Vibro-Sense: A Bio-Inspired Vibration-Based Tactile Sensor for Robotics

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***Abstract*— Tactile sensors are crucial for many robotic applications, such as dexterous robotic gripping, prosthetics, and surgical robots. However, only a few companies offer this type of sensor. Additionally, these sensors are too expensive and fragile to be used in many applications. We are developing a vibration-based tactile sensor integrated into a robotic hand as a demonstration. We focus on improving machine learning algorithms for texture recognition, object detection, and localization of touch stimuli using body-borne vibrations, creating a more efficient and cost-effective solution for diverse applications such as robotics. We are transferring the technology to a start-up developing robotics hands and grippers.**

I. Introduction

Tactile perception is a key technology enabling applications such as dexterous robotic grasping, intelligent prosthetics, and surgical robots [1]. Tactile sensors primarily aim to mimic mechanoreceptors, i.e., determining the location, shape, and intensity of contacts [2]. Instantaneous pressure or force can be used to measure force and multiple contact points. In contrast, dynamic tactile sensations are better suited to extract information about texture and rolling or slipping [3].

Over the years, several technologies have been explored [4], including capacitive (e.g., [5]), piezoelectric (e.g., [6]), piezoresistive (e.g., [7]), optical (e.g., [8], [9]), fiber optic (e.g., [10]), and magnetic (e.g., [11]) sensors. While experimental sensors cover many technologies, commercial solutions are less diverse. The most common commercial sensors are based on optics/cameras (e.g., PapillArray from Contactile or DIGIT from GelSight), magnetic (e.g., uSkin sensor from Xela Robotics), or piezoelectric (e.g., FTS Tactile Pressure Sensors from Seed Robotics and BioTac sensor from SynTouch now discontinued). Further information on haptic perception can be found in [1], [4].

Over three decades ago, vibrotactile sensing was proposed for robotic perception (e.g., [12]). Over the years, only a few others have attempted to develop such sensor types, due to technological limitations, which are now slowly being overcome, wider adoption has not yet been possible. Among the recent approaches to this technology, we can highlight:

For texture recognition in prosthetics, microphones have been proposed [13]. Specifically, vibrations captured by a microphone when brushing materials of different textures are converted into electrotactile feedback. Despite using a commercial microphone without artificial skin to amplify vibrations, the setup provides sufficient information for humans to distinguish textures with an accuracy of 85%.

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Fingerprint-like structured skin has also been used capacitively and piezoelectrically to enhance both static and dynamic tactile perception, such as grooves [14], [15] and peaks [16]. Specifically, Navaraj et al. [14] used a 3D-printed pattern containing ridges 500 μm wide, 2 *mm* long, and 500 μm thick. The vertical spacing of the ridges was 1500 µm (three times higher than typically observed in human fingerprints), and the horizontal spacing was 3000 μm [14]. The proposed setup achieved a maximum accuracy of 99.45%.

These results confirm the viability of using vibrations, structured skins, and microphones for dynamic tactile perception. However, the design decisions for the fingerprint pattern are not clearly defined. In most cases, the goal is to resemble human fingerprints without considering the differing mechanical properties of artificial skin or transducers. In contrast, our most recent article [17] presented an approach to optimizing 3D-printed fingerprints for dynamic tactile sensing aimed at increasing the spectral size of the vibration signal and improving the signal-to-noise ratio. Based on these and previous lab results, we are now transferring the technology to Nibotics, a start-up specializing in producing humanoid hands and grippers. The current and planned work of this collaboration is described in this extended abstract.

II. Method

The planned approach for conducting the three key tasks of localization, texture recognition, and object recognition includes data collection and selecting the corresponding data processing techniques.

A. Localization Task

For the localization task, we used a UR5e robotic arm [18] equipped with an indenter. The UR5e arm was programmed to "poke" the Seed Robotics's RH8D hand [19] at various random positions, and the same process will be replicated on the Nibotics hand. These pokes allow us to gather data on how the sound and vibrations propagate through the robotic hand. These data will later be used to localize tactile stimuli on the robotic hand. The RH8D hand is equipped with seven *Harley Benton CM-1000 contact microphones*, which are placed at different areas on the hand's surface to capture a range of vibrational signals during the poking process, see Fig. 1. These microphones are sampled at a frequency of 400 kHz, ensuring that sufficient data is captured for analysis. We are now working on the machine-learning models to localize tactile stimuli on the hand. Further, we will work on determining the ideal number of microphones, their placement, and minimal sampling frequency.

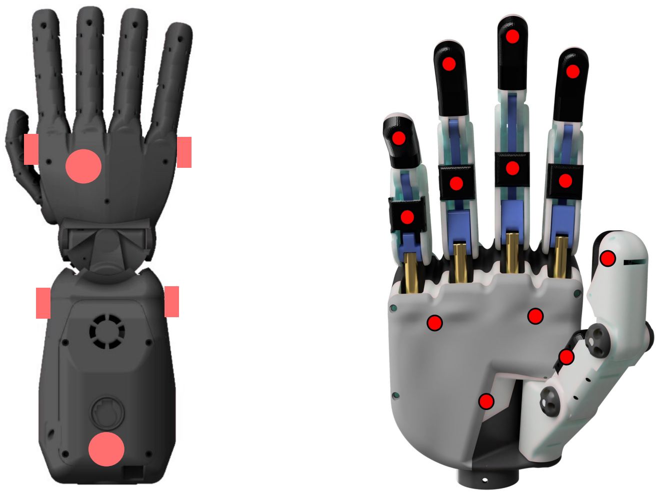

Fig. 1. Schematic diagram of the microphones' localization, represented by red area. The microphones on the RH8D hand are mounted from the outside, whereas on the Nibotics hand are mounted inside the hand.

B. Texture Recognition Task

For texture recognition, the setup resembles the localization task but differs by how the robotic hand is engaged. Instead of poking, the UR5e arm will stroke it with objects of varying materials and textures. The microphones on the hand will record the vibrations from these interactions, sampled at 400 kHz, to capture material- and texture-specific patterns. We will then train machine learning models with these data. Similarly, we will investigate the lower boundary of the sampling frequency and number of microphones to complete this task.

C. Object Recognition Task

Finally, for the object recognition task, we will utilize objects from the YCB (Yale-CMU-Berkeley) dataset [20], a widely used collection of standardized objects in the robotics community. The RH8D hand will be used to grasp these objects, and the microphones will record the vibration signals generated during the grasping process. These recorded signals will capture the vibrations produced as the hand manipulates different objects. The YCB dataset offers a diverse range of objects, from everyday items to more complex shapes, allowing us to collect data on how different objects generate distinct vibrational signatures when manipulated which will later be used for training machine learning models to recognize and differentiate between various objects based on their corresponding vibrational patterns.

D. Data Processing and Machine Learning Models

The data collected from the localization, texture recognition, and object recognition tasks will be processed to extract meaningful features that can be used to train machine learning models. The primary type of data we will be working with is time-series data, which is well-suited for analysis using Convolutional Neural Networks (CNNs) after transforming the signals into a spectrogram. Additionally, Transformers will be explored to capture long-range dependencies and temporal relationships within the time-series data. CNNs and Transformers are just examples of methods that will be considered for analysis; we will also investigate other potential approaches to determine the most effective techniques for these three tasks. The models will be trained using the data collected from the three tasks to identify the key features associated with localization, texture recognition, and object recognition. Pre-processing techniques, such as noise filtering and signal normalization, will be applied to the raw data to improve the quality of the input and the performance of the machine-learning models. Moreover, we will conduct an ablation study to determine the minimum required number of microphones, their placement, and the minimum required sampling rate.

III. Conclusion

The field of robotics is rapidly advancing, with tactile sensing playing a vital role in enabling robots to interact with their environments more intuitively and dexterously. In this project, we aim to address the challenges of texture recognition, object detection, and the localization of tactile stimuli. By further developing a vibration-based dynamical tactile sensor and its integration on a robotic hand, we will ensure seamless integration, moving these technologies closer to their commercial potential.

The planned methodology involves collecting tactile data through structured experiments on three distinct tasks. The data will be gathered using a UR5e robotic arm, an RH8D hand, and the Nibotics hand equipped with contact microphones. These datasets will serve as the foundation for training machine learning algorithms. CNNs and Transformers are among the methods that will be explored for analysis, with each method being assessed for its ability to extract both local and long-range features from the time-series data.

Our ultimate goal is to enable dexterous robotic manipulation at lower costs, thereby enhancing the role of haptic perception in addressing critical societal challenges.

Acknowledgment

This research was partially funded by the Bundesministerium für Bildung und Forschung (BMBF) under the Programme DATIPilot Innovationssprints project No. 03DPS1242A (Vibro-Sense).

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