Social Gesture Recognition Through Fabric-Based Tactile Sensing

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***Abstract*—Humans can convey a variety of messages through touch alone. By enabling robots to recognize social touch, we add another communication modality between humans and robots. In this work, we introduce a social gesture recognition system that utilizes a fabric-based, large-scale tactile sensor mounted on the arms of a humanoid robot. We created a social gesture dataset with data from multiple participants and extracted temporal features for classification. By gathering tactile data from a humanoid robot, our system offers insights into human-robot social touch and demonstrates that fabric-based sensors could potentially advance social-physical human-robot interaction (spHRI) systems for more natural and efficient communication.**

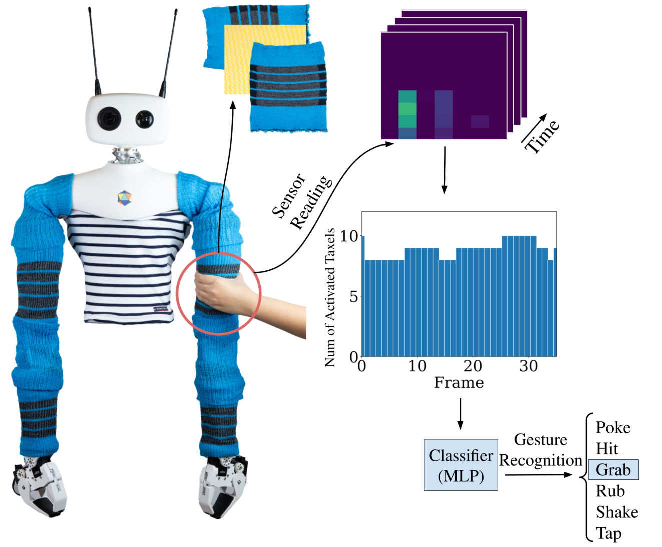

Fig. 1. Our machine knitted large scale sensor has the ability to detect different types of gestures. Features are extracted from the sensor reading and fed into a model to classify the gesture being performed. The sensor is composed of three layers, two conductive and one insulting forming a resistive based tactile sensor.

I. Introduction

Human beings communicate through a wide range of modalities, and touch is one of the most inherent forms of interaction. Social touch plays a variety of roles, such as promoting bonding, facilitating allogrooming, and aiding in communication [1]. For example, a handshake can signify appreciation [2], while a gentle touch can communicate affection or comfort [3]. With the increasing deployment of robots, particularly humanoid robots in public spaces [4], enhancing robot sociability through touch [5] is essential for fostering more natural human-robot interactions. Achieving this requires robots to be equipped with advanced tactile sensors capable of recognizing and responding to diverse social-physical interactions (spHRI).

Although the need for effective gesture recognition in humanoid robots is well-established, finding a robust solution remains challenging. Many studies on gesture classification rely on data not collected from humanoid robots [6], [7], and those that use robotic platforms often employ small-scale sensors or miniature robots [8], [9]. Despite advancements in robotic skin development, existing technologies are often low-resolution, difficult to fabricate, or lack the flexibility needed to adapt to various robot forms [10]–[12], which hinders their application in humanoid robots designed for spHRI.

We introduce a system for recognizing social gestures that uses a large-scale, fabric-based tactile sensor attached to a humanoid robot's arms. To train the classifier, we created a dataset by gathering gesture data from multiple participants and extracting temporal features for analysis. Our machine-knitted sensor's flexibility allows for easy customization to fit different robot shapes. Furthermore, data collection on a real humanoid robot provides a deeper understanding of human-robot interactions through touch. We believe that improving gesture recognition systems will lead to more natural and engaging human-robot social interactions.

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II. Gesture Recognition

Based on the touch dictionary [13], we selected six gestures for our algorithm to classify (Fig. 2 (A)) . We chose a subset of gestures because some were not suitable for humanoid robots. For example, gestures like 'finger idly' and 'cradle' are more appropriate for animal-like robots, so we excluded them. Additionally, certain gestures were left out due to their similarity in sensor signals, which made them hard to distinguish. For example, 'pat' and 'tap' generated almost identical readings, and even humans might find it difficult to tell them apart, so they were not included in our final selection.

A. Data Prepossessing and Feature Extraction

We processed and extracted temporal features from our 3D spatiotemporal data. We removed any frames that were recorded before the sensor made initial contact, as the sensor output was captured prior to the interaction. The feature we focused on was the number of activated taxels per frame (Fig. 2 (C)). A taxel was considered activated if its digital reading

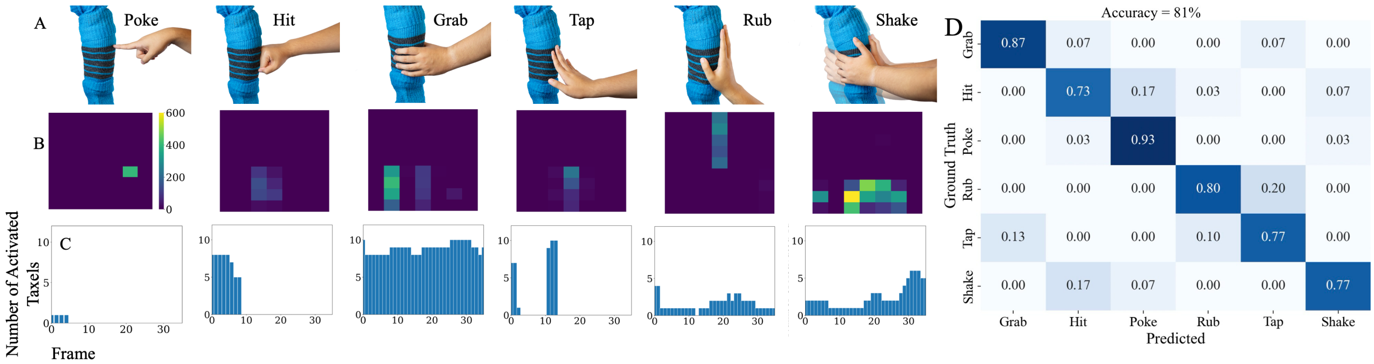

Fig. 2. Display of the gestures and the signal reading. (A) A visual of the gesture being performed on the upper portion of the sensor. (B) A grid displaying what the raw signal looks like. The values shown are the mean taxel value. (C) the feature extracted from the sensor reading, the number of taxels activated per frame. (D) Confusion matrix of gesture recognition result

exceeded 10. For each frame, we calculated the total number of activated taxels, creating an array of numbers representing this count for every frame. Since each gesture had a different frame length, the data was either padded or trimmed to a standard length of 150 frames. The number of activated taxels was generally unique to each gesture. Other potential features, such as pressure or additional spatial data, did not improve accuracy.

B. Experiments

1) Data Collection: To develop a system that can interpret social gestures, we gathered data from 16 volunteers to create a gesture dataset, consisting of six gestures, using our sensor.

Our experimental setup featured the sensor mounted on Pollen Robotics' Reachy 2023, along with a monitor for displaying information. The sensor's upper section included a 5x7 grid, while the lower section featured a 4x7 grid. The design of the sensor follows the work previously done by Si ([14]). Data was sampled at approximately 50 Hz. To build our dataset, we recorded gesture data from several participants.

The assignment of participants to either the training or test set determined how many trials they would perform for each gesture. Each participant's data was exclusively assigned to either the training or test set to avoid overlap. Participants in the training set completed each gesture 15 times: nine trials on the robot's upper arm and six on the lower arm. Participants in the test set performed each gesture five times, with three trials on the upper arm and two on the lower arm. We collected more data on the upper arm since, without guidance, participants tended to favor it. To ensure balanced data from the lower arm, we instructed participants to focus on specific locations when performing gestures. The order of gestures was randomized, but repetitions were performed consecutively. Sixteen participants (50% female, aged 19 to 28, M = 23.12, SD = 2.18) contributed to the dataset. Our dataset consisted of 1,080 samples, with 900 in the training set and 180 in the test set. The training set included 150 gestures per class, while the test set contained 30 gestures per class.

2) Results: Our method achieved an accuracy of 81.16% (Fig. 2 (D)). However, some gestures were often misclassified. For example, the gestures "hit" and "poke" were frequently confused with each other, as were "shake" and "grab." This issue arose because the signals for "hit" and "poke" were sometimes similar. Specifically, when a participant struck the sensor with an extended bone or knuckle, only one or two taxels were activated, resulting in a signal similar to that of a poke. While the results show promise, more data is needed to examine the system's performance when individuals perform gestures in different ways.

III. CONCLUSIONS

In this work, we presented a system capable of distinguishing between various gestures, highlighting the potential of textiles in human-robot interaction. We developed a fabric-based tactile sensor using machine knitting and created a social gesture dataset. The dataset was collected with the sensor mounted on a humanoid robot. However, the study is in its early stages and has several limitations. Currently, the dataset consists of able-bodied young adults, but people with diverse abilities may interact with the system differently, potentially causing misclassifications due to variations in gesture execution. Moreover, our focus has been on recognizing the gestures themselves, without fully addressing the meaning or context behind them.

Future work will expand the study to include individuals with various abilities, helping us understand how gesture variations can improve sensor design and make it more inclusive. This will enhance the system's accuracy in recognizing gestures across different user groups, ensuring better responsiveness.

Gesture misclassification can lead to the robot misunderstanding user intent. To improve this, we plan to explore models that handle both spatial and temporal data and to better understand the meaning behind gestures for more effective communication with the robot. While this paper represents an initial step in exploring textiles for interaction, we hope to focus on how gesture variations affect robot interactions, with the goal of refining the system to accommodate a broader range of users.

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