Fast Texture Classification Using Tactile Neural Coding andSpiking Neural Network

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Motivation

- It is hard to differentiate textures by vision, thus **touch sense** is very important in this task.
- State-of-the-art texture classification techniques use Artificial Neural Network (ANN) based methods which are “*power and data hungy*”.
- On the other hand, a Spiking Neural Networks (SNNs) are *power efficient and has lower latency* than ANNs.
- Hence, we need to convert the raw continuous real time tactile signal into spike trains to learn texture classification using SNNs using neural coding.

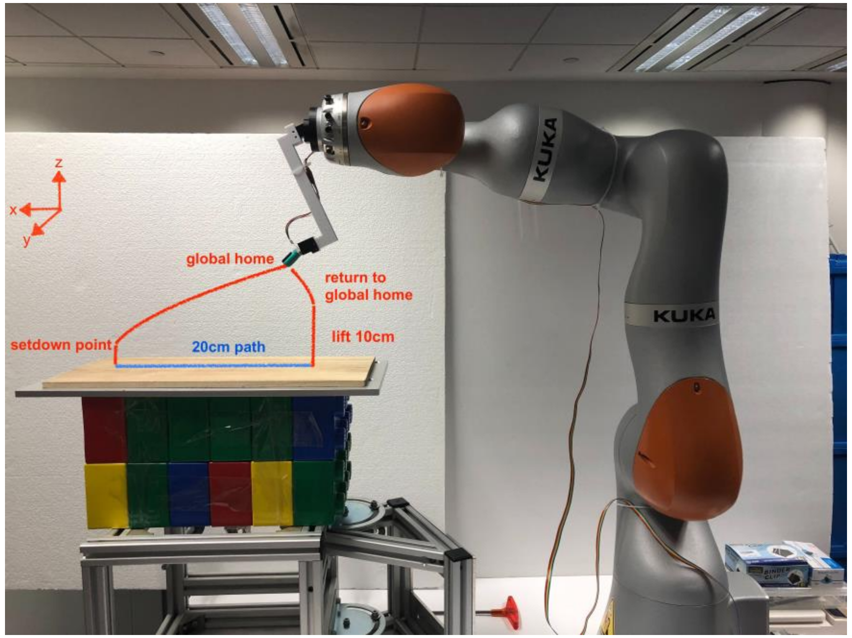
Problem statement

In this paper, we tackle the following questions:

1. Given the raw continuous real valued tactile signal, how do we encode so that the encoded data preserves sufficient information about texture classification?
2. Does encoded tactile spike trains simplify the data so that it is easily learnable? Can it classify in a short amount of time?
3. How does SNNs on encoded tactile spike trains perform compare to state-of-the-art ANN methods?

Datasets: data collection

Two different tactile datasets collected from different data collection setups are used to test our models.



1. **BioTac dataset:**
   a. BioTac attached to Kuka LBR is used to collect data
   b. Closed loop force and velocity control exerted during data collection

2. **iCub dataset:**
   a. iCub's forearm is used to collect data
   b. Loose control and high variance due to tendent based mechanical structure of the forearm
   c. No velocity or force control exerted

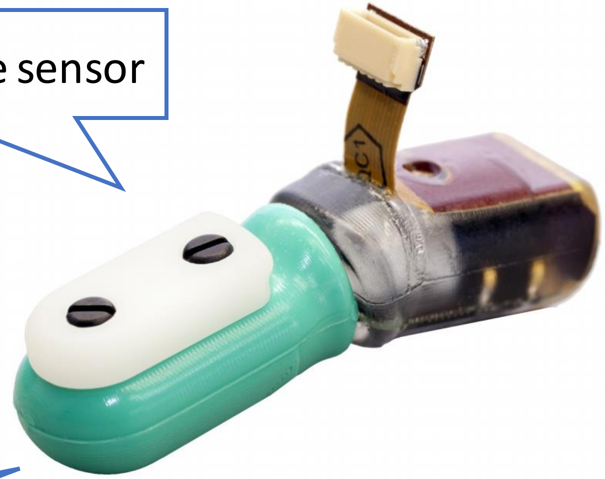
Datasets: tactile sensors

Barometric tactile sensor

23 taxels

100 Hz sampling rate

Signal length: 4 s



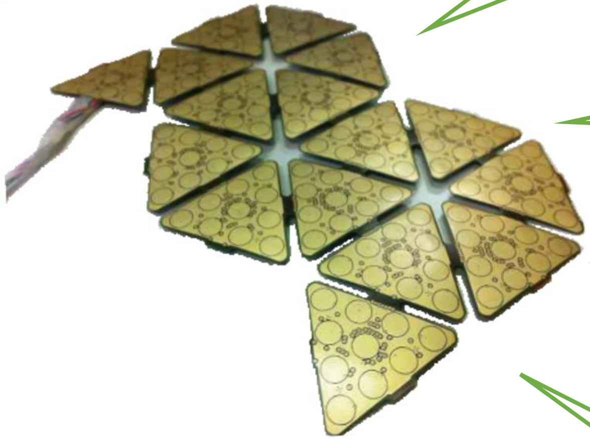
BioTac

Capacitive tactile sensor

6 patches with 10 taxels = 60 taxels

50 Hz sampling rate

Signal length: 1.5 s



iCub's tactile sensor

Proposed Neural Encoding

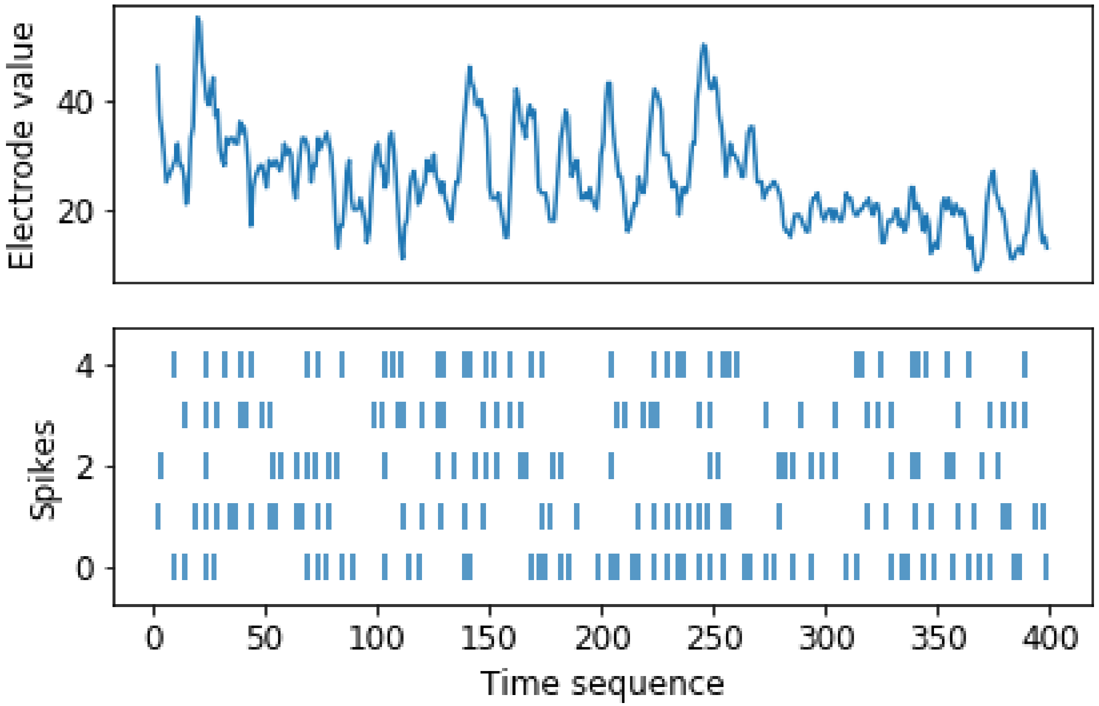
Neural encoding converts continuous tactile signal into spike trains. Given raw tactile signal for i-th taxel, $y_i(t)$, the encoded spike train for k-th neuron, s_i^k, is defined as:

$$s_i^k(t) = \begin{cases} 1, \quad k \leq K, y_i(t) \geq k, y_i(t-1) < k \\ 1, \quad k+1 \leq k \leq K, \leq y_i(t) \leq \frac{k}{2}, y_i(t) > \frac{k}{2} \\ 1, \quad k+1 \leq 1,\ y_i(t) = \max\{y_i(t)\} \\ 0, \quad otherwise \end{cases}$$

Where $k \in [1, \dots, K, \dots, 2K + 1]$. In total, it outputs $2K+1$ spike trains.

Neural Encoding: example

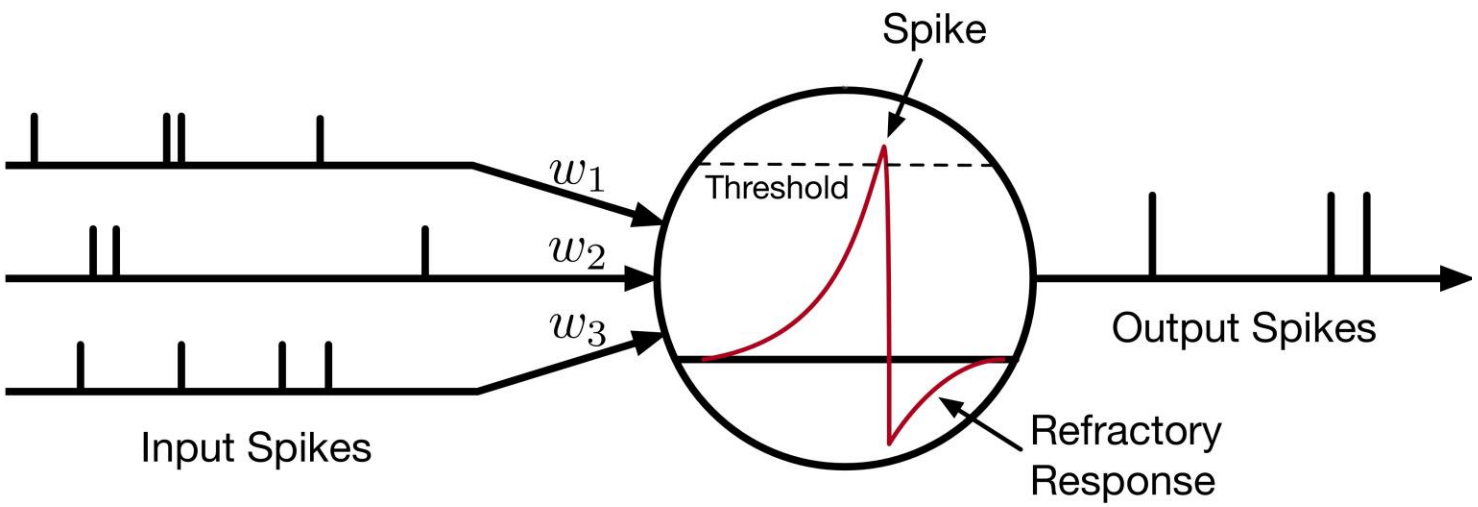
We chose $K = 2$ for both BioTac and iCub tactile data.



Example of proposed neural encoding for a taxel.

$$s_i^k(t) = \begin{cases} 1, & k \leq K, y_i(t) \geq k, y_i(t-1) < k \\ 1, & k+1 \leq k \leq K, \leq y_i(t) \leq \frac{k}{2}, y_i(t) > \frac{k}{2} \\ 1, & k+1 \leq 1,\ y_i(t) = \max\{y_i(t)\} \\ 0, & otherwise \end{cases}$$

Neural Model: SRM

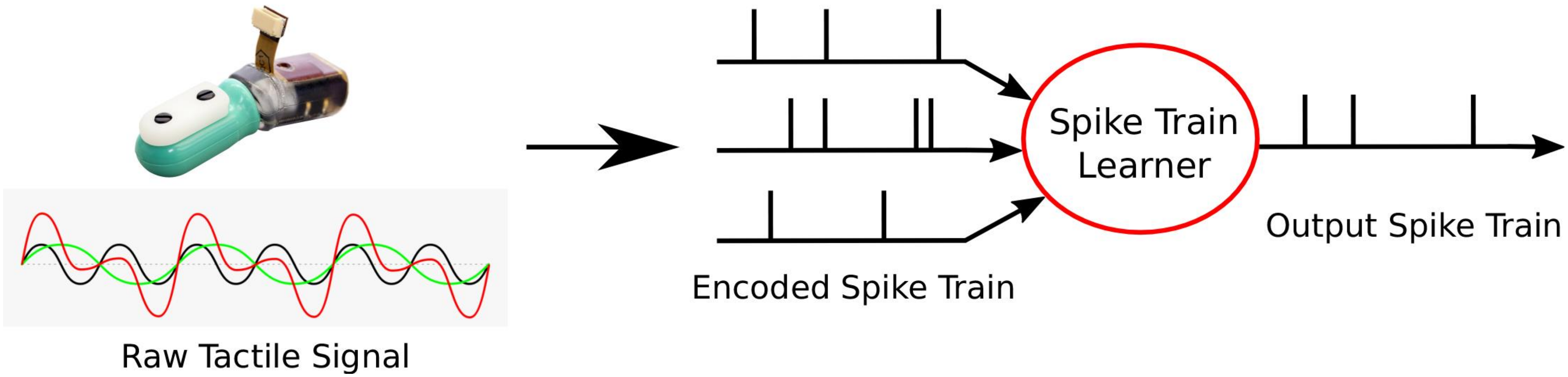


We use **Spike Response Model (SRM)** as a neural model. Spikes are generated when membrane potential $u(t)$ exceeds a predefined threshold ϕ. The neuron in **SRM** depends on the incoming spikes to be convolved by a response kernel, $\epsilon(\cdot)$, and refractory response, $\nu(\cdot)$:

$$u(t) = \sum \omega_i (\epsilon * s_i)(t) + (\nu * o)(t)$$

where ω_i is a synaptic weight, $*$ indicates convolution, $s_i(t)$ are the incoming spikes from input i, and $o(t)$ is the neuron's output spike train.

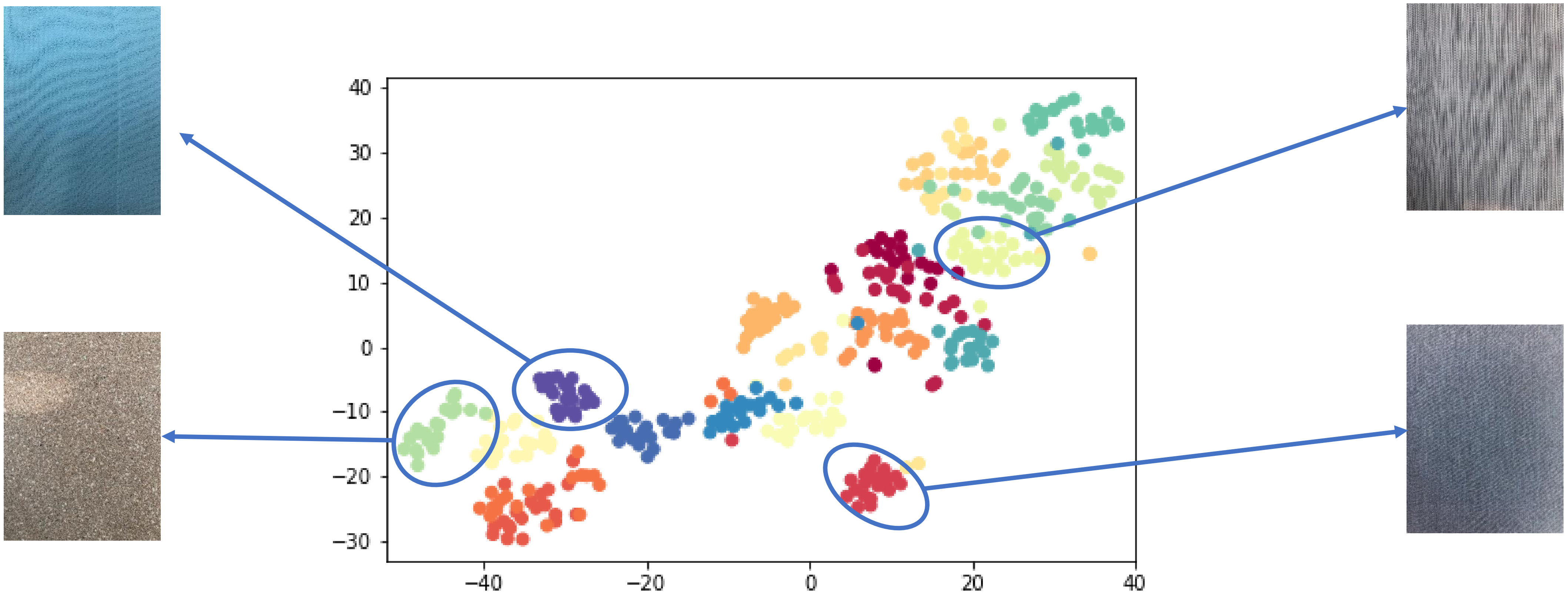
A Spiking Neural Network (SNN)



- We have 20 different textures to be classified.
- Our SNN model contains 2 FC layers and is trained in **SLAYER** framework.
- Train-test split is set to be 70:30.
- Input sizes are $95\ (23 \times 5)$ and $300\ (60 \times 5)$ for BioTac and iCub respectively.
- We use standard Spike Count Loss to train our SNN.

$$\mathcal{L} = \frac{1}{2}\sum_{t=0}^{T}\left(\underbrace{\sum \boldsymbol{s}^{\boldsymbol{o}}(t)}_{\text{Output spikes}} - \underbrace{\sum \tilde{\boldsymbol{s}}^{\boldsymbol{o}}(t)}_{\text{Desired spikes}}\right)^2$$

Results: Neural Encoding



t-SNE performed on encoded iCub tactile data using Van-Rossum distance. The clusters are visually separable. Some examples of clusters are indicated with respective textures.

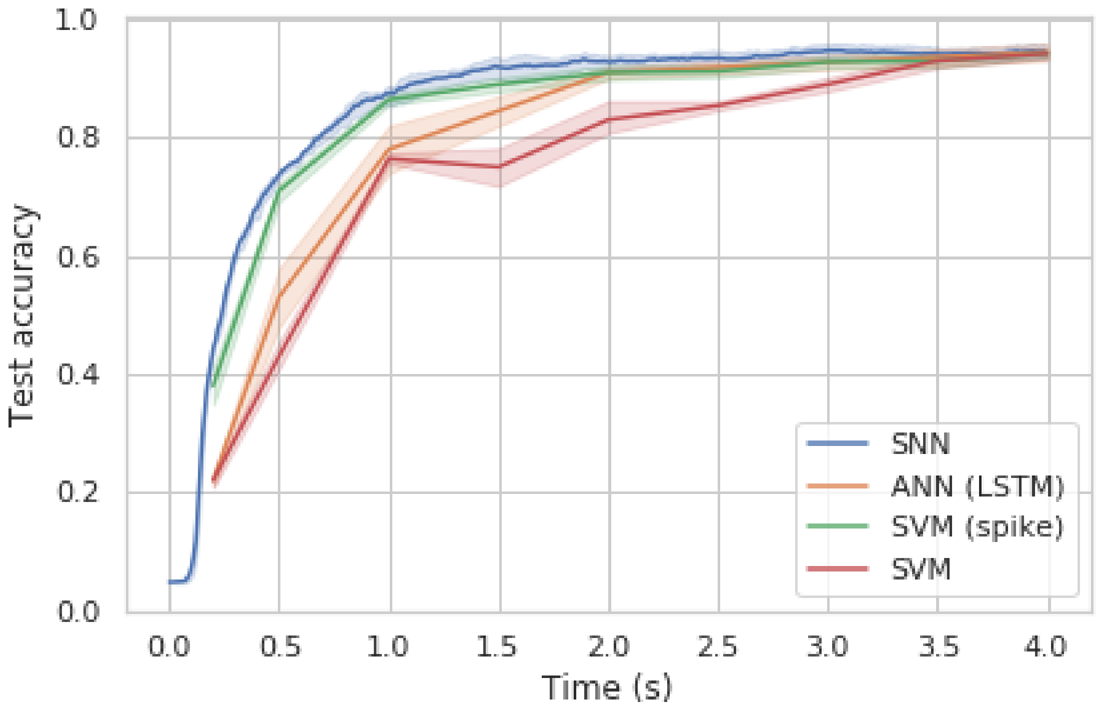
Results: test accuracies

We compared our SNN model to

1. **MLP-LSTM based ANN** model that mimics our SNN
2. **SVM (spike)** with inputs of *encoded* tactile data where time dimension is summed.
3. **SVM** with inputs of *raw* tactile data where time dimension is summed.

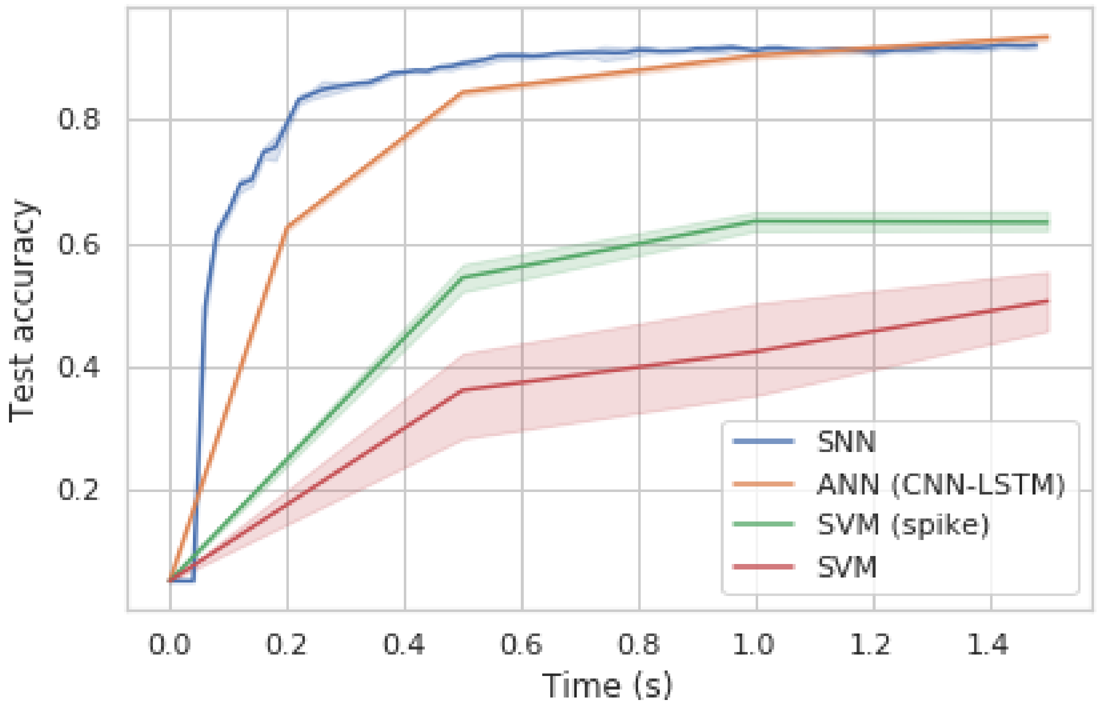
Models	BioTac	iCub
SNN	0.946 (0.013)	0.922 (0.005)
ANN	0.945 (0.015)	0.935 (0.005)
SVM (spike)	0.935 (0.015)	0.633 (0.018)
SVM	0.942 (0.007)	0.505 (0.056)

Results: fast classification for BioTac



- Even though "final testing accuracy" is similar for all models, the SNN slightly outperforms the rest at the early classification.
- SVM results show that the data is easily learnable even with "first moment" approximation.
- SVM (spike) results show that encoding improves learnable information and makes it simpler to learn.

Results: fast classification for iCub



- SVM does not perform well for overall classification, implying complexity of learning this dataset.
- As in case with BioTac data, encoded spike trains makes it easier to learn as shown in SVM (spike) results.
- Again, SNN outperforms the ANN for early classification.

Conclusion

Our work is preliminary study of neural encoding and learning the representation for texture classification. Throughout the work, we have shown:

- Tactile Neural Encoder that extracts spike trains and makes a learning process easy.
- SNN model that can classify textures with in a short time amount.
- Comparing the encoder and model with state-of-the-art ANN techniques using two different tactile datasets.