Towards Effective Tactile Identification of Textures using Hybrid Touch Approach

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If you're in a hurry (TL;DR)

- Our robot can classify surface texture with both **sliding** and **touch** movements up to 98% accuracy under *loose constraints*.
- **Three different ML** models comprising statistical machine learning and connectionist approaches were benchmarked for texture classification.
- **A tactile dataset** of 23 textures is available for download

Motivation

PROBLEM

In most cases, tactile data for texture classification comes from constrained robot set-up:

- Constant velocity while performing exploratory procedure such as sliding or touch.
- Constant force acting upon object surface.
- Sliding follows linear trajectory.
- Tactile data recorded with high frequency.

Learning from raw data usually requires a *large amount of data.*

CONTRIBUTIONS

✓ Relaxed constraints on robot set-up for *easier* data collection:
  - No strict constraint on velocity and force.
  - Non linear trajectory for sliding.

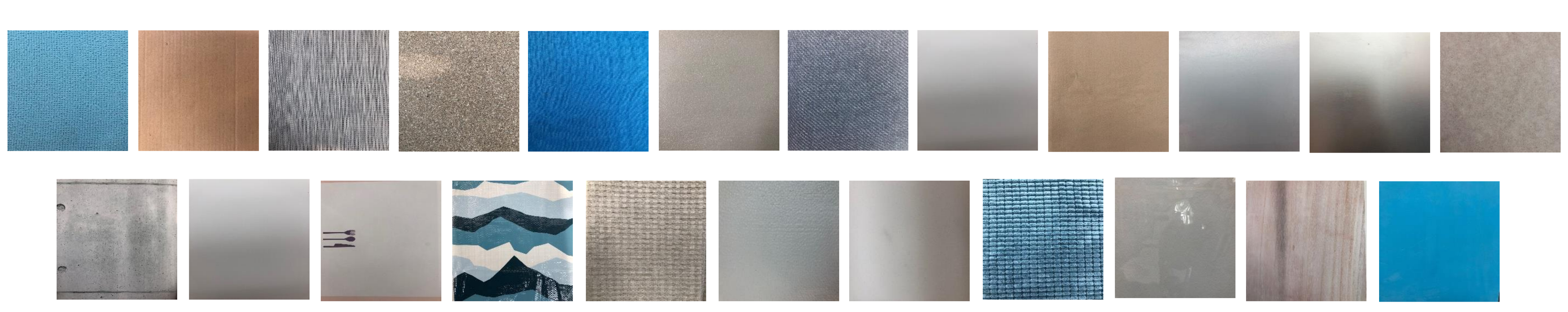
✓ Combined different exploratory movements such as sliding and touch during data collection to achieve better accuracy.

✓ Created a publicly available tactile dataset for future use

Tactile Dataset

EXPERIMENT SET-UP

- Tactile Data is collected using **iCub's forearm** tactile sensor through two exploratory behaviors: *touch* and *sliding*. Data is recorded at 50 Hz.
  - **Touch:** robot forearm moves vertically onto object surface with $1°/s$. The motion is actuated by shoulder through adduction for range of 6°.
  - **Sliding:** robot forearm moves horizontally on object surface with $5°/s$. The motion is actuated by elbow joint flexion and extension for range of 60°.
- The tactile data is collected for *23 different surface textures*:



- Due to the tendon-based actuation of iCub and non-linear movement, the *forearm was not subject to strict constraints*.
- **2852** sample were collected.

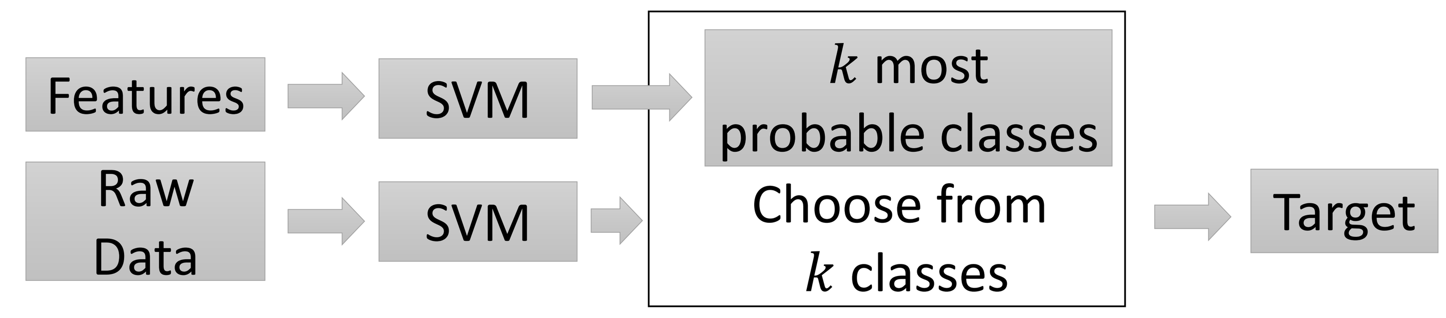
Example of instances of tactile data collection during sliding

- Collected data also includes **force and torque estimations** provided from iCub's shoulder. This can be used for future work.

Texture Classification: Models & Results

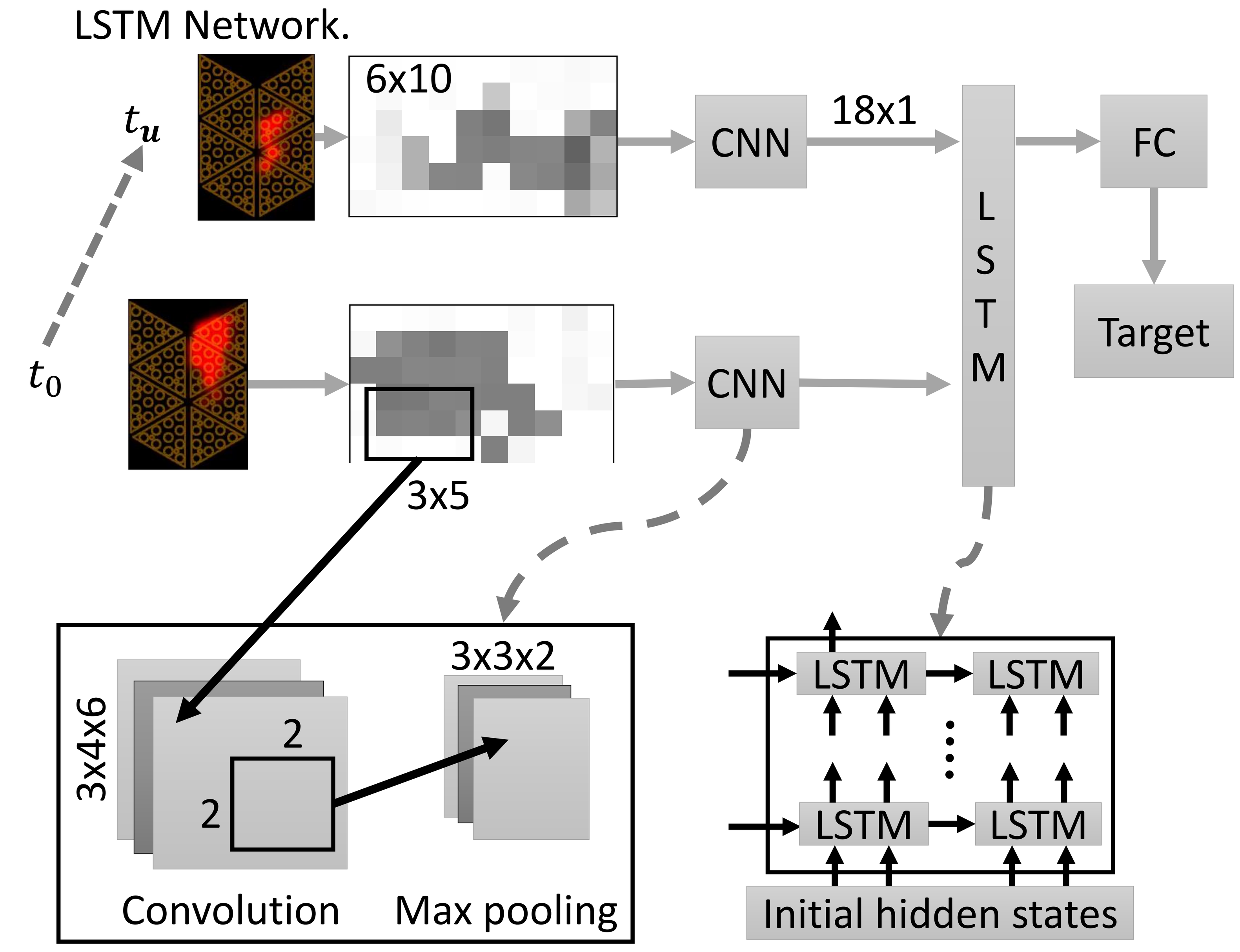
SVM-LSTM

- SVM with hand-crafted features narrows down possible target classes, then LSTM chooses target within those classes. We use following features:
  - **Sliding features:** roughness, fineness, frequency at maximum intensity by Discreate Fourier Transform and statistical features such as mean and standard deviation.
  - **Touch features**: empirical mean and standard deviation of approximate slope of tactile data value.



CNN-LSTM

- Raw tactile data is *considered as sequences of images*. At each instance the image is passed through CNN and supplied to LSTM Network.



MAIN RESULTS

- The LSTM and CNN were trained to minimize the multiclass **entropy loss** for C classes with predictive probability p_c:

$$\mathcal{L} = -\sum_i \sum_{c=1}^{C} \mathbb{I}(c, y_i)\log(p_{i,c})$$

- We use following **accuracy** measure:

$$Acc = \frac{1}{N}\sum_i^N \mathbb{I}(\hat{y}_i, y_i)$$

where $\hat{y}_i$ and y_i are predicted and ground truth labels.

- Accuracy is tested for **touch, sliding** and **combination** of both.

Methods	Touch	Sliding	Combination
SVM	0.61 (0.028)	0.77 (0.019)	0.88 (0.037)
SVM-LSTM	0.61 (0.028)	0.86 (0.035)	0.96 (0.028)
CNN-LSTM	0.85 (0.054)	0.86 (0.038)	0.98 (0.022)

Interesting: texture can be recognized using only touch, but sliding *for a short time* improves classification!

Future Work: What's Next?

- Incorporate texture classification into grasping stability.
- Evaluate the proposed frameworks on tactile data from different tactile sensors.

Download tactile data from:
https://github.com/crslab/TactileLearning

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