parameters revealed by the gripper.

Ward-Cherrier *et al.* have developed an optical tactile sensor that can be mounted to the M2 gripper [8] and which measures the deformation of markers underneath the sensing surface using a camera. Their sensor extracts a 2D pressure profile, with the maximum signal frequency being the frame rate of the camera capturing the markers. They do not specify texture recognition as a goal.

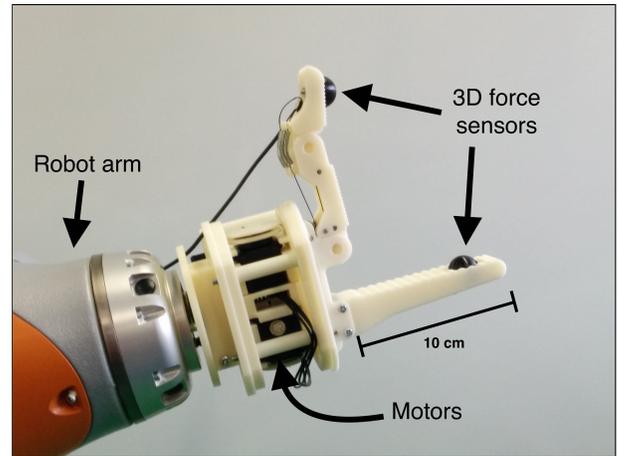


Fig. 3. The gripper mounted on a robot arm. The thumb is at the bottom.

Ho *et al.* [9] proposed a fabric sensor for identifying texture via a sliding motion. They test it on three fabrics using different signal processing approaches, reporting success rates of up to 90 % on the three materials. They report the highest success rates on Discrete Wavelet Transforms of their signal.

Jamali *et al.* [10] dispersed strain gauges and piezoelectric vibration sensors in an artificial finger, mimicking the human fingertip's slow- and fast-acting nerve cells, and moved it over different materials. They extracted local maxima of the recorded frequency spectrum as features, and report success rates of 80 % using one sample, and 95 % using several samples.

As of yet, no agreed-upon set of benchmark textures exists, which makes the comparison between different works difficult.

III. HARDWARE

We use a NAIST OpenHand M2S, a wire-actuated open source gripper with two degrees of freedom based on the Yale OpenHand M2 [11].

The agonist motor closes the second finger joint and results in an underactuated grasp, while the antagonist motor results in a fully actuated grasp where the second finger joint does not close. With this setup a tangential force can be applied to an object while it is held in a precision grasp, simply by actuating one of the motors and releasing tension on the other.

Two hemispherical Optoforce 3D force sensors (OMD-20-SE-40N) are mounted to the fingertips, and additional bearings are used in the finger's joints to reduce hysteresis and friction, and to increase position repeatability. Fig. 3 shows the hand mounted on a robot arm.

While each sensor reports three scalar force values, the whole surface of the sensors is sensitive and contributes to the force reading. As the movement of the finger is planar, only two of the three force values are used in our approach.

IV. RECOGNITION

An ideal exploratory motion reveals a maximum of characteristic information while being repeatable and quick to perform. The features we extract from the raw signals should

³SynTouch LLC

⁴Clothes Perception and Manipulation. <http://www.clopema.eu/>

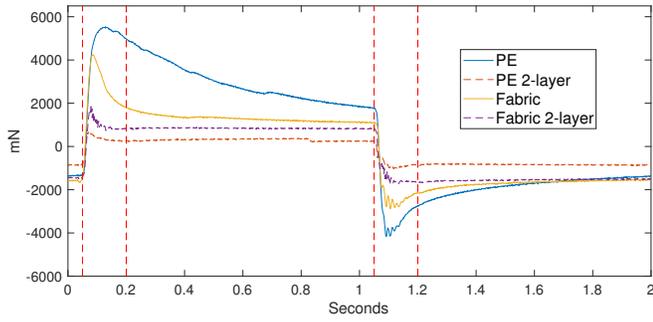


Fig. 4. The horizontal force signal of one of the sensors during a rubbing motion. The *movement phases* take place inside the red dotted lines. While a single layer of PE causes the highest force, multiple layers slide off on one another with the least effort.

reduce the amount of data, contain the characteristic information, and be robust to noise and small changes in the way the data is collected. Robustness to noise is especially important when using the 3D-printed and wire-actuated gripper we use, where mechanical tolerances are high, and friction phenomena between all parts of the system can affect the positions of and forces acting on the sensors.

Fig. 1 shows the back-and-forth rubbing motion between the fingertips. The movement is defined as follows: First, the finger is closed slowly so that the two sensors touch lightly. The index finger is extended further at p_1 than at the second point p_2 , so the point of contact on the thumb’s sensor is farther away from the robot. The position values of the two motors are recorded at this point. Next, the finger’s sensor is positioned so that the point of contact lies closer to the base. The motors’ position values are recorded for this point p_2 as well.

To execute one rubbing motion, the finger is moved between the two defined points by setting the motor positions to p_1 , p_2 and p_1 again. After each target setting of the motors, we wait for a short time t_d . Each rubbing motion starts and ends at the same point p_1 , and thus consists of two *movement phases* and two *relaxation phases*. Fig. 4 shows the different phases during one motion.

During each *relaxation phase*, some of the stored mechanical energy in the sensors, materials and grippers is released. This can be seen in the decreasing force signal after the motors arrive at their destination (after about 100-150 ms). As the eventual force value as well as the behavior during this phase can differ between materials, we wait for $t_d = 1s$ before sending the next motor instruction.

When measuring, multiple rubbing motions are executed sequentially. During preliminary experiments, we observed that the first motion after closing the fingers yields less reliable values than the later movements, as shown in Fig. 5. This may be due to factors such as the initial configuration of the textile and the undefined state of internal forces in the sensors at the start. As these are hard to predict, we consider the first motion to be preparation, and only include the later motions as data for the recognition.

The proposed back-and-forth motion is only one specific exploratory motion, but it has several advantages:

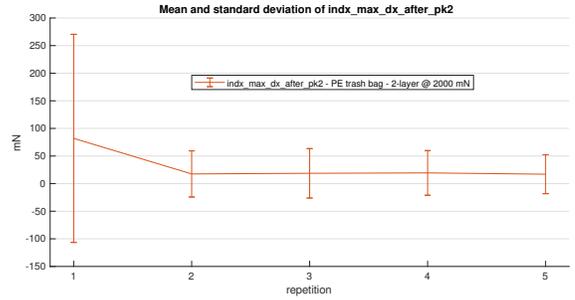


Fig. 5. The mean and standard deviation of a feature over the course of successive rubbing motions. The noise in the first motion after closing the hand can be very high.

- It can be executed while the hand is stationary, and requires no robot arm movement.
- It is simple to define.
- It is fast, requiring only a few seconds.

Furthermore, the sensors rotate relatively to one another, which increases the relative motion inside the contact interface. We surmise that this increases the amount of data issued by friction phenomena, allowing for easier detection.

A. Feature extraction

We propose a set of manually defined features that can be extracted from the force values recorded during a rubbing motion.

Four force signals are recorded during one back and forth motion. From each, we propose to use the following values as features:

- The peak value during or just after the movement phase
- The amount of time between start of the movement phase and the occurrence of the peak value
- The absolute maximum value of the gradient in the relaxation phase after the peak value
- The static values at the end of the relaxation phases
- The values at the start and end of the motion

The bulk of the features, such as the peaks and the stationary force levels, are related directly to the friction coefficients. When a single layer of material is being measured, the friction coefficients are those of the interface between the sensor and the material. When multiple layers are present, it is predominantly the friction coefficient between the material itself that is being sensed, as the sensors’ high-friction rubber surface experiences little slippage.

B. Classification

Based on the extracted features, a classifier can be trained to recognize the material held in the gripper. We propose the use of a one-vs-one multiclass SVM [12] (OVO-MSVM) with automatic kernel scaling, which yielded correct classification results in over 94% of cases in our experiments.

TABLE I. LIST OF MATERIALS. ORDERED AS IN FIG. 6 LEFT-TO-RIGHT, TOP-TO-BOTTOM.

ARTICLE	MATERIAL
Place mat	60% Cotton, 40% Polyester
Bath mat	90% Polyester, 10% Nylon
Cushion	Polyester, Polyurethane
Floor mat	Polyester, Latex
Carpet	Bitumen, Polyamide
Scarf	Polyester
Fabric	Cotton
Basket	Polyester
PE trash bag	Polyethylene
Pencil case	Polyester
Paper	Paper
Belt	Polyester
Saran wrap	Polyvinylidene chloride
Laundry net	Polyester
Curtain - rose	Nylon
Curtain - white	Polyester
Banknote	Paper, treated
Aluminium foil	Aluminium



Fig. 6. Single and multiple layers of the 18 materials were differentiated during the recognition for a total of 36 cases. The two layers of cushion (top row, 3rd from the left) are excluded.

While our method requires training and data collection, this could be performed in an automated manner if the robot is able to pick up and select materials by itself.

V. EXPERIMENTS

We evaluated our method by testing it on a representative set of 18 materials that are taken from different household objects, such as aluminium foil, saran wrap, cotton or carpet. Fig. 6 shows the full set listed in Table I. As shown in Fig. 8, some of the materials had a structured surface that changes according to the orientation. To avoid adding complexity to these cases, all materials were arranged in the same direction during all measurements.

A. Classification

We train different SVMs on the obtained features, and compare the effect of using different kernels as well as PCA compression. Specifically, we evaluate one-vs-all and one-vs-one SVMs using polynomial and radial basis function kernels. We also evaluate the inclusion of the time value of each feature.

In order to compare the SVMs' performance, we evaluate an alternative frequency-based set of features as well as a neural network. To extract the frequency-based features, we define two windows of 150 ms length that begin when the motion command is sent to the motors, as most frequency

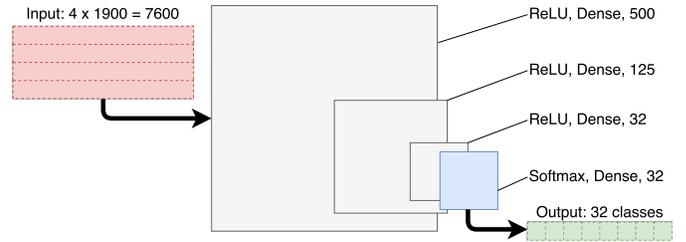


Fig. 7. Structure of the neural network classifier used to compare our method. All layers are fully connected.

variation will occur during and shortly after the movement phases. We extract the frequencies present in each of these windows via fast Fourier transform from the raw sensor data.

After extracting the single-sided amplitude spectrum, the values are split into 10 bins and averaged. This results in a total of 80 features extracted per rubbing motion. The classification results based on these features are compared to the manual features on a reference SVM method.

Finally, we compare the classification performance of the neural network classifier shown in Fig. 7. As each motion of 2 seconds was repeated 5 times in a row, small latencies caused the number of recorded samples in each motion to be slightly higher or lower than exactly 2000 samples. To deal with this, the length of was reduced to 1900 recorded samples for each of the 4 force signals, so that the input of the classifier is a vector of 7600 force values. The data was normalized before training.

B. Procedure

As shown in Fig. 2, the gripper is mounted horizontally with the rigid finger's sensor pointing upwards, with a small guard around the thumb so that the material would not fall off. For each measurement, after the material is placed on the rigid finger's sensor, the index finger is closed to position p_1 , five rubbing motions are executed, and the finger is opened again.

As explained in Section ??, each rubbing motion consists of moving to p_2 , then p_1 , with a wait time $t_d = 1$ s after each movement command is sent. Thus, each rubbing motion consists of 2 seconds of data from 4 force signals.

We limited the number of successive rubbing motions to avoid damaging the material. The order of materials was randomized so that neither deterioration of the sensor nor possible debris from a fabric or other factors such as softeners would contaminate the measurements.

The sensors recorded at 1000 Hz. For the manual feature extraction and the neural network training, we filtered the signal using a moving average filter with $n = 9$. The 2-layer case of the cushion was omitted, as the thickness of the material was too high for the gripper.

VI. RESULTS

In total, 9000 motions over 5 sessions on different days were recorded. Of these, 1800 motions were preparatory as described in Section IV, and another randomly distributed 1200 contained data affected by transmission issues, resulting over

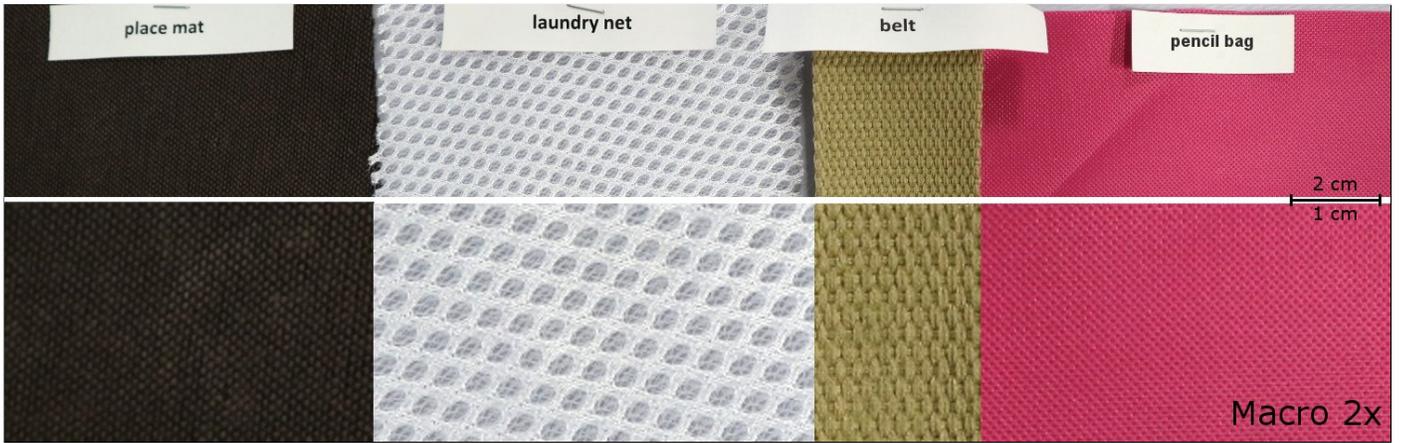


Fig. 8. Close-up of some structured surfaces in the material set. The texture in a linear section would depend on the orientation of the material, so it is kept constant throughout the experiments.

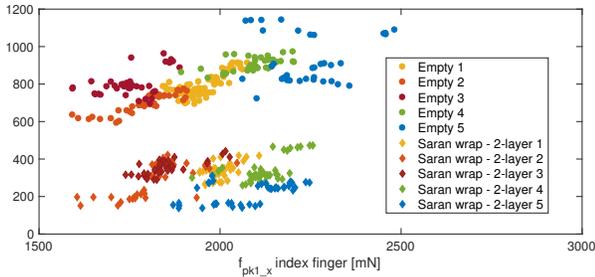


Fig. 9. Different distributions of samples on different days. Each day's samples are plotted in the same color. The noise within samples of the same day is lower than when all samples are taken together.

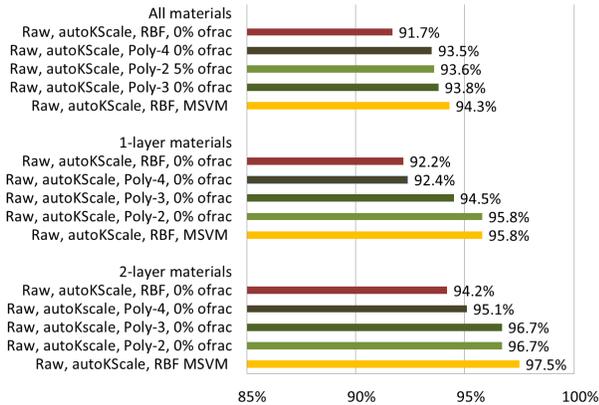


Fig. 10. Recognition rates of different SVM kernels and types when using manually defined features.

6000 usable samples. The data acquisition required about 15 hours in total.

Fig. 9 shows that the results are clustered differently on different days, indicating that sensor, motor, and/or material parameters drift in between measurement sessions. While this implies that a general issue concerning repeatability exists in the setup, it does not invalidate the results.

A. Manually defined features

Fig. 10 shows the performance of different SVM kernels and types using the manually defined features. The highest recognition rate obtained on the global data set was 94 % for all materials, and 97.5 % for the 2-layer cases. Including each feature's time value in the feature vector generally caused performance to decrease by 0 to 3 %.

The principal component analysis showed that the features causing the most variance were those describing the peak force levels. However, the performance of the PCA-compressed and dimensionality-reduced features did not exceed 85 % recognition rate in any SVM, and training on the raw data yielded better results.

B. Frequency-based features and deep learning

Training the OVO-MSVM with the frequency-based features, we obtained a recognition rate of about 81 %. To train the neural network, we used 80 % of the data and tested on the remaining 20 %. The model recognized 98 % of the training batch and 96 % of the test batch.

VII. DISCUSSION

Even though our sensory intuition would lead us to expect that vibrations due to roughness and surface structure may play a larger role in the recognition, the higher performance of the manually extracted features compared to the feature-based ones indicates that a significant part of the information in our signal is contained in the friction coefficients. At the same time, it is possible that our data contains fewer vibrations, as our gripper's finger moves over the textile relatively quickly. Both Jamali *et al.* [10] and Fishel *et al.* [5] have used slower and longer movements under 5 cm/s, which would yield more vibrations.

The recognition rate is remarkably high, despite the lack of strong vibration information and despite the use of a 3D printed gripper with high manufacturing tolerances. This implies that features based on friction measurements are a good basis for robust and reliable perception of textiles.

The high friction coefficient of the sensor surface is fundamentally responsible for the range of measurement in this application. In our setup, the maximum tangential force values are measured when no material is grasped and the rubber surfaces of the sensor rub on one another. Effectively, this maximum value marks the top end of the measurement range, with all the other materials' friction coefficients ranging between it and a low minimum (in our case, two layers of polyethylene). Further, when two layers are between the fingers, with the high friction coefficient of the sensors the rubbing motion generally causes the two materials to move relative to each other, as the friction coefficient between layers of the same material is usually lower. A sensor with very low friction would simply glide over the materials, and while it would be able to perceive a surface profile using vibrations, it would hardly be able to recover differences in friction coefficients.

It is also noteworthy that the recognition rate was higher for multiple layers than for single layers. Part of this may be due to a few materials having differently structured sides (e.g. PE-coated cotton, carpet), but we consider it more likely that richer tribological interactions exist between the materials than between the textiles and the sensors.

We note that the neural network performs slightly better than the SVM trained on manually extracted features, but that it required more manual tuning to achieve this result. The optimal model of the network was determined heuristically: inserting an additional layer of 1900 neurons in the front of the network, or removing the layer of 500 neurons, caused the recognition rate to decrease by over 15 %. More data may require a different model, and require additional setup to achieve comparable performance. By contrast, the OVO-MSVM trained on the manually extracted features is computationally lighter and requires less manual interaction with the training parameters.

The underactuated gripper we use has both advantages and limitations. A limitation is that the wire-actuation and lack of angular encoders means that the position of the tactile sensors is not precisely known, although it would be of interest to use their position to separate the tangential from the normal force, as cleaner data may be extracted this way. An advantage is that the compliance of the finger and the actuating wire likely compensate, to some degree, for the position accuracy of the motors.

The proposed method requires that the sensors be trained with the different materials in advance. This could be avoided if the sensor values could be connected to physical parameters, such as roughness, surface structure, stiffness and the like. Evaluating this possibility will be part of future work.

Another avenue to be investigated is the speed of and normal force applied during the rubbing motion. Slow movements with light pressure should yield different tactile information than fast ones with a lot of applied force. Future work includes finding an appropriate handling range for textile recognition.

VIII. CONCLUSION

We have shown that a considerable number of textiles can be identified reliably based on their friction parameters

obtained through a human-inspired finger motion. We also presented an inexpensive solution to recognize textiles, to confirm their successful grasp, and to detect if single or multiple layers have been grasped. Our results indicate that low-dimensional force data generated by a rubbing motion is sufficient to recognize a variety of common textiles if the friction parameters. Future work includes relaying the measured data to textile parameters and descriptions (e. g. roughness, stiffness) and investigating the effect of different speeds and contact forces on the measured signal.

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