Unsupervised Learning and Adaptive Classification of Neuromorphic Tactile Encoding of Textures

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***Abstract*—In this work, we investigated the classification of texture by neuromorphic tactile encoding and an unsupervised learning method. Additionally, we developed an adaptive classification algorithm to detect and characterize the presence of new texture data. The neuromorphic tactile encoding of textures from a multilayer tactile sensor was based on the physical structure and afferent spike signaling of human glabrous skin mechanoreceptors. We explored different neuromorphic spike pattern metrics and dimensionality reduction techniques in order to maximize classification accuracy while improving computational efficiency. Using a dataset composed of 3 textures, we showed that unsupervised learning of the neuromorphic tactile encoding data had high classification accuracy (mean=86.46%, sd=5 .44%). Moreover, the adaptive classification algorithm was successful at determining that there were 3 underlying textures in the training dataset. In this work, tactile information is transformed into neuromorphic spiking activity that can be used as a stimulation pattern to elicit texture sensation for prosthesis users. Furthermore, we provide the basis for identifying new textures adaptively which can be used to actively modify stimulation patterns to improve texture discrimination for the user.**

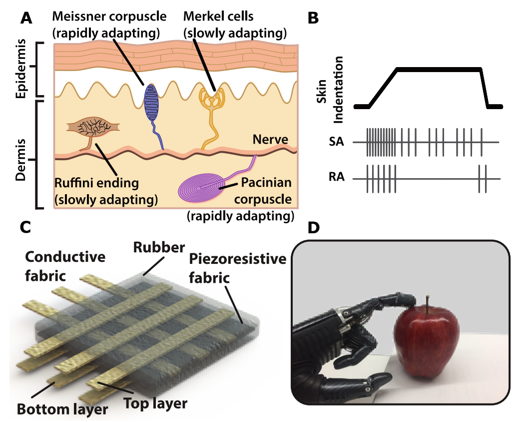

Fig. 1. (A) The mechanoreceptors of glabrous human skin, which detect and encode different features of tactile sensation. (B) An exemplar of spiking response of SA and RA mechanoreceptors. SA mechanoreceptors respond to the static amplitude of the force. RA mechanoreceptors respond to rapid changes in the force. (C) The multilayer tactile sensor composed of two 3x3 grids of taxels. For this paper, the force from the top and bottom layers are encoded as RA and SA mechanoreceptors respectively. (D) Potential application of the sensor on a prosthesis fingertip to characterize object texture.

I. Introduction

Active touch sensing is a critical information-seeking sensory system used to learn about and explore a person's environment and to control ongoing behavior [1]. For upper limb amputees, touch sensation is lost, and it is an important goal for upper limb prostheses to restore this sensory system. The sensation of touch in human glabrous skin is mediated by four main cutaneous mechanoreceptors: Meissner and Pacinian corpuscles, which are considered rapidly adapting (RA), and Merkel cells and Ruffini endings, which are considered slowly adapting (SA) (Fig. 1a). While these receptors produce complex spiking activity in response to stimuli, by and large these receptors are known to specialize in the sensations of skin movement, vibration, indentation and stretch, respectively. These receptors are distributed over multiple layers in the skin. SA mechanoreceptors respond primarily to the static amplitude of force whereas RA mechanoreceptors respond to transient changes in force [2] (Fig. 1b). The information from populations of these mechanoreceptors is then used to understand the form and texture of objects that the person interacts with [3]. This sensory information is used by humans for object identification and dexterous manipulation.

The first step towards restoration of touch sensation in amputees is the development of tactile sensors which can be used to detect and characterize the prosthesis's interaction with the environment (Fig. 1c). For example, in [4], Song et al developed a texture sensor that could measure and classify fabric texture. Tactile information has been used as prosthesis feedback for slip prevention and compliant grasping [5]. Additionally, the measurements from tactile sensors can be transformed into receptor-like spiking activity (which we define as *neuromorphic*). Stimulation of the mechanoreceptor afferents results in characteristic spike patterns which amputees can use to discriminate between different textures [6] or experience noxious tactile perceptions [7]. Tactile feedback has been used to characterize object compliance [8] and categorize textures [9], [10] (Fig. 1d). Furthermore, an unsupervised learning method (k-means clustering) was used to discriminate surface roughness [11]. For prostheses, it is helpful to transform tactile information into a spiking signal for nerve stimulation and sensory feedback to the user [6], [7].

In this work, we used the Izhikevich neuron framework [12] with multilayer tactile information to create a neuromorphic model of RA and SA mechanoreceptor behavior. Additionally, we used an unsupervised learning method and developed a novel adaptive classification algorithm to allow for the dynamic identification of new textures.

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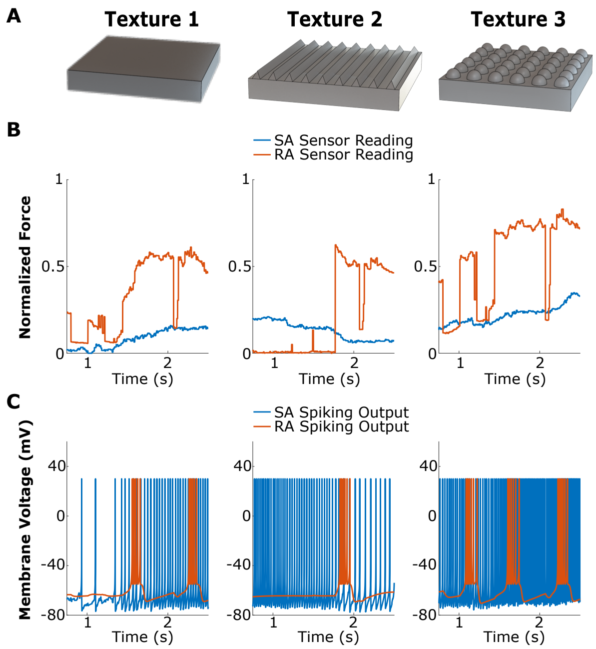

Fig. 2. (A) The textures designed to test discrimination. Texture 1 is flat. Texture 2 has horizontal gratings. Texture 3 has a grid of hemispheres. (B) Example input voltage from one SA and RA taxel for each texture. (C) The spiking output response of the SA and RA neuron models.

II. Materials & Methods

A. Experimental Setup

1) Tactile Sensor: A multilayer tactile sensor shown in Fig. 1c based on [13] was used to characterize tactile sensation. The sensor has two layers of a 3x3 grid of *taxels* (tactile pixels) spaced at 5 mm intervals. The sensor works by utilizing a piezoresistive fabric to transform force into changes in voltage. The taxels of the top layer of the sensor were modeled as RA mechanoreceptors that respond to acute changes in force. The taxels of the bottom layer of the sensor were modeled as SA mechanoreceptors that respond to static levels of force magnitude.

2) Texture Design: Three different applied textures, flat, grated, and hemispheres, shown in Fig. 2a, were designed to activate the entire surface area of the multilayer tactile sensor at one time. The horizontal gratings have a width of 2 mm and spacing of 2 mm. the hemispherical features have a diameter of 4 mm and spacing of 2 mm edge to edge.

3) Data Collection: The multilayer tactile sensor was placed on a flat scale while the different textures were applied. An automated robot brought the texture load vertically down onto the scale until the measured force was 5 N. For each trial, the robot moved the texture horizontally over the sensor. The voltages from the 18 taxels were sampled throughout the 5 second period at 100 Hz which results in 501 samples. There were 197, 243 and 224 trials for Textures 1, 2 and 3 respectively. The voltage waveforms were normalized between 0 and 1 based on the maximum and minimum observed readings.

B. Neuromorphic Encoding

The force readings from each taxel of the tactile sensor are translated separately into neuromorphic spiking patterns using the Izhikevich neuron models from [12] defined by (1), (2), and (3) where v and u are the membrane voltage and recovery variables, respectively:

$$\frac{dv}{dt} = \tau(0.04v^2 + 5v + 140 - u + kI) \tag{1}$$

$$\frac{du}{dt} = \tau(a(bv - u)) \tag{2}$$

$$\text{if } v \geq 30 \text{ mV, then } \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases} \tag{3}$$

Equation (1) calculates the change in voltage as a function of v, u, τ (a time-scaling coefficient), I (the injected current) and k (a gain coefficient for the current). Equation (2) calculates the change in the recovery variable as a function of v, u, τ, a (time-scale recovery of u) and b (sensitivity of u to v). Equation (3) resets v and u to new values when v reaches 30 mV and is a function of u, c (reset voltage) and d (recovery reset increment). In [14], this model was used to implement various spiking patterns. Of particular interest are the Tonic Spiking (TS) model and the Phasic Bursting (PB) model. The TS model primarily responds to the amplitude of the injected current and was used as the basis for the SA neuron model. The PB model primarily responds to the positive change in injected current (a 'rising-edge detector') and was used as the basis for the RA neuron model. The values of the parameters a, b, c, d and τ for the SA and RA neuron models are shown in Table I. The unitless scaling factor k was tuned for each sensor individually in order to produce spikes for the force profile they were presented with, but it was in the range of 65-200 for the SA models and 0.7-3 for the RA models. Fig. 2b-c show typical spiking patterns in response to readings from the tactile sensors when different textures are applied.

For $\tau = 1$, the Izhikevich model assumes that the samples are spaced by 1 ms. Because of this, our data which is sampled every 10 ms is up-sampled by a factor of 10 before being transformed into spiking activity. As a result, the output of the neuromorphic encoding is 5010 samples long.

C. Unsupervised Learning

1) Dimensionality Reduction: For accuracy and computational efficiency reasons, the neuromorphic spiking activity waveform needs to be reduced to lower dimensions.

a) Spiking Metrics: The first step is to reduce the 5010-dimensional waveform v (5 seconds sampled at 1000 Hz) down to two metrics as shown in Table I. For the SA neuron model the metrics are Mean Spike Rate (MSR) and Mean Inter-Spike Interval (MISI) and for the RA neuron model they are Burst Count (BC) and Mean Inter-Spike Interval. For both MSR and BC, the spiking waveform is divided into non-overlapping windows of size *bin*. For MSR, the spike rate is calculated for each window and the MSR is the average spike

TABLE I
RECEPTOR MODELING

	a	b	c	d	τ	1st Metric	2nd Metric
SA	0.02	0.2	-65	8	1	MSR	MISI
RA	0.02	0.25	-55	0.05	0.2	BC	MISI

rate of the non-zero spiking windows. BC is the number of windows with non-zero spiking activity. MISI is calculated by averaging all the ISI's that are shorter than a window of size *buffer* (since the spikes are then considered to be unrelated). Typical values for *bin* and *buffer* are 100 ms (long enough to capture windows of spiking activity and short enough to ignore periods of spiking inactivity) and 1 s (approximately the interval between unrelated spikes) respectively.

b) Principal Component Analysis: At this point, each trial has been reduced to 36 dimensions (18 taxels with 2 spiking metrics each). Principal Component Analysis (PCA) can be used to further decrease dimensionality by reducing the data to the orthogonal components that maximally account for the variance in the data. Initially, the first 3 Principal Components were used for the purposes of visualizing the data. At a later point, we varied the number of Principal Components but saw empirically that 3 Principal Components were optimal for classification accuracy with the existing dataset.

2) Gaussian Mixture Model: From the trials, 50 training datapoints per class were chosen randomly and the remaining were designated as test data. The training data was used to train a Gaussian Mixture Model (GMM) with 3 mixtures. The GMM is obtained through an Expectation-Maximization Algorithm. The means, covariances and mixing proportions of the Gaussians are randomly initialized. In the Expectation step, these parameters are used to classify the training data into clusters. In the Maximization step, the classified clusters are used to recalculate the means, covariances and mixing proportions of the GMM. These two steps are repeated until the clusters stabilize. The test data is then classified using this GMM as shown in Fig. 3.

D. Adaptive Classification

Algorithm Adaptive Classification Pseudocode

```
procedure ADAPTIVE CLASSIFICATION
    numClusters ← initial number of classes
    numTrain ← number of training datapoints
    outlierProp ← proportion to increment numClusters
    numOutlier ← ∞
    outlThresh ← probability threshold to be outlier
    while numOutlier ≥ (numTrain ∗ outlierProp) do
        gmModel ← gmm(trainingData,numClusters)
        trainProbs ← max(pdf(trainData,gmModel))
        numOutlier ← sum(trainProbs ≤ outThresh)
        numCluster ← numCluster + 1
```

The Adaptive Classification Algorithm describes the adaptive process of finding the appropriate number of clusters

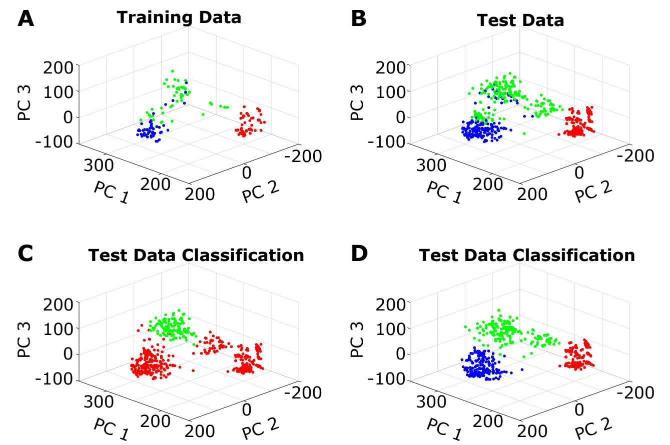

Fig. 3. (A) The training data used to train the GMM with the colors corresponding to the true texture labels of the trial (the GMM is unaware of the labels when being trained). (B) The test data that was classified by the GMM with the colors corresponding to the true texture labels of the trial. (C) The classification of the test data by the GMM into only 2 clusters with the colors corresponding to the classified cluster. (D) The classification of the test data by the GMM into 3 clusters with the colors corresponding to the classified cluster. Note that for (C) and (D) the original texture labels do not necessarily correspond directly to the cluster labels but that approximately the same clusters emerge unsupervised.

(corresponding to textures) that is captured by the training data. The training data is used to create a GMM with the current number of expected classes. For each datapoint in the training set, the probability of that datapoint is calculated for each Gaussian in the mixture using the multivariate normal probability density function (pdf). If none of the calculated probabilities for that datapoint are greater than *outThresh*, then that datapoint is considered an outlier. *outThresh* is the threshold probability to classify outliers. If the number of outliers is larger than the number of training datapoints multiplied by *outlierProp*, then the algorithm predicts that there is another texture that is not being modeled and the number of clusters is incremented. *outlierProp* is a scalar between 0 and 1 that determines the proportion of the training data that needs to be an outlier in order to add a new cluster. This process is repeated until there are fewer outliers than the number of training points multiplied by *outlierProp*. The values of *numClusters*, *numTrain*, *outlierProp* and *outThresh* used were 2, 150 (50 per texture), $1/6$ and 2.5×10^{-7} respectively.

III. RESULTS AND DISCUSSION

The neuromorphic encoding scheme, unsupervised learning GMM and the Adaptive Classification Algorithm were applied to the data 100 times and the results were averaged. The GMM was initially trained to find 2 clusters, but the algorithm identified that there was a 3rd texture class and retrained the GMM with 3 clusters. The confusion matrix is shown in Fig. 4 with an overall classification accuracy of 86.46%.

Overall, this work indicates that neuromorphic encoding of tactile information can serve as the basis for unsupervised classification of textures. Using a multilayer tactile sensor and the Izhikevich neuron spiking model allowed for a neuromorphic approach: translation of force into natural SA and RA mechanoreceptor spiking activity, mimicing behavior in

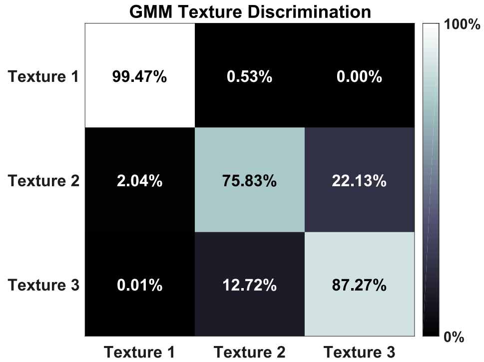

Fig. 4. The overall confusion matrix after running the encoding and classification algorithm 100 times and averaging the results. This represents an overall classification accuracy of 86.46%.

glabrous human skin (Figs. 1 and 2). In contrast to previous work in which the derivative of the force measurement was input into the RA mechanoreceptor model [10], in this work, the RA model was computed directly upon the original taxel output and responded to the rising edge of the force, more closely mimicing biology.

Even after reducing the entire spiking waveform from each taxel into two metrics and then further reducing the data from the 18 taxels into 3 principal components, there was enough separability in the training data to create a GMM that successfully clustered the data with 86.46% (sd=5.44%) overall accuracy as shown in Figs. 3 and 4. The flat texture (Texture 1) was nearly perfectly discriminated (99.47%) with the horizontal grating and hemisphere textures (Textures 2 and 3) averaging to about 80% accuracy. Using more principal components can potentially improve the classification accuracy, but with this dataset the accuracy actually worsened with more principal components. This is probably because the dataset is small (664 trials between 3 textures) and with higher dimensional representation the training data is not sufficient to capture the shape of the clusters when training the GMM. Larger datasets potentially can allow for more sophisticated and accurate classification.

This work demonstrated the potential to learn new textures as they are encountered dynamically using the Adaptive Classification Algorithm. This is important as the dynamic texture identification can be used to actively modify the neuromorphic encoding (for instance, after classification, use the encoding corresponding to the median datapoint of the cluster) to improve the texture discrimination of the user. The algorithm correctly transitioned from a GMM with 2 clusters to a GMM with 3 clusters by calculating the number of outliers based on a probability threshold which was determined manually and can be used to add successively more clusters. In this case, the training dataset had a fixed number of trials and therefore the number of outliers to trigger an increase in the number of clusters was fixed but the parameter *outlierProp* allows for this transition point to scale with the number of training points as they arrive dynamically.

IV. Conclusion

We showed how unsupervised learning and neuromorphic encoding of tactile sensor measurements can adaptively classify textures during active touch sensing. To further verify and expand the utility of these methods, larger datasets with a wider variety of textures should be collected to demonstrate the ability to discriminate more classes of tactile sensation which would potentially be encountered in everyday life. The feature resolution and sensitivity of the tactile sensor and neuromorphic encoding scheme should be explored to understand the limits of texture discrimination and to suggest new improvements for future tactile sensing systems. Potentially, the classification accuracy can be increased by creating new metrics to summarize the spiking activity of the taxel which will further separate the texture classes for clustering. Finally, methods to automatically calculate the probability threshold to determine outlier datapoints in the training set should be developed to more autonomously determine the number of relevant textures to classify. Altogether, these directions will enable future tactile sensing systems to adaptively learn new textures while also providing neuromorphic feedback to users for active touch sensing.

Acknowledgment

This research was funded by the Johns Hopkins Space Consortium through the Space@Hopkins funding initiative and by the Neuroengineering Training Initiavitive through the National Institutes of Health grant T32EB003383.

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