Exploring Feature Extraction And Machine Learning With A Piezoelectric Tactile Skin For Robotic Fingertips

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INTRODUCTION

Tactile sensing is crucial for dexterous object manipulation, allowing force prediction and adaptive grip control to maintain stability and prevent slippage [1]. Sensory integration in closed-loop control enables robotic hands to replicate human-like capabilities and dexterity [2]. Among various sensing technologies, i.e., capacitive or resistive sensors, piezoelectric sensors emerged for their high sensitivity, high bandwidth, and flexibility, making them particularly promising for contact and slippage detection [3][4]. This study explores a Piezoelectric Tactile Skin (PTS) using machine learning on time-frequency features, with experiments performed on human and robotic hands.

TACTILE DATA ACQUISITION

The tactile data acquisition setup consisted of (*i*) a Piezoelectric Tactile Skin (PTS, Fig. 1a) recording tactile signals at 315 Hz, (*ii*) a metal plate fixed on an ATI Multi-Axis Force/Torque Sensor (Fig. 1b) measuring normal force (f_z) at 500 Hz, (*iii*) an AR10 Humanoid Robot Hand, and (*iv*) a ROS-based system on a host PC for data synchronization and recording, triggering, graphical interface visualization, and robotic hand control.

The PTS is a flexible sensor array based on screen-printed P(VDF-TrFE) piezoelectric sensors by Joanneum Research [5]. Each sensor consists of a bottom electrode on a 100 μm PCB, a 5.1 μm P(VDF-TrFE) layer, a top electrode (PEDOT:PSS), and a UV-curable protective layer. The 8-sensor array is embedded in silicone caps and connected via FPC cable. Five PTSs interface with an embedded system featuring a 64-channel A/D converter (DDC232) and an ARM Cortex-M0 microcontroller [6]. For the experiments, we used the PTS corrisponding to the index finger.

Tactile data were acquired in two scenarios (Fig. 1c). In the first scenario (PTS worn on a human hand), a pressure task required the subject to follow a trapezoidal reference signal (f_{ref}) targeting 2 N, 4 N, and 6 N, with real-time visual feedback via PlotJuggler (ROS). A sliding task was also performed, involving 21 movements (linear, rotational, rest) of varying durations (3 s, 3.5 s, 4 s), repeated four times while maintaining $f_z = 2 \pm 0.25$ N. In the second scenario (PTS on the robotic hand), a different pressure task was executed through automated opening and closing phases of the robotic index finger. Each task was repeated twice.

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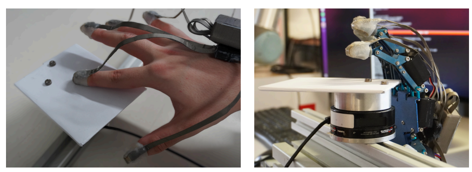
EXPERIMENT METHODS

Using tactile data from the described tasks, we conducted experiments on: (*i*) classification of contact states, force levels, and slippage; (*ii*) contact regression for continuous force prediction. Contact ($f_z < 0.2$ N) and non-contact ($f_z \geq 0.2$ N) states were defined based on force readings, as well as five force levels ($f_z < 1$ N, $1\text{ N} \leq f_z < 3$ N, $3\text{ N} \leq f_z < 5$ N, $5\text{ N} \leq f_z < 7$ N, and $f_z \geq 7$ N). Labels for sliding (linear, rotational, rest) were derived from proper trigger signals. Data processing was performed as follows.

First, triggers and f_z were downsampled from 500 Hz to 315 Hz to align with tactile timestamps, with the initial 3 s discarded and recordings labeled. Then, two time-frequency features were extracted using moving window spectral analyses. The Short Time Fourier Transform (STFT) was applied by sliding a fixed window to compute the Fourier transform at each step [7]. Discrete Wavelet Transform (DWT) marginals were extracted to balance time and frequency resolutions by employing scaled and time-shifted wavelets [8]. In addition, tactile raw signals were linked, sample by sample, to the related labels without windowing.

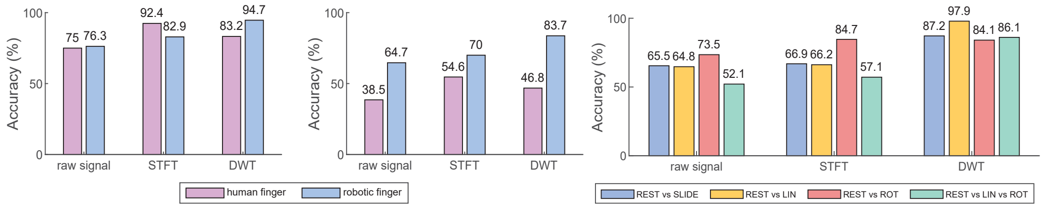
The three feature types were fed into machine learning algorithms. Support Vector Machines (SVMs) separate classes via hyperplanes, while Neural Networks (NNs) minimize prediction error by adjusting weights [9]. Each dataset was split 50% for training and 50% for testing. Evaluation metrics included accuracy (%) and RMSE.

(a) PTS (b) Force sensor



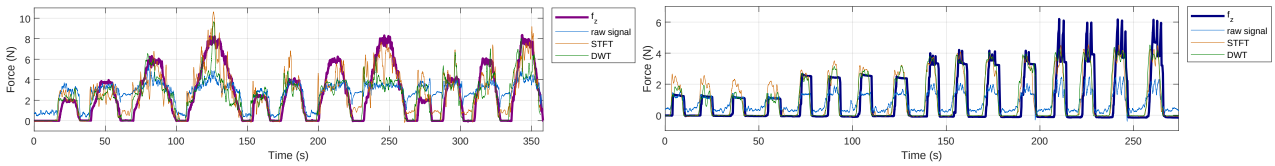
(c) First (*left*) and second (*right*) acquisition scenarios.

Fig. 1: Tactile data acquisition setup and instrumentation.



(a) Contact states (*left*) and force levels (*right*) in pressure tasks. (b) Sliding task in the first acquisition scenario.

Fig. 2: SVM accuracy for pressure and sliding tasks.



(a) Regression in the first acquisition scenario. (b) Regression in the second acquisition scenario.

Fig. 3: Qualitative representation of contact regressions for pressure tasks.

A preliminary grid search evaluated wavelet-based features using SVM and NN models. Wavelet parameters included different window lengths (0.2 s, 0.4 s, 0.5 s, 0.6 s, 0.8 s, 1 s) and overlaps (40%, 60%, 80%, 98%, maximum), wavelet bases from Daubechies, Symlets, and Coiflets families, and 4 decomposition levels. For SVMs, we tested linear, polynomial, and RBF kernels, with gamma set to automatic or fixed values (2, 4, 8, 16), and various regularization C (0.25, 0.5, 1, 2). For NNs, we explored architectures with 1, 2, 3 hidden layers, with 32, 64, 128, 256 neurons per layer, and ReLU as activation function. Parameters that balanced performance and computational efficiency were selected: *db4* wavelets with length of 0.2 s (for SVMs) and 0.4 s (for NNs), and maximum overlap; RBF kernel with automatic gamma and $C = 0.5$ for SVMs, and 3 hidden layers of 128 neurons each for NNs.

EXPERIMENT RESULTS

Bar plots showing classification accuracy are presented in Fig. 2a for pressure and in Fig. 2b for sliding tasks. Contact classification performs well in distinguishing whether a force is applied or not, effectively separating noise from useful signals. Wavelet and STFT representations outperform raw signals in both scenarios. Force level classification improves with multi-resolution tactile information, with better performance observed using the robotic hand, likely due to a partial increase of repeatability w.r.t. the human hand. In sliding tasks, DWT marginals outperform other features, especially in the 3-class problem. The performance hierarchy (DWT marginals > STFT > raw signal) reinforces the value of joint time-frequency analysis for tactile signals.

Qualitative force predictions in Fig. 3a and Fig. 3b show a clear distinction between contact and non-contact states, with better force level discrimination using signal transformations, confirming SVM results. Spikes above 3 N in Fig. 3b are due to hardware limitations but appear consistently across all features. Prediction errors were higher for the human finger (RMSE = 1.86, 1.22, 1.41 for raw signal, STFT, and DWT marginals, respectively) compared to the robotic finger (RMSE = 1.14, 0.62 for raw signal and time-frequency features, respectively), with raw signals performing worst.

CONCLUSIONS

This pilot work contributes to tactile sensing research for robotic grasping and manipulation by demonstrating the feasibility of piezoelectric tactile skins in detecting force variations and classifying tactile events like slippage. The results suggest that multi-resolution features, such as DWT marginals, are the most effective for machine learning algorithms in extracting information from PTS tactile signals, which could be confirmed in future investigations as a follow-up to this pilot study. Future research will explore additional movement types, such as rolling, broader investigations across motion patterns, and real-time testing to validate PTS capabilities.

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