Vibro-Tactile Foreign Body Detection in Granular Objects based on Squeeze-Induced Mechanical Vibrations

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Abstract*— Granular particles, filled within an elastic material, produce mechanical vibrations in structures or air when squeezed. This refers to structure-borne noise, is defined as a noise that occurs from the impacts of particles hitting each other due to their momentum. The momentum depends on both properties of particles and velocity of squeezing. Therefore, the structure-borne noise is highly correlated with the properties of particles. In this connection, we study a vibro-tactile sensor for detecting the mechanical vibrations from squeezing granular objects. Specifically, we explore machine learning solutions to detect foreign body within these objects using detected vibrations. We evaluated multiple learning approaches on a collected data set of 900 squeezing experiments across 15 different granular materials. In our experiments, the most successful method was convolutional neural network that achieved an accuracy of 91% on unseen test data. Remarkably, the foreign body was detected with a higher success rate for the majority of material types except salt and coffee granules.

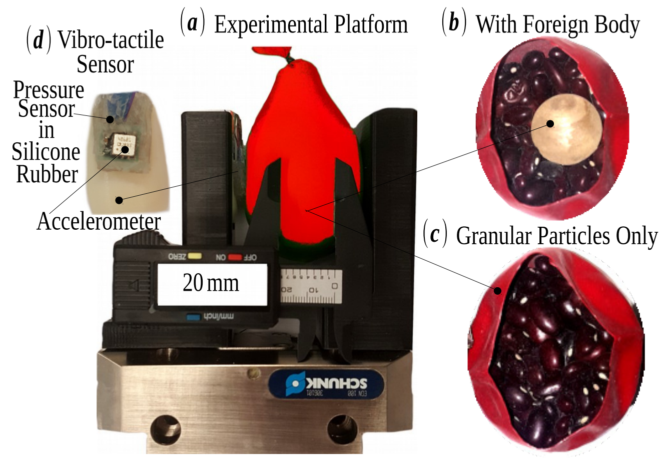

Fig. 1: A foreign body mixed with granular particles changes properties of mechanical vibrations when an object filled with them is squeezed. (a) Robot gripper with a vibro-tactile sensor squeezing granular objects (b) with and (c) without the foreign body. (d) The vibro-tactile sensor.

I. Introduction

Humans can do reasoning on the quality of the material they touch. They actively move their fingers and manipulate objects in order to do such reasoning thanks to the somatosensory system. The renowned physiologist Sechenov called this phenomenon a "dark muscle sense" [1]. For example, one can use vibrations from sliding over a textured surface to recognize objects [2] or to detect slippage [3]. Indeed, previous works have shown that humans can create haptic information about objects' physical characteristics based on the properties of the perceived vibro-mechanical signal. For example, Hayward et al. [4] have shown that humans are able to classify walked-upon materials using the feedback from the ground. On the other work, Pittenger et al. [5] demonstrated the ability of humans to guess the size of granules inside an opaque container by shaking it.

In robotics, the sense of touch is provided by various force-sensing technologies, including capacitive, piezoresistive, magnetic, and optical to name a few of them [6], [7]. This sensing ability allows robots to preempt slippage [8] and distinguish surface roughnesses [9]. Presumably, the ability to sense and process vibrations would also allow robots to recognize granular material types and detect irregularities within them [10], [11].

Unfortunately, vibro-mechanical signals produced by granular materials have attracted only limited attention from researchers. To the best of our knowledge, there are no general methods for recognizing granular particles based on tactile sensors. With regard to vibro-tactile recognition, majority of the studies have targeted surface textures [9], [12], [13], [14], whereas only a few and abrupt studies have targeted granular materials [15], [16] despite the fact that they are abundant and commonly found in human-made products such as salt, sugar, soda, coffee, and others. These materials consist of small and rigid objects (particles or grains) of various shapes which can be classified using existing machine learning techniques [17]. However, modeling the mechanics of induced vibrations over granular particles is challenging [11].

In this work, we aim to make a step towards filling this gap. It is for the first time, the detection of a foreign body within a soft object filled with granular particles is explored (see Fig. 1). Specifically, we employ conventional and deep learning (DL) based approaches to classify the data acquired from squeezing 30 deformable objects corresponding to 15 different materials with and without a foreign body.

In the remainder of the paper, we review the vibro-tactile based methods for object recognition in Sec. II. Section III describes the mechanics of granular vibrations

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and sensor design for measuring them. We introduce the silicone molding-based design and fabrication of the sensor in Sec. III-B.2. The utility of vibro-mechanical signal for the foreign object detection task is evaluated in Sec. IV. The last section concludes this work.

II. Related work

Within robot applications driven by tactile feedback, the classification of objects based on their deformability has gained momentum as there is an increasing demand for industrial and service robotics tasks in soft object manipulations [18]. Object-wise, the taxonomy of soft objects is given by fabric sheets (e.g. clothes), soft cables (e.g. electric wires) and ropes (e.g. shoelaces), cast deformable objects (e.g. silicone rubber, sponge, and squishy toys), and soft granular objects that vibrate when squeezed (e.g. granulated latex pillows, snowballs, and bags filled with granules as salt, sugar, and etc.).

In the latter two cases, i.e. deformable objects, the sense of touch has a pivotal role as the softness of objects cannot be inferred based on their shapes, which could be easily acquired using vision sensors [19]. Depending on a transduction technology of tactile sensors (sensed signals can be dynamic or static with respect to the time response and may represent an array of data, vector or scalar), these soft objects can be recognized from contact forces [20], contact pressure profile [21], and friction-induced vibrations [9].

Using contact forces, deformable objects were distinguished based on their stiffness properties [22]. An alternative way was implemented using an array of pressure sensors detecting an area of contact [23]: when the sensing arrays was pushed against a soft object, the area of contact increased, whereas it did not change in the case of a rigid object. Inspired by this idea, we presented a magnetic tactile sensing array [24]. However, in such method, we assumed that the sensing surface was always larger than the object. In this connection, we proposed another method, classifying soft from rigid objects, that incorporated both a proprioceptive, i.e. joint effort (current) sensors and an exteroceptive, array of pressure sensors, sensing systems [25]. In the experiments, there were no soft objects filled with granular particles.

Indeed, we did not find tactile data sets of deformable granular objects as exemplified in Table I. Almost all of the sets include quasi-static pressure signals similar to grayscale images [26], [27], [28], [29]. In [30], the data set consists of vibration signals from sliding over different textures.

To the best of our knowledge, the closest work exploits sound vibrations to estimate the amount of granular objects dropped while pouring them [15]. DL methods were used as the computational means to perform the task. The pouring-induced vibrations were detected by a microphone.

In this work we developed a vibro-tactile sensor, which consists of an accelerometer and an absolute pressure sensor molded in silicone rubber, and collected a Vibro-Tactile Data Set[1] for 30 soft granular objects (one half is with a foreign body with granules and another half is without the foreign body). When were squeezed, all granular objects caused mechanical fluctuations resulting in mechanical vibrations so that the granular objects with the foreign body could be distinguished by DL methods.

[1]https://gitlab.com/roboticsNU/granular-objects-data-set-.git

TABLE I: Tactile Data Sets.

Tactile Data Set	Description
BioTac Grasp Stability Dataset [29]	Signals from BioTac sensors using a three-finger robot hand
Contact localization [28]	Signals from BioTac sensors of 18 rigid objects while grasping with a three-finger robot hand
Sensors stitched in a glove [26]	Data from an array of pressure sensors collected from human grasps
Visual and haptic features learning [27]	Signals from both BioTac sensors and a camera while grasping rigid and soft non-granular objects
Vibro-tactile features learning [30]	Signals from BioTac sensors from sliding over surfaces of 60 non-granular objects

III. Methods

A. Mechanical Vibrations of Granular Objects

When a solid object (e.g. one granular particle within many of the same kind) collides with another object, its surface starts to vibrate producing pressure changes in the surrounding medium (other objects). These changes are perceived: as sound if they are in the audible range and as tactile stimuli, if they occur at a contact point in a detectable range (i.e. up to 1 kHz [31]). Occurring vibrations are modulated by colliding objects' shapes and material. Therefore, one can identify these objects [4].

There at least three sources of squeeze-induced vibrations in granular objects:

1) Impact Force-Induced Vibrations: The surface vibrations produced due to an impact force applied to a single granular solid particle. They can be modeled as a sum of exponentially descending waveforms [32]

$$q_{impact}(t) = \sum_n \Phi_n e^{-\delta_n t} \cos w_n t \tag{1}$$

where $q_{impact}(t)$ is the resultant vibration waveform at the time t after the impact, Φ_n is the initial value of the partial when $q_{impact}(0) = \sum_n \Phi_n$ which is proportional to the impact force, $e^{-\delta_n t}$ is the damping term that is related to the material of the particle (e.g., plastic and glass objects produce different sounds), $\cos w_n t$ is the partial frequency term that depends on the size and configuration of the particle.

2) Acceleration Noise-Induced Vibrations: When one solid particle ("impactor") hits its neighbor ("impactee"). The simplified vibration model for spherical particles – derived based on Hertzian approach of elastic collision forces – is described in [33] and given by the function $q_{collision}(r, \theta, t)$ that depends on the distance between spheres centre and the locations of a sensing point r, the angle between collision normal and the direction towards the sensing point θ, and the time t as the function is different during and after the collision.

3) Slip-Induced Vibrations: There is the sliding noise due to the friction between interacting particles. Given the surface profile $r(x)$ along horizontal axis and position x_t at the time t, vibrations $q(t)$ due to vertical displacements is given by $q_{slide}(t) = r'(x_t)\dot{x}$ [34].

The resultant vibration

$$q(t) = q_{impact}(t) + q_{collision}(t) + q_{slide}(t) \tag{2}$$

depends on various material constants and physical interaction properties. Moreover, in the mentioned models, the collision of a foreign body with uniform granular particles is not considered. Therefore, we apply DL methods (Sec. IV-B) to detect the foreign body within the granular particles. The accuracy of the method would depend on the performance of a sensor, which is described next.

B. Vibro-Tactile Sensor

In order to register the described above vibrations, our vibro-tactile sensor (Fig. 1 d) incorporates one vibration sensing module and one pressure sensing module.

1) Accelerometer: The vibration sensing module consists of a high-bandwidth-two-axes accelerometer (Analog Devices, ADXL203) with analog outputs. This accelerometer measures accelerations along vertical and horizontal axes tangential to the sensing surface.

The accelerometer has a physical bandwidth that exceeds 1 kHz. Such bandwidth allows us to capture vibrations generated by interactions of granular particles. An ordinary first-order filter (with the time constant $\tau_{RC} = 1\mu s$) was used as an anti-aliasing filter.

We used a Data Acquisition Module (DAQ, National Instruments, NI 6221) installed in a Ubuntu running Linux workstation (CPU Core i9-7900, 32 Gb RAM DDR4) to sample accelerometer readings at 4 kHz. The Kinetic distribution of Robot Operating System (ROS) was used to acquire signals and synchronize them with force sensing signals from the second sensing module.

2) Silicone Rubber Embedded Pressure Sensor: We embedded a pressure sensor into a silicone rubber (MPL115A2, NXP Semiconductors) to estimate the strength of squeezing an object [35]. The pressure sensor is a micro electro-mechanical sensor (MEMS) technology-based barometer that measures absolute pressure. The pressure sensor was sampled at 100 Hz using a microcontroller unit connected with the same workstation via USB protocol.

We designed a custom fingertip holder using a rapid prototyping printer (Extended2+, Ultimaker) from PLA material with a deepening (6 mm depth) inside to embed a single vibro-tactile module from the accelerometer and pressure sensor and two deepenings (9 mm depth) at the bottom to fix fingertip to two teeth on the gripper. A silicone compound (SortaClear18, Smooth-on) – mixed in the ratio of 10:1 of parts A and B – was poured into a deepening inside the fingertip up to 4 mm level with barometer placed at the bottom. The mixture was preliminarily degassed in a vacuum chamber to remove air bubbles and cured with ultraviolet for 12 hours. The labor-intensive process took less than one day.

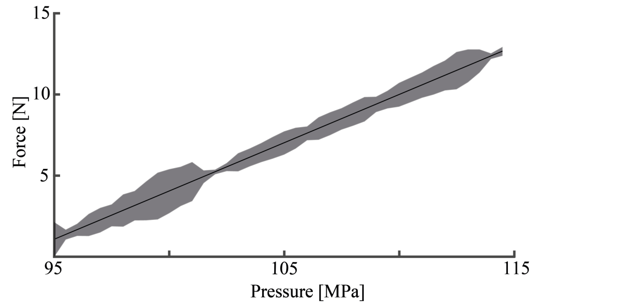

Fig. 2: Pressure to Force map of the absolute pressure sensing barometer embedded in a silicone rubber.

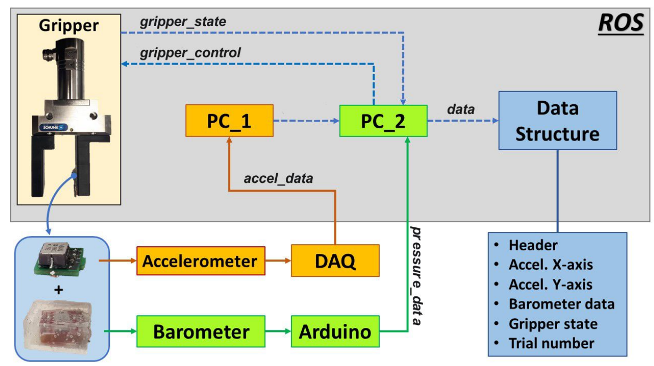

Fig. 3: Robot Gripper Control and Data Acquisition Block Diagram.

All 3D-printed molds were firmly fixed using glue in order to get high precision and repeatability of the sensor geometry. The total weight of the sensor elastomer is around 6 g.

We calibrated the embedded into the silicone rubber pressure sensor's readings using a force sensor with the same contact area of silicon rubber for both calibration and experiment scenarios (Weiss WTS-40). The calibration results of the pressure sensor with average values from ten measurements are shown in Fig. 2. As can be seen from the graph, the range of the pressure sensor's sensed force is between 1 N and 15 N.

IV. Experiments

Vibro-tactile sensor was installed onto a robot gripper (SCHUNK EGN 80, SCHUNK GmbH) controlled using ROS installed on another workstation at 100 Hz (with the same parameters as the workstation for the sensor). Computers were connected via Ethernet (Fig. 3).

The vibro-tactile data was collected by squeezing 30 objects (rubber balloons) filled with granular particles, where first 15 were distinct granular objects (Fig. 4) and other 15 were same granular objects with a foreign body inside (a solid ball of 2 cm diameter printed with FormLab Form 2 clear resin cartridge). The objects were removed from their original packages and placed into the balloons (Fig. 1 b and c) to avoid effects and noise caused by different packaging materials. All balloons filled with the materials were inflated with small portion of air to make them more elastic and of the same shape with average mass around 100 g.

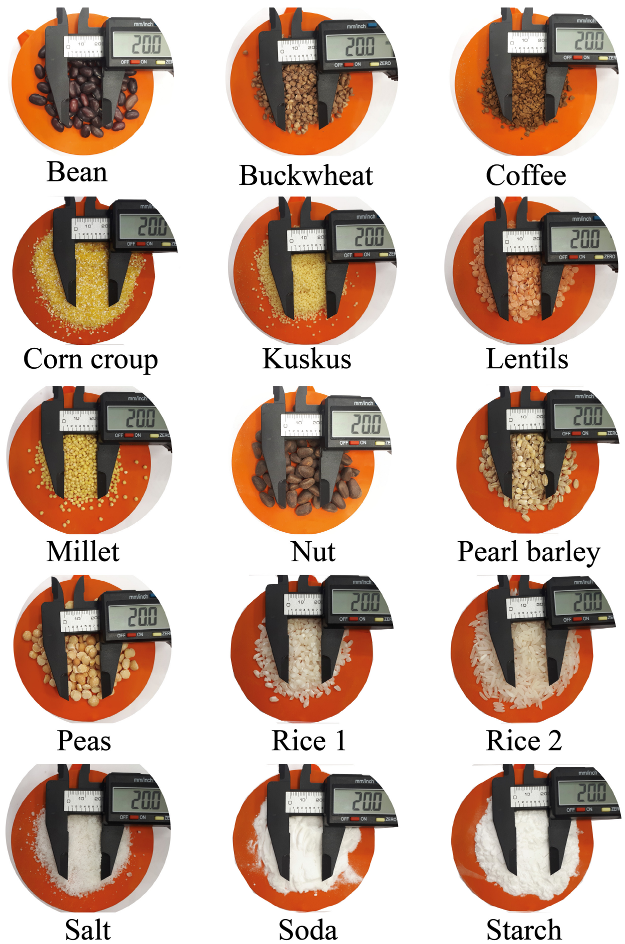

Fig. 4: Granular objects used in experiments for foreign body detection.

A. Data Collection

For data collection squeezing and releasing motions were produced on the 30 objects.

1) *Squeeze:* Gripper received a command (gripper position reference set point of 0 mm) to squeeze a balloon with granular objects.
2) *Releasing:* After gripper reached the reference set point, it received a release command towards open position (20 mm).

These motions were repeated ten times at three different velocities: slow (40 mm/s), medium (60 mm/s), and fast (80 mm/s). In total, there were 900 recording sequences with 2,900 samples in each sequence for accelerations in horizontal and vertical axes, and normal force readings (7,830,000 samples in overall).

An example of the force history applied by the robot gripper and squeeze-induced vibrations of two balloons filled with nuts (one with a foreign body and one without it) are exemplified in Fig.5.

The initial experiments showed that the vibrations induced at the stage of squeezing was more informative; whereas utilizing releasing signals were deteriorating the performance of the model. In this connection, DL methods fed by squeeze-induced vibration signals by far outperformed the ones fed by the release-induced vibration signals and force signals, and thus are not present in the next section.

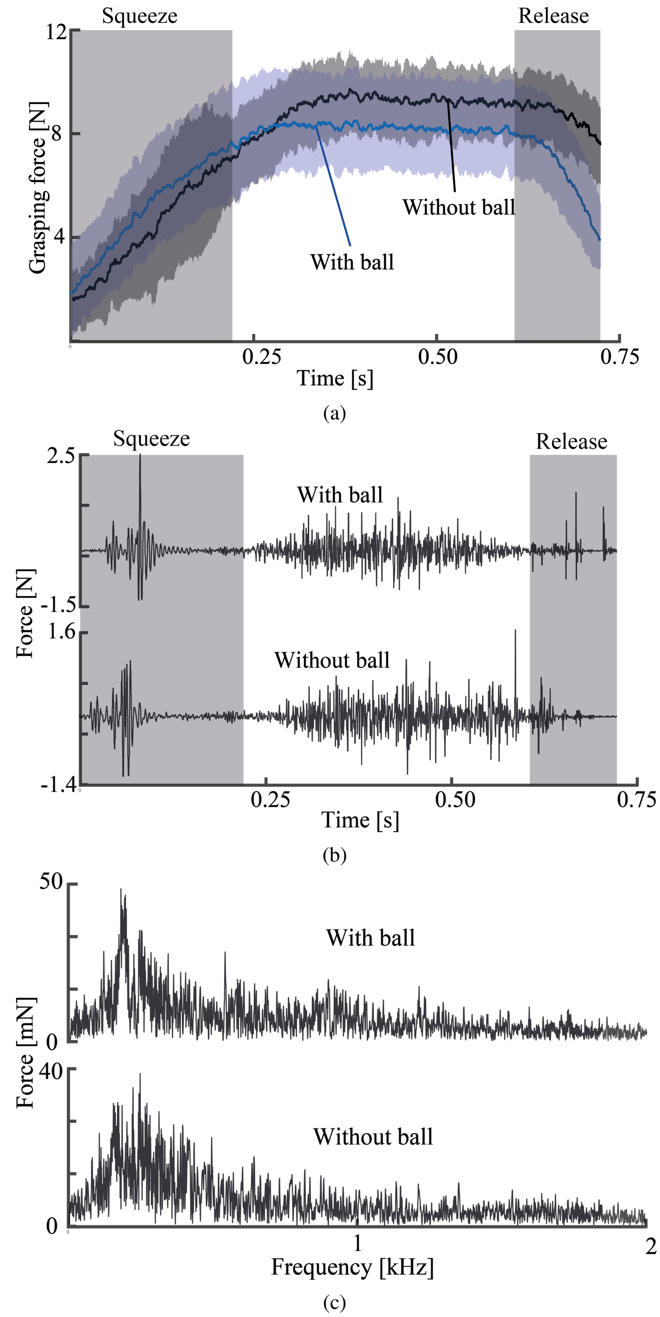

Fig. 5: Nut squeezing results: (a) Force history, (b) Vibrations, and (c) Harmonics of vibrations.

B. Foreign Body Detection

We split the data into three sets of train, dev and test using stratified sampling to ensure an equal proportion of materials with and without the foreign body. The train set was used to learn the parameters of the models, whereas the dev set was used to fine-tune the hyperparameters and select the best performing model which is then evaluated on the test set.

We explored both conventional and deep learning based machine learning techniques. The conventional techniques were adopted from Matlab's Classification Learner toolbox, which includes $k-$NN, Support Vector Machines (SVM), and other models. While the DL-based models were implemented using PyTorch. In particular, we implemented two different model architectures: feedforward neural networks (FNN) and convolutional neural networks (CNN). The FNN model consisted of two hidden layers with 512 units each and with ReLU activation functions. The CNN model consisted of three convolutional layers followed by two fully connected layers: the first layer had 512 units with ReLU acitvation and the second layer was a linear projection with sigmoid activation for binary classification. In the convolutional layers, we used four filters with a receptive field of 1×16 and stride of four. Both models were optimized using Adam algorithm with the initial learning rate set to 10^{-5} and regularized using dropout. The number of training epochs was set to 10,000 and we evaluated the model after each epoch on the dev set. The models are trained on a single Tesla V-100 GPU on the Nvidia DGX machine.

The experimental results are shown in Table II. For the conventional techniques, we report only three best performing models out of 16. For the deep learning based techniques, we report both FNN and CNN. The best result was achieved by CNN which significantly outperformed other models. To boost the performance of other models, we pre-processed the raw input data using a fast Fourier transform (FFT). Although the performance of other models considerably improved, they were still inferior to CNN. Note that the CNN model didn't benefit from the pre-processed data as it can implicitly learn the high-level discriminative features from the raw input.

To analyze the impact of different materials on foreign body detection capability, we computed the accuracy of the CNN model for each material separately (see Table III). The material IDs from 1 to 15 correspond to nut, bean, lentils, peas, buckwheat, baking soda, salt, couscous, rice1, rice2, millet, corn croup, pearl barley, coffee, starch respectively. Interestingly, we found that for the majority of material types the foreign body could be detected with a high accuracy above 70% except for salt and coffee materials, IDs 7 and 14 in Table III. These findings suggest high robustness of foreign body detection systems based on squeeze-induced vibrations, which are modeled in Eq. (2), to different material types.

TABLE II: Foreign Body Detection Results. SVM1 - Cubic SVM, SVM2 - Medium Gaussian SVM.

ID	**Model**	**Input feature**	**Dev set** (%)	**Test set** (%)
1	SVM1	raw	79	77
		FFT	81	83
2	SVM2	raw	79	75
		FFT	79	84
3	k-NN	raw	84	79
		FFT	72	81
4	FNN	raw	88	74
		FFT	89	87
5	CNN	raw	**96**	**91**
		FFT	83	81

TABLE III: Foreign Body Detection Results of CNN Model for Different Material Types.

Material ID	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Accuracy	100	100	90	100	100	100	70	80
Material ID	**9**	**10**	**11**	**12**	**13**	**14**	**15**	
Accuracy	90	80	100	90	100	70	90	

V. Conclusion

In this paper, we designed a mechanical vibration detection system consisting of a high-bandwidth accelerometer attached to a soft silicone-molded fingertip with an embedded absolute pressure sensor. We collected vibro-tactile signals from squeezing 15 different granular materials with and without a foreign body inside. The obtained dataset was used to identify the presence of a foreign body using both conventional and deep learning based approaches. The experimental results show the high efficacy of vibro-tactile signals for the foreign body detection task were 91% accuracy is achieved using CNN models. Moreover, the trained model was found to be invariant to the physical properties of granular particles.

As future work, we envision to enrich the sensor with other sensing modalities (e.g. temperature) and increase the sensitivity to vibrations. However, there are methods of breast lump detection like sonography that based on the screening test data [36], we believe that preliminary inspection of lumps in breasts by initial palpation [37] may benefit from our vibro-tactile sensing approach.

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References

[1] L. Liutsko, "Proprioception as a basis for individual differences," *Psychology in Russia: State of Art*, vol. 6, no. 3, pp. 107–119, 2013.

[2] S. J. Lederman and R. L. Klatzky, "Hand movements: A window into haptic object recognition," *Cognitive Psychology*, vol. 19, no. 3, pp. 342 – 368, 1987.

[3] M. A. Srinivasan, J. M. Whitehouse, and R. H. LaMotte, "Tactile detection of slip: surface microgeometry and peripheral neural codes," *Journal of Neurophysiology*, vol. 63, no. 6, pp. 1323–1332, 1990, pMID: 2358880.

[4] B. L. Giordano, Y. Visell, H.-Y. Yao, V. Hayward, J. R. Cooperstock, and S. McAdams, "Identification of walked-upon materials in auditory, kinesthetic, haptic, and audio-haptic conditions," *The Journal of the Acoustical Society of America*, vol. 131, no. 5, pp. 4002–4012, 2012.

[5] J. B. Pittenger and M. D. Mincy, "Haptic and auditory information support perception of size: Fine granules," *Studies in Perception and Action V*, pp. 68–72, 1999.

[6] Z. Kappassov, J.-A. Corrales, and V. Perdereau, "Tactile sensing in dexterous robot hands," *Robotics and Autonomous Systems*, pp. 195–220, Jul 2015.

[7] Y. Massalim and Z. Kappassov, "Array of accelerometers as a dynamic vibro-tactile sensing for assessing the slipping noise," in *Proc. of IEEE/SICE International Symposium on System Integration (SII)*, Jan 2019, pp. 438–443.

[8] S. Teshigawara, T. Tsutsumi, S. Shimizu, Y. Suzuki, A. Ming, M. Ishikawa, and M. Shimojo, "Highly sensitive sensor for detection of initial slip and its application in a multi-fingered robot hand," in *2011 IEEE International Conference on Robotics and Automation (ICRA)*, May 2011, pp. 1097–1102.

[9] D. Xu, G. Loeb, and J. Fishel, "Tactile identification of objects using bayesian exploration," in *Robotics and Automation (ICRA), 2013 IEEE International Conference on*, May 2013, pp. 3056–3061.

[10] A. Kudrolli, "Size separation in vibrated granular matter," *Reports on progress in physics*, vol. 67, no. 3, p. 209, 2004.

[11] "Transient sound radiated by spheres undergoing an elastic collision," *Journal of Sound and Vibration*, vol. 27, no. 1, pp. 59 – 75, 1973.

[12] J. A. Fishel and G. E. Loeb, "Bayesian exploration for intelligent identification of textures," *Frontiers in Neurorobotics*, vol. 6, no. 4, 2012.

[13] N. Wettels, J. Fishel, and G. Loeb, "Multimodal tactile sensor," in *The Human Hand as an Inspiration for Robot Hand Development*, ser. Springer Tracts in Advanced Robotics, R. Balasubramanian and V. J. Santos, Eds. Springer International Publishing, 2014, vol. 95, pp. 405–429.

[14] H. Liu, X. Song, J. Bimbo, L. Seneviratne, and K. Althoefer, "Surface material recognition through haptic exploration using an intelligent contact sensing finger," in *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, Oct 2012, pp. 52–57.

[15] S. Clarke, T. Rhodes, C. G. Atkeson, and O. Kroemer, "Learning audio feedback for estimating amount and flow of granular material," in *Proceedings of The 2nd Conference on Robot Learning*, ser. Proceedings of Machine Learning Research, A. Billard, A. Dragan, J. Peters, and J. Morimoto, Eds., vol. 87. PMLR, 29–31 Oct 2018, pp. 529–550.

[16] Tomoaki Nakamura, Takayuki Nagai, and Naoto Iwahashi, "Multimodal object categorization by a robot," in *2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct 2007, pp. 2415–2420.

[17] N. F. Lepora, A. Church, C. de Kerckhove, R. Hadsell, and J. Lloyd, "From pixels to percepts: Highly robust edge perception and contour following using deep learning and an optical biomimetic tactile sensor," *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 2101–2107, Apr 2019.

[18] J. Sanchez, J.-A. Corrales, B.-C. Bouzgarrou, and Y. Mezouar, "Robotic manipulation and sensing of deformable objects in domestic and industrial applications: A survey," *The International Journal of Robotics Research*, vol. 37, no. 7, pp. 688–716, 2018.

[19] A. Vasquez, Z. Kappassov, and V. Perdereau, "In-hand object shape identification using invariant proprioceptive signatures," in *Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2016, pp. 965–970.

[20] H. Liu, X. Song, J. Bimbo, L. Seneviratne, and K. Althoefer, "Surface material recognition through haptic exploration using an intelligent contact sensing finger," in *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct 2012, pp. 52–57.

[21] Z. Pezzementi, E. Plaku, C. Reyda, and G. Hager, "Tactile-object recognition from appearance information," *Robotics, IEEE Transactions on*, vol. 27, no. 3, pp. 473–487, June 2011.

[22] G. Bscher, M. Meier, G. Walck, R. Haschke, and H. J. Ritter, "Augmenting curved robot surfaces with soft tactile skin," in *Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Sept 2015, pp. 1514–1519.

[23] A. Drimus, G. Kootstra, A. Bilberg, and D. Kragic, "Design of a flexible tactile sensor for classification of rigid and deformable objects," *Robotics and Autonomous Systems*, vol. 62, no. 1, pp. 3 – 15, 2014.

[24] Z. Kappassov, D. Baimukashev, O. Adiyatov, S. Salakchinov, Y. Massalin, and H. A. Varol, "A series elastic tactile sensing array for tactile exploration of deformable and rigid objects," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Oct 2018, pp. 520–525.

[25] A. Mazhitov, A. Adilkhanov, Y. Massalim, Z. Kappassov, and H. A. Varol, "Deformable object recognition using proprioceptive and exteroceptive tactile sensing," in *2019 IEEE/SICE International Symposium on System Integration (SII)*, Jan 2019, pp. 734–739.

[26] S. Sundaram, P. Kellnhofer, Y. Li, J.-Y. Zhu, A. Torralba, and W. Matusik, "Learning the signatures of the human grasp using a scalable tactile glove," *Nature*, vol. 569, no. 7758, p. 698, 2019.

[27] Y. Gao, L. A. Hendricks, K. J. Kuchenbecker, and T. Darrell, "Deep learning for tactile understanding from visual and haptic data," in *2016 IEEE International Conference on Robotics and Automation (ICRA)*, May 2016, pp. 536–543.

[28] A. Molchanov, O. Kroemer, Z. Su, and G. S. Sukhatme, "Contact localization on grasped objects using tactile sensing," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Oct. 2016, pp. 216–222.

[29] Y. Chebotar, K. Hausman, Z. Su, A. Molchanov, O. Kroemer, G. S. Sukhatme, and S. Schaal, "Bigs: Biotac grasp stability dataset," 2016.

[30] V. Chu, I. McMahon, L. Riano, C. G. McDonald, Q. He, J. Martinez Perez-Tejada, M. Arrigo, T. Darrell, and K. J. Kuchenbecker, "Robotic learning of haptic adjectives through physical interaction," *Robot. Auton. Syst.*, vol. 63, no. P3, pp. 279–292, Jan. 2015.

[31] R. S. Johansson and J. R. Flanagan, "Coding and use of tactile signals from the fingertips in object manipulation tasks," *Nat. Rev. Neurosci.*, vol. 10, pp. 345–359, 2009.

[32] W. W. Gaver, "How do we hear in the world? explorations in ecological acoustics," *Ecological Psychology*, vol. 5, no. 4, pp. 285–313, 1993.

[33] L. Koss and R. Alfredson, "Transient sound radiated by spheres undergoing an elastic collision," *Journal of Sound and Vibration*, vol. 27, no. 1, pp. 59 – 75, 1973.

[34] H. Yao and V. Hayward, "Design and analysis of a recoil-type vibrotactile transducer," *The Journal of the Acoustical Society of America*, vol. 128, no. 2, pp. 619–627, August 2010, doi: 10.1121/1.3458852

[35] Y. Tenzer, L. P. Jentoft, and R. D. Howe, "The feel of MEMS barometers: Inexpensive and easily customized tactile array sensors," *IEEE Robotics & Automation Magazine*, vol. 21, pp. 89–95, 2014.

[36] H. Cheng, J. Shan, W. Ju, Y. Guo, and L. Zhang, "Automated breast cancer detection and classification using ultrasound images: A survey," *Pattern Recognition*, vol. 43, no. 1, pp. 299–317, Jan. 2010.

[37] A. Rodriguez-Ruiz, K. Lng, A. Gubern-Merida, M. Broeders, G. Gennaro, P. Clauser, T. H. Helbich, M. Chevalier, T. Tan, T. Mertelmeier, M. G. Wallis, I. Andersson, S. Zackrisson, R. M. Mann, and I. Sechopoulos, "Stand-Alone Artificial Intelligence for Breast Cancer Detection in Mammography: Comparison With 101 Radiologists," *JNCI: Journal of the National Cancer Institute*, 03 2019.