Vibrotactile Recognition of Surface Textures by a Humanoid Robot

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SUMMARY

This study investigates the use of a vibrotactile sense for surface texture recognition by a humanoid robot. The sensor is an artificial fingernail with an attached 3-axis accelerometer, which the robot uses to scratch different surfaces. Our method combines frequency-domain analysis of the acceleration measurements with the Support Vector Machine (SVM) learning algorithm to recognize surfaces. Using this approach the robot was able to recognize twenty different surfaces with accuracy significantly better than chance. The experimental results also show that combining predictions from multiple different scratches on a test surface results in higher recognition accuracy than any isolated scratch alone.

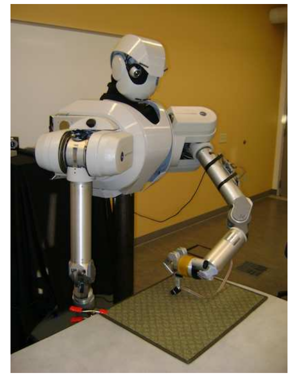


Fig. 1: The robot, shown here scratching one of the 20 surfaces used in the experiments.

MOTIVATION

There is evidence that humans use two different sensory modalities to represent surface roughness: a *tactile modality* for coarse surfaces and a *vibrotactile modality* for finer surfaces.[1] The tactile modality is facilitated by specialized cortical neurons, which perceive spatial variations through slowly adapting SA1 mechanoreceptors.[1] The vibrotactile modality, in contrast, is facilitated by perception of cutaneous vibrations primarily via Pacinian afferents.[1]

Humans also use exploratory behaviors such as scratching to recognize objects from tactile interactions.[2] Exploratory behaviors applied to surfaces were observed in human infants as young as 6 months old.[3] Our goal is to combine exploratory behaviors with vibrotactile data to enhance robotic perception of material textures. In particular, our robot applied five different scratching behaviors on twenty surfaces in order to recognize the surfaces. These behaviors are analogous to the *lateral motion* exploratory procedure observed in adults by Lederman and Klatzky[2] and the *rubbing* exploratory behavior observed in infants by Bourgeois et al.[3]

RELATED WORK

Kuchenbecker[4] proposed using accelerometers, strain gauges and other types of contact sensors to record tactile sensations with the idea of reproducing them later so that similar sensations can be experienced again. Howe and Cutkosky[5] suggested detecting slip from the readings of a 3-axial accelerometer. They also reported that the accelerometer's output is affected mostly by the sliding velocity, a bit less by the surface roughness and only slightly by the normal force applied. Hosoda et al.[6] used a robotic finger to apply two exploratory behaviors (pushing and rubbing) to objects made of five different materials. The

[1] M. Hollins and S. Bensmaïa "The coding of roughness," Canadian Journal of Experimental Psychology, vol. 61 (3): 184-195, 2007.

[2] S. Lederman and L. Klatzky "Hand movements: a window into haptic object recognition," Cognitive Psychology, vol. 19(3): 342-368, 1987.

[3] K. Bourgeois et al. "Infant manual exploration of objects, surfaces, and their interrelations," Infancy 8(3): 233-252, 2005.

[4] K. Kuchenbecker. "Haptography: capturing the feel of real objects to enable authentic haptic rendering," In Proc. of the 2008 Ambi-Sys workshop on Haptic user interfaces in ambient media systems, 2008.

[5] R. Howe and M. Cutkosky. "Sensing skin acceleration for slip and texture perception," In Proc. of the 1989 IEEE International Conference on Robotics and Automation, vol. 1, pp. 145-150, 1989.

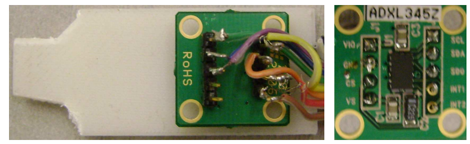
[6] K. Hosoda et al. "Anthropomorphic robotic soft fingertip with randomly distributed receptors," Robotics and Autonomous Systems, vol. 54(2): 104-109, 2006.

finger contained polyvinylidene fluoride (PVDF) films and strain gauges sensors. de Boissieu et al.[7] used three-axial force sensors embedded in an artificial finger that was mounted on a plotter to discriminate between 10 different types of paper. Iwamoto et al.[8] proposed embedding an accelerometer inside a ring that a human can wear. The device was used to implement a "virtual mouse."

RESULTS

Experimental Setup

All experiments were performed with the upper-torso humanoid robot shown in Fig. 1. The robot has two 7-DOF Barrett Whole Arm Manipulators as its arms, each of the WAMs has a three-finger Barrett Hand as its end effector. A plastic fingernail and a 3-axis accelerometer (see Fig. 2) were mounted on the middle finger of the robot's left hand. The ADXL345 accelerometer manufactured by Analog Devices was used along with the EVAL-ADXL345Z evaluation board provided by the manufacturer. The accelerometer data was read over the USB bus at 400 Hz using the Arduino Duemilanove microcontroller.



(a) (b)

Fig. 2: The sensor: **(a)** the plastic fingernail with the attached accelerometer; **(b)** the other side of the accelerometer board (the ADXL345 is in the center).

The robot scratched the 20 surfaces shown in Fig. 3. Data was also recorded as the robot performed a scratch without a surface (i.e., scratching in mid-air) and added as the 21st surface in the dataset. With each surface the robot performed 10 trials. Each trial consisted of 5 scratches (3 lateral and 2 medial) executed at different velocities. Thus, the total number of behavioral interactions performed by the robot was $21 \times 10 \times 5 = 1050$. To minimize transient noise effects due to wear and tear of the fingernail and, possibly, minor sliding of the sensor along the finger, the surface was changed after every trial and not scratched again until the robot scratched all other surfaces. In addition, this procedure also ensured that the position of the target surface was somewhat different during each trial, thus avoiding the possibility of providing overly regular inputs to the learning algorithm.

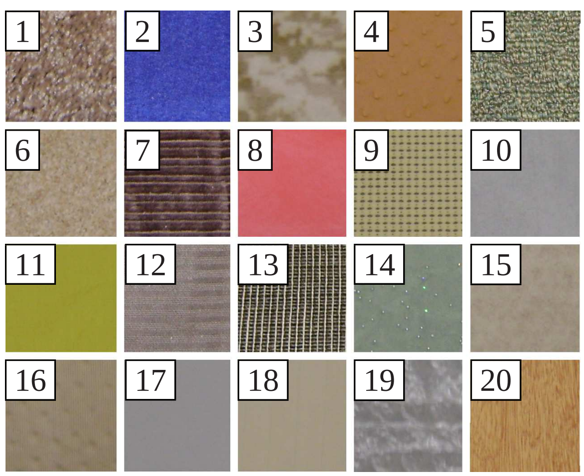


Fig. 3: The 20 different surfaces scratched by the robot: 1) thick floor mat; 2) thin blue mat; 3) soft cloth; 4) leather with bumps; 5) thin floor mat; 6) bulletin board; 7) corduroy; 8) leather (flat); 9) plastic kitchen roll; 10) table; 11) bed sheet; 12) back of corduroy; 13) back of thin floor mat; 14) cloth with sparkles; 15) cotton wool (back of 8); 16) plastic pattern (back of 4); 17) paper, white; 18) paper, yellow; 19) back of the bubble wrap; 20) wood. Surface 21 is a control condition corresponding to the robot scratching in mid-air.

[7] F. de Boissieu et al. "Tactile texture recognition with a 3-axial force MEMS integrated artifical finger," In Proc. of Robotics: Science and Systems, 2009.

[8] T. Iwamoto and H. Shinoda "Finger ring device for tactile sensing and human machine interface," In Proc. of SICE Annual Conference, pp. 2132-2136, 2007.

Learning Methodology

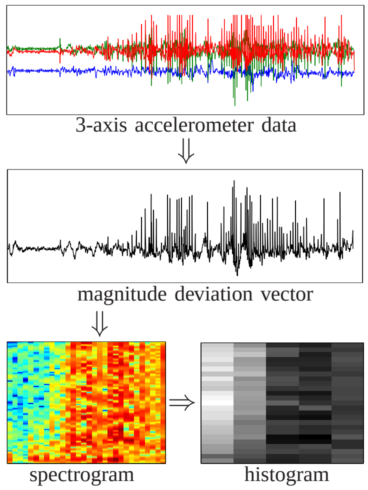


Fig. 4: Feature extraction.

For each of the 1050 behavioral interactions, the robot recorded n readings from the accelerometer in vectors X, Y, Z which correspond to the three axes so that $[X_i, Y_i, Z_i]$ is the i-th reading for $i = 1, \ldots, n$. A magnitude acceleration vector M was computed: $M_i = \sqrt{X_i^2 + Y_i^2 + Z_i^2}$. M was smoothed using a running average filter with a window size of 100 to produce a smoothed acceleration vector S. A magnitude deviation vector D was computed: $D = M - S$ (see Fig. 4). Discrete Fourier Transform with 129 frequency bins and a window of size 100 was applied to D to produce a spectrogram. This spectrogram was converted to a 25×5 spatial-temporal histogram. This histogram was used as a feature vector by SVM with polynomial kernel of exponent 2 (applying other machine learning algorithms, e.g., k-NN and Bayesian Network resulted in similar, but slightly lower, recognition performance).

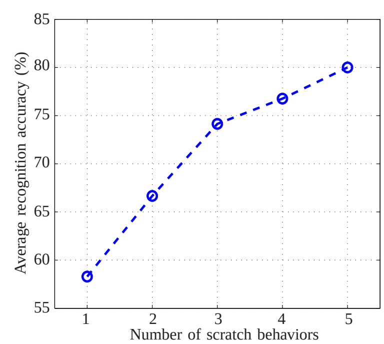
Recognition Results

The accuracy of the robot's surface recognition model was estimated from the dataset using 10-fold cross-validation. Faster scratches usually resulted in better accuracy than slower ones (see Fig. 5(a)). For each scratch, the surface recognition accuracy was better than random (chance accuracy is $1/21 \approx 4.76\%$).

When individual predictions from multiple behaviors are combined (using weights estimated from the training set for each scratch), the accuracy increases (see Fig. 5(b)). This suggests that a combination of several different behaviors informs the robot about the texture better than any single behavior alone. Combining predictions from all 5 exploratory scratches results in 80% recognition accuracy.

Scratch Type	Duration	Accuracy
Lateral (fast)	3.9s	64.8%
Lateral (med.)	7.5s	65.7%
Lateral (slow)	14.7s	58.6%
Medial (fast)	4.6s	56.7%
Medial (slow)	8.7s	45.7%
Average	7.9s	58.3%

(a) Surface recognition accuracy.



(b) Combining multiple scratches.

Fig. 5: Recognition results for single and multiple scratches. **(a)** Surface recognition accuracy for individual scratching behaviors; **(b)** Accuracy after combining the predictions from multiple scratching behaviors.

The pairwise confusion matrix was estimated for this model (see Fig. 6). A 2D Isomap[9] embedding of the distance metric computed from the confusion matrix was also calculated (see Fig. 7). The confusion matrix provides a measure of similarity between any two surface textures as perceived by the robot. For example, the two paper surfaces (17 and 18) were often confused with each other and also with other thin surfaces – bed sheet (11) and the table (10). Another example of a group of similar surfaces is the group of the softest surfaces – cloth (3), wool (15) and air (21).

[9] J. Tenenbaum et al. "A global geometric framework for nonlinear dimensionality reduction," Science, vol. 290 (5500): 2319-2323, 2000.

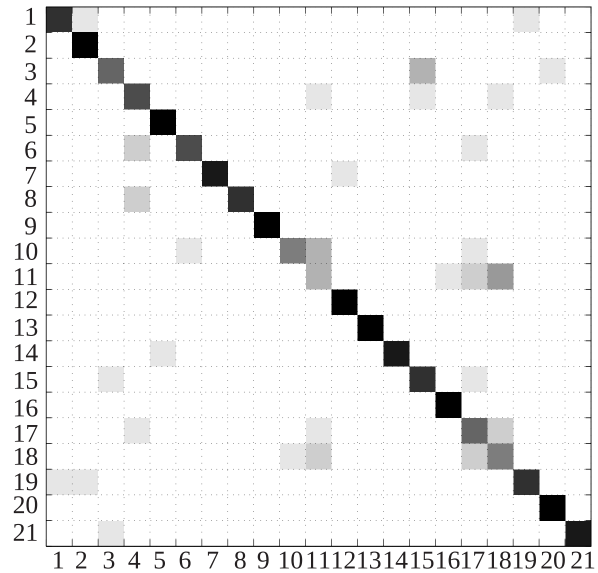


Fig. 6: The confusion matrix for surface recognition using a weighted combination of predictions from all 5 scratches.

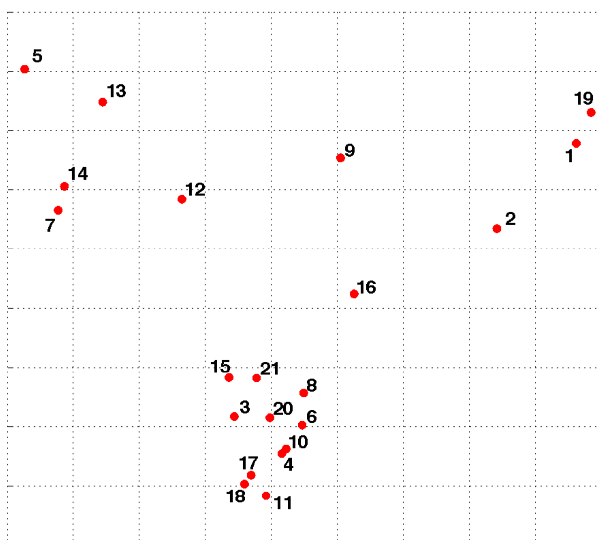


Fig. 7: The confusion matrix embedded in a 2D Isomap.

CONCLUSIONS AND FUTURE WORK

This paper evaluated the effectiveness of a robotic vibrotactile sense for surface recognitions tasks. The sensor was an artificial fingernail with an attached 3-axis accelerometer. The robot performed five scratching behaviors multiple times on twenty different surfaces. The acceleration data captured during these exploratory behaviors was used to recognize the surfaces. The recognition accuracy reached with the SVM learning algorithm was significantly better than chance. An important observation from our experiments is that by combining data from two or more behaviors the robot was able to achieve higher recognition accuracy than for any single behavior alone. When the robot used all five exploratory behaviors the accuracy reached 80%.

Analysis of the confusion metric for different surfaces indicates that in many cases the surfaces that are most similar to each other (e.g., the two papers) are often confused by the robot. This fact suggests that a robot could build a meaningful surface categorization from vibrotactile data. Building such a categorization by extending the approach described in this paper is an interesting area of future work.

ACKNOWLEDGEMENTS

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