Introduction: SA-I mechanoreceptive afferent endings embedded in the skin of fingertips are particularly sensitive to spatial details for example: edges, corners and different radii of curvature [1]. A Biomimetic tactile sensor, called BioTac®, has been designed to provide most of sensing modalities on the human fingertips including tri-axial force vectors detected by changes in conductance between electrodes as fluid pathways deform, slip-related micro-vibration which propagate through the skin and fluid, and thermal properties as detected by a thermistor capable of detecting heat flow between the preheated rigid core and contacted objects (Fig. 1). This study discusses using the conductance signals from the BioTac electrode array to extract object's spatial feature. A probabilistic sensory model and state estimation method is applied, which are Gaussian Mixture Model and Bayesian filter, respectively.

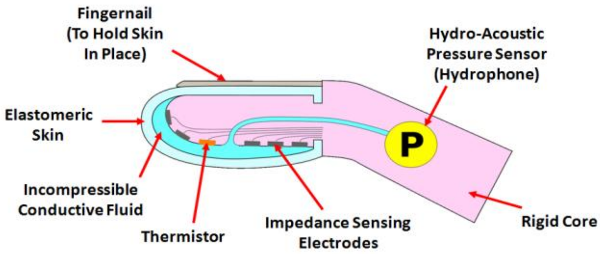

Figure 1: Schematic diagram of the BioTac.

Method: Similar as human fingers, the most sensitive region of the BioTac sensors is the figure tip, which has a cluster of four electrodes (E7, E8, E9, and E10 in Fig. 2). It is used to characterize the spatial features from the contacted objects, including edge, corners, flat surface, sphere and sharp probes. We have first collected different patterns of conductance changes on the electrode array to differentiate these different patterns of spatial features. Then, we apply a Gaussians Mixture Model to model the probability of conductance pattern based on known spatial features: P(V|States), where V represents conductance pattern and States (Edge, Corner, Flat, Sphere and Sharp) [2]. Given initial probability of spatial features, P(States) are equally distributed, the probability of each state conditioned on new conductance pattern is estimated by Bayesian filter: $\mathrm{P}(\mathrm{States}|\mathrm{V}') = \mathrm{P}(\mathrm{V}'|\mathrm{States})\,\mathrm{P}(\mathrm{States})/\mathrm{P}(\mathrm{V}')$, where V' is the new conductance pattern.

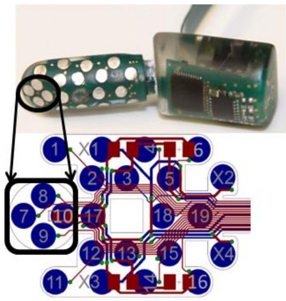

Figure 2: Electrode array for spatial coding.

Results: A large testing set of each spatial feature is designed, including 573 samples for edge, 901 samples for corner, 835 samples for flat surface, 790 samples for sphere probe, and 769 samples for sharp probe. 3-D bar graph of the detection confusion matrix is presented in Figure 3. The designed algorithm performs well when the BioTac is applied to detect corner and sphere curve. The results show that an edge tends to be confused with a corner under low load forces, similar results hold on the test for the flat surface and sphere curve. Since the contacts are manually controlled, the point of contact cannot be accurately controlled which could cause the confusion of a sharp probe with a sphere.

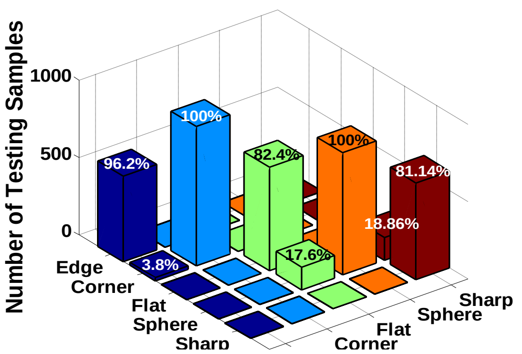

Figure 3. 3-D bar graph of detection confusion matrix.

Conclusion: The preliminary results show that this designed algorithm can differentiate curves, corners, and different radii of curvature for known point of contact. This algorithm will be generalized to train Gaussian mixture models for multiple point of contact. Then, this algorithm will identify the point of contact, and then select the Gaussian mixture model of spatial feature corresponding to that particular point of contact.

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[1] J. R. Philips and K. O. Johnson, *J. of Neurophysiology*, 46, 1192-2003, 1981.

[2] G. MaLachlan and D. Peel, *Wiley*, 2000.

Spatial Features Extraction Using a Biomimetic Tactile Sensor and Implementation in LabVIEW

Z. Su, Y. Li and G. E. Loeb
Department of Biomedical Engineering, USC, Los Angeles, CA, zhesu@usc.edu

Abstract:
A biomimetic tactile sensor, called BioTac® has been developed to mimic most tactile sensing modalities of the human fingertips including localized deformation, force, micro-vibration and thermal flux. This paper discusses a method for extracting spatial features from the impedance signals on the sensor using a probabilistic sensory model: Gaussian mixture model. We also implement this method into a graphic user interface (GUI) in LabVIEW. A real-time demonstration of this method will be present during the poster session of Grodins Symposium.

Introduction:
Human's sense of touch is rich in the amount of information it can acquire simultaneously. Unlike vision, haptic sensing can extract information about many attributes of an object: shape, mass, volume, rigidity, texture, and temperature etc. A variety of technologies have been used in tactile sensors, but commercially available tactile sensors tend to be limited to relatively coarse arrays of normal force sensors based on compression of elastic materials. In fact, most of the commercially available robotic and prosthetic hands are not supplied with any tactile sensing.

Many technologies are difficult to apply to the curved, deformable "skin" that facilitates grip and few are able to resist damage in the electromechanically hostile environments in which hands are often used (moisture, grit, sharp edges, etc). One promising new candidate is the BioTac, a biomimetically designed, multimodal array that provides most of the dynamic range of human tactile sensing for location, magnitude and vector direction of contact forces, micro-vibrations associated with slip and textures, and thermal flux resulting from contact with objects that differ in thermal effusivity (Figure.1), [1, 2, 3].

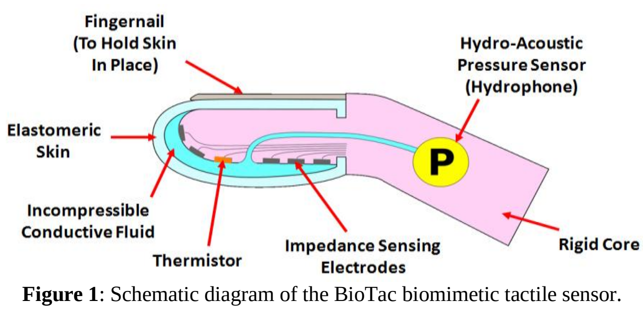

Figure 1: Schematic diagram of the BioTac biomimetic tactile sensor.

The mechanism of implementing these sensing modalities are: measurement of normal and shear forces detected by changes in impedance between electrodes as fluid pathways deform, detection of slip-related micro-vibration which propagate through the skin and slued and are detected by the hydro-acoustic pressure sensor, and thermal properties as detected by a thermistor capable of detecting heat flow between the preheated core and contacted objects.

Phillips and Johnson [4] showed that SA-I mechanoreceptors embedded in the skin of fingertips are particularly sensitive to spatial details for example: points edges, corners and different radii of curvature. Psychological experiments also show that human are able to differentiate several forms of spatial pattern independent of contact force [5]. To replicate this dedicated spatial feature extraction scheme, we developed a novel algorithm to facilitate spatial features differentiation on a BioTac sensor. These spatial features include edges, corners, and radii of curvatures. We implement this algorithm in a LabVIEW program and showcase the discrimination results in a graphic user interface (GUI).

Method:

We have found that Gaussian mixture model and regression is the most effective at extracting three dimensional force vectors [3]. In this paper, we characterize spatial features including edges, corners and different radii of curvatures using Gaussian mixture model.

To model our sensor, we have collected different patterns of impedance changes on the electrodes array of the tactile sensor corresponding to different spatial features including edges, corners and radii of curvatures. Just like human fingers, the most sensitive region of our tactile sensors is located on the tip which has a cluster of four electrodes. We used the impedance signals from this cluster of four electrodes (E7, E8, E9, and E10) (Fig. 2) to characterize the spatial features from contacted object.

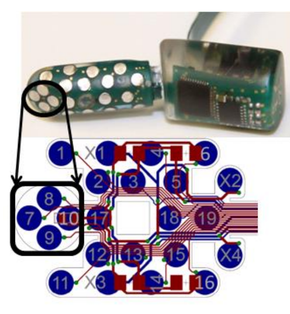

Figure 2: Stimulation pattern of spatial coding on the human fingertip.

Probabilistic sensory model: Gaussian mixture model

A training data set with samples N and dimensionality D (number of electrodes), $\{\xi_j = \xi_{V,j}, \xi_{S,j}\}_{j=1}^{N}$, ($\xi_{V,j}$: impedance signals, $\xi_{S,j}$: States) can be modeled by a mixture of Gaussian distributions (mixture of Gaussian distributions is also called mixture of K-components) [6]:

$$p\left(\xi_j\right) = \sum_{k=1}^{K} \pi_k \mathrm{N}\left(\xi_j;\ \mu_k, \Sigma_k\right) \qquad (7)$$
$$= \frac{1}{\sqrt{(2\pi)^D |\Sigma_k|}} e^{-\frac{1}{2}((\xi_j-\mu_k)^T \Sigma_k{}^{-1}(\xi_j-\mu_k))}$$

where $\{\pi_k, \mu_k, \Sigma_k\}$ are the prior probability, mean, and covariance matrix of the Gaussian mixture component k. Expectation-Maximization (EM) algorithm is applied to estimate the $\{\pi_k, \mu_k, \Sigma_k\}$ by optimizing the maximum likelihood. K-means clustering is used to set the initial estimation of $\{\pi_k, \mu_k, \Sigma_k\}$.

After we model spatial features (edges, corners and radii of curvatures of probes) with a mixture of Gaussians, we apply a Bayes filter framework to estimate the states of tactile sensor, (Fig. 3).

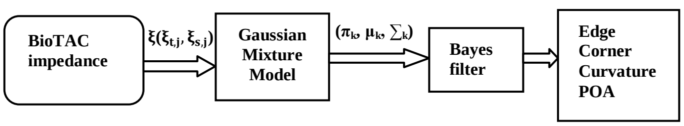

Figure 3: Schematic of information flow during state estimation.

Results:

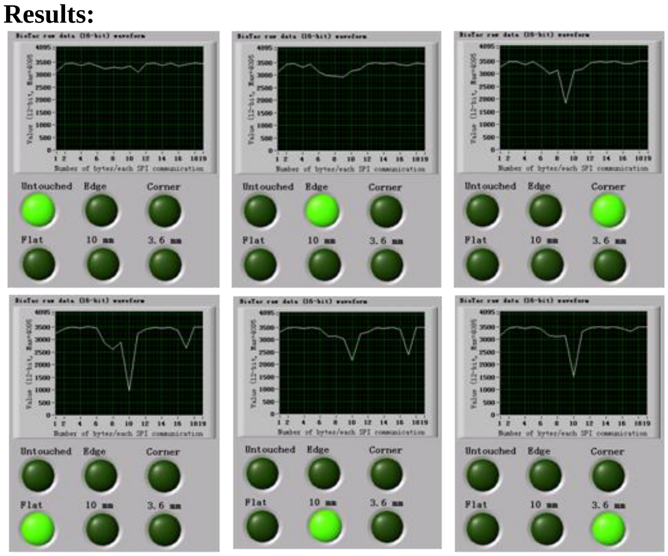

Figure 4: Graphic User Interface in LabVIEW, the curve above shows the impedance pattern on the electrode array corresponding to each spatial features, the indicators below show the estimated spatial details.

We implement our spatial features extraction algorithm into a graphic user interface in a LabVIEW program. First, the program estimates the point of application on a tactile sensor. By differentiate the point of application, the program decides the corresponding Gaussian mixture model to estimate the edge, corner, or radii of curvature. The predicted states are showed by lighting up the indictors on the screen, (Fig. 4).

Discussion:

The major limit of these methods is using static signal to make the prediction of edge, corner or radius of curvature; however, human and primates are able to perceive the spatial details of the objects by sensing the dynamic signals from the mechanoreceptors. Thus, our future work will involve developing algorithm which can discriminate the spatial features by using dynamic signals.

Inspired by several robotic mapping and localization papers [10, 11], we will implement mapping algorithm for point of application estimation to build a 2-D coordinate fingerprint frame. Impedance patterns from a tactile sensor will be collected for each point in this 2-D coordinate fingerprint frame when a tactile sensor is contacted with different spatial features. We will generate one Gaussian mixture model for each spatial feature and one Gaussian mixture model for three-dimensional force vectors at each point of application in the 2-D fingerprint frame.

A systematic feature extraction algorithm will be developed for the BioTac. First, this algorithm needs to identify the point of contact using Gaussian mixture model for point of contact. Then, it will locate the Gaussian mixture models of spatial feature and three-dimensional force corresponding to that particular point of contact. At last, it will differentiate the spatial features using Bayes filter and predict the three-dimensional force using Gaussian mixture regression.

References:

[1] N. Wettels, V. J. Santos, R. S. Johansson and G. E. Loeb, "Biomimetic Tactile Sensor Array," *Advanced Robotics*, 22(7), 829-849, 2008.

[2] C. H. Lin, T. W. Erickson, J. A. Fishel, N. Wettels, G. E. Loeb, "Signal Processing and Fabrication of a Biomimetic Tactile Sensor Array with Thermal, Force and Microvibration Modalities," *IEEE Intl Conf on Robotics and Biomimetics*, 2009.

[3] N. Wettels, J.A. Fishel, Z. Su, C.H. Lin, G.E. Loeb, "Multi-modal Synergistic Tactile Sensing," *IEEE International Conference on Humanoid Robots*, 2009.

[4] Philips, J. R., Johnson, K. O., "Tactile spatial resolution: II. Neural representation of bars, edges, and gratings in monkey primary afferents," *Journal of Neurophysiology*, 46, 1192-2003, 1981.

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[8] S. Thrun, D. Fox, and W. Burgard. "A probabilistic approach to concurrent mapping and localization for mobile robots," *Machine Learning*, 31:29-53, 1998.

Spatial Feature Extraction for a Biomimetic Tactile Sensor

Zhe Su, Chia_Hsien Lin, Yao Li, Gerald E. Loeb

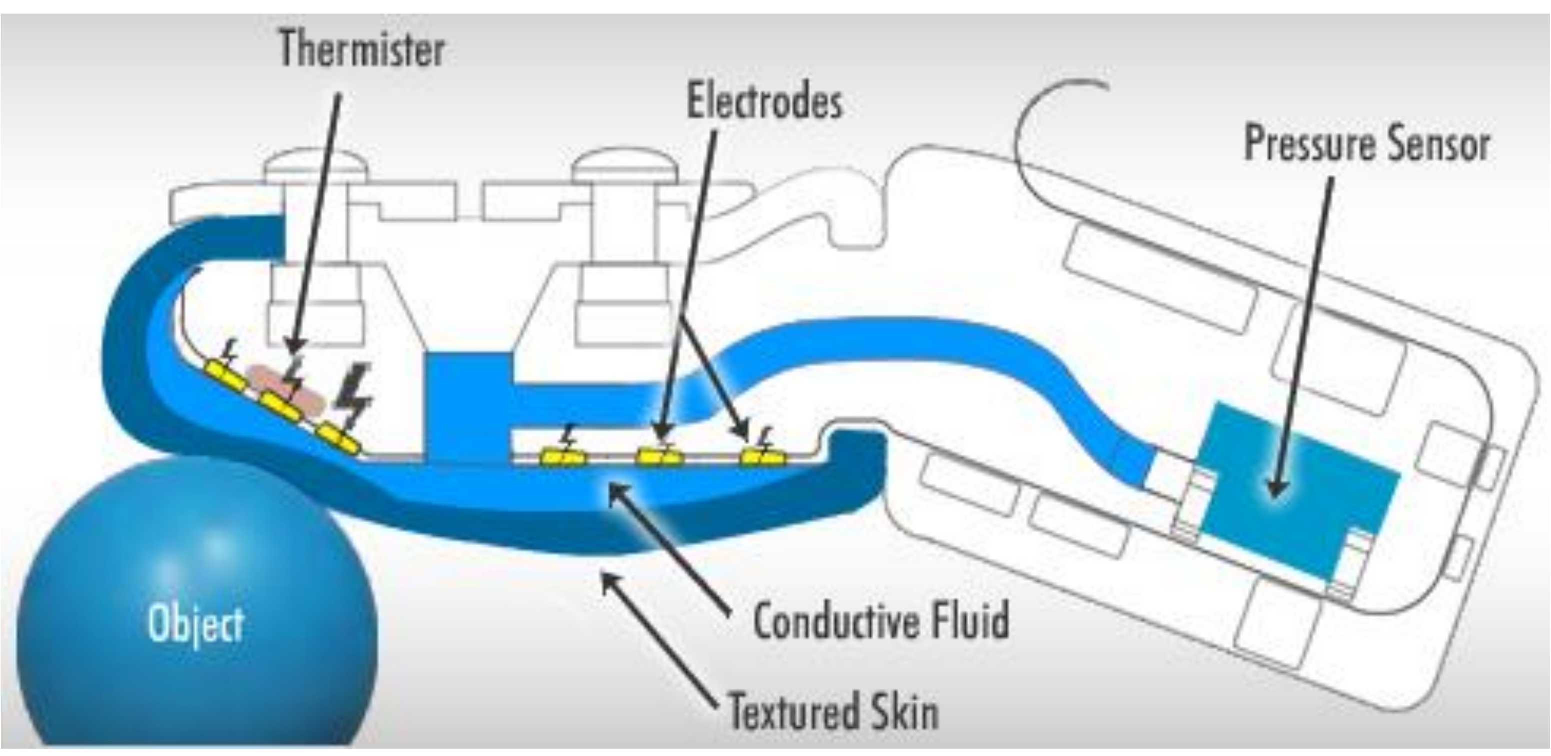
Department of Biomedical Engineering, USC, Los Angeles, CA

USC VITERBI SCHOOL OF ENGINEERING

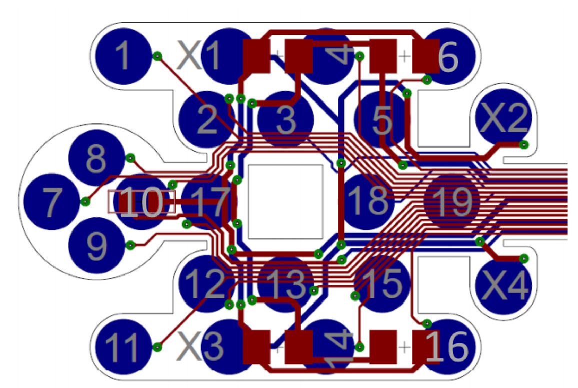
Introduction

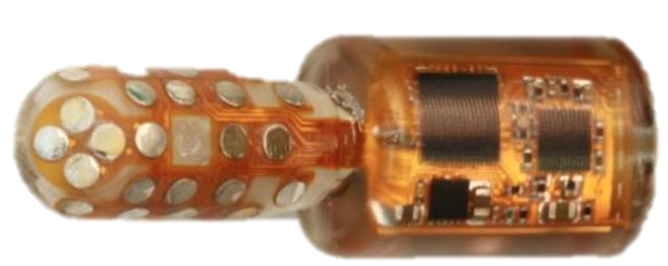
Objects can be identified by tactile shape.

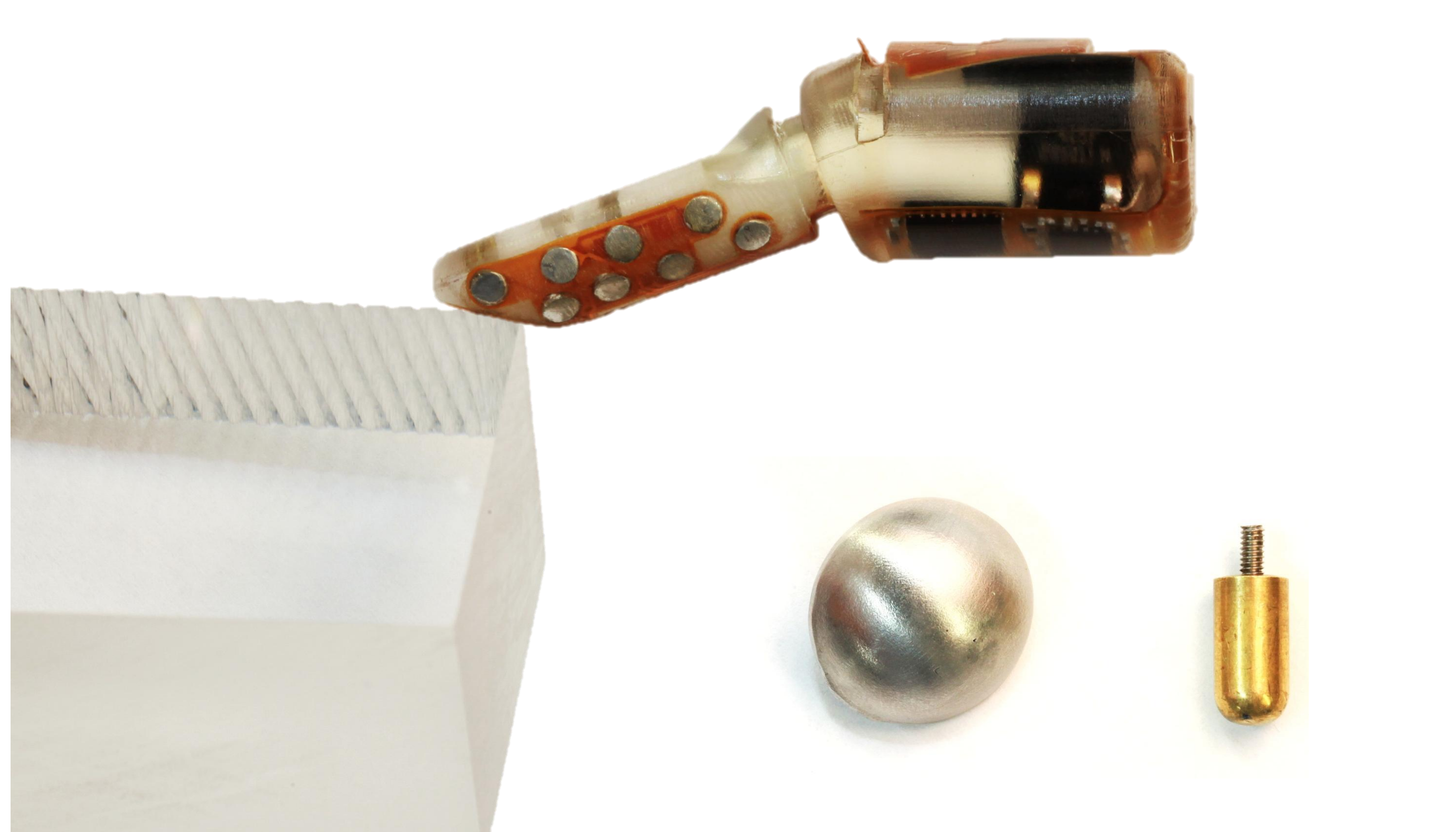
We designed an algorithm to estimate edge, corner and radius of curvature using a biomimetic tactile sensor, called BioTac®.



Contact with an object deforms the skin and the fluid path, changing the conductance of electrodes arranged on the surface of the core.

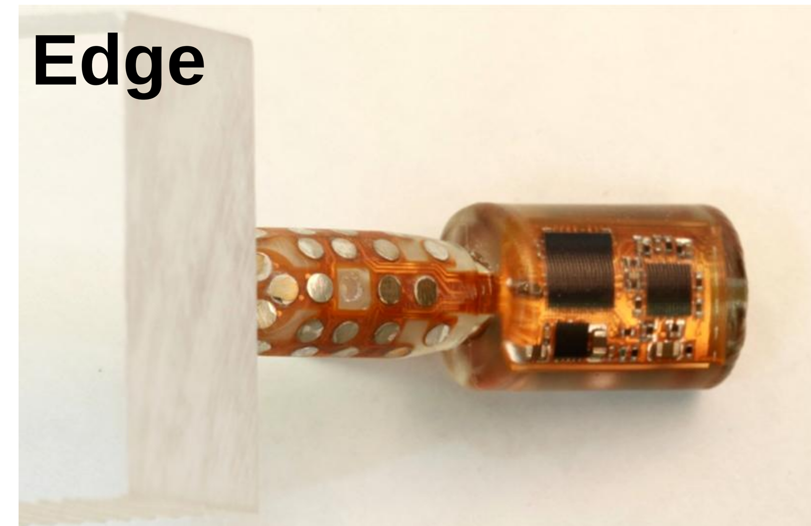


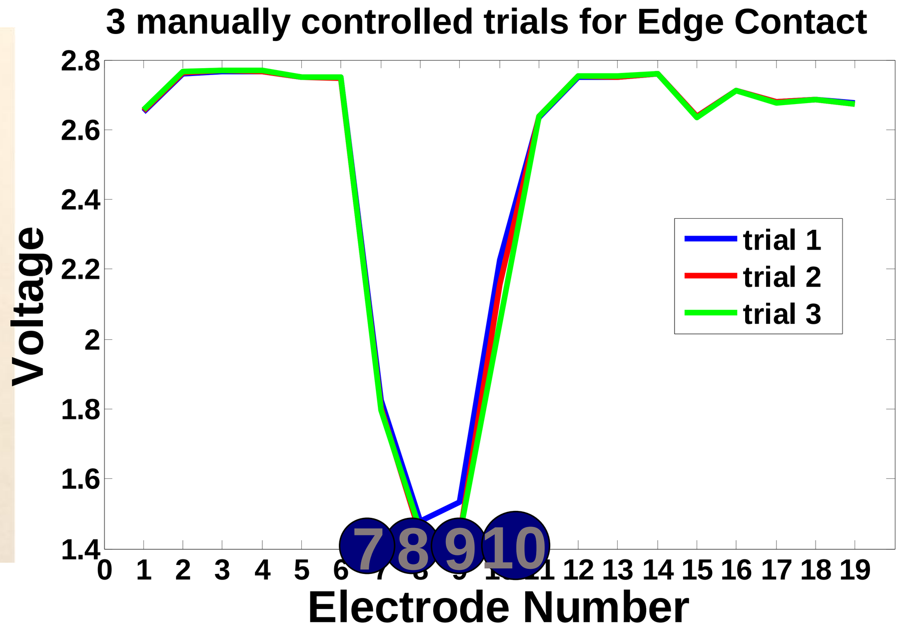




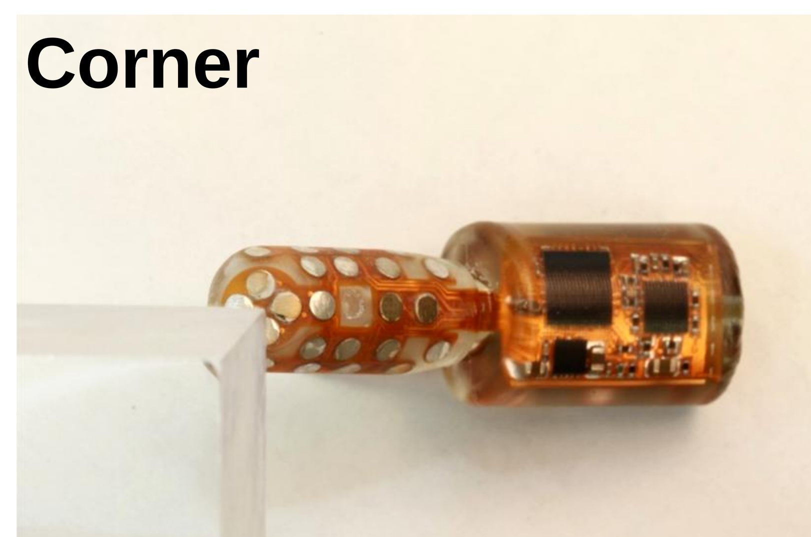
Experimental Methods / Training Database

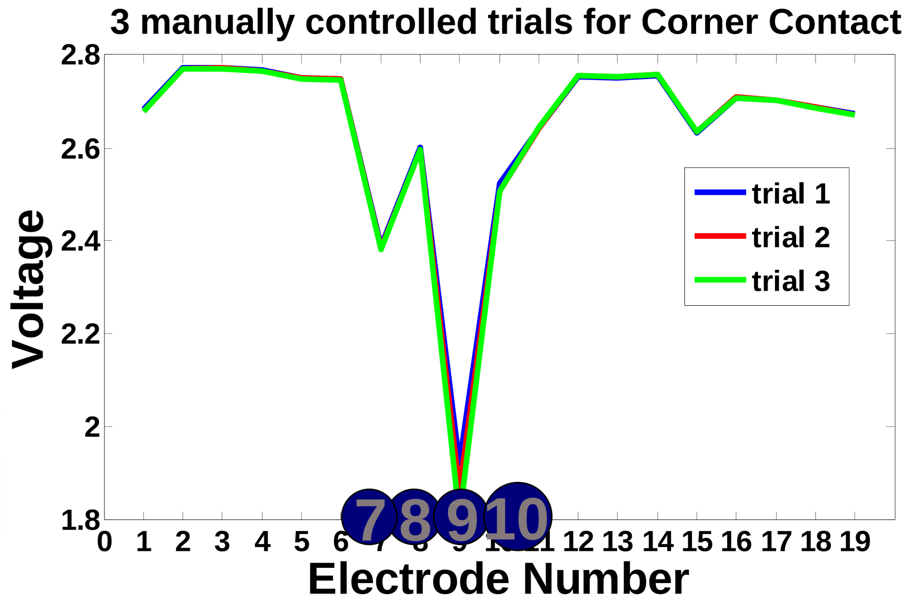
Edge



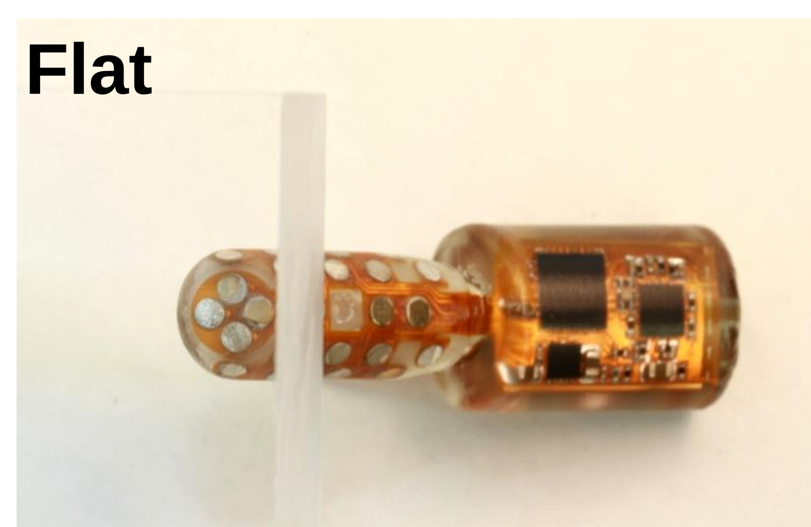


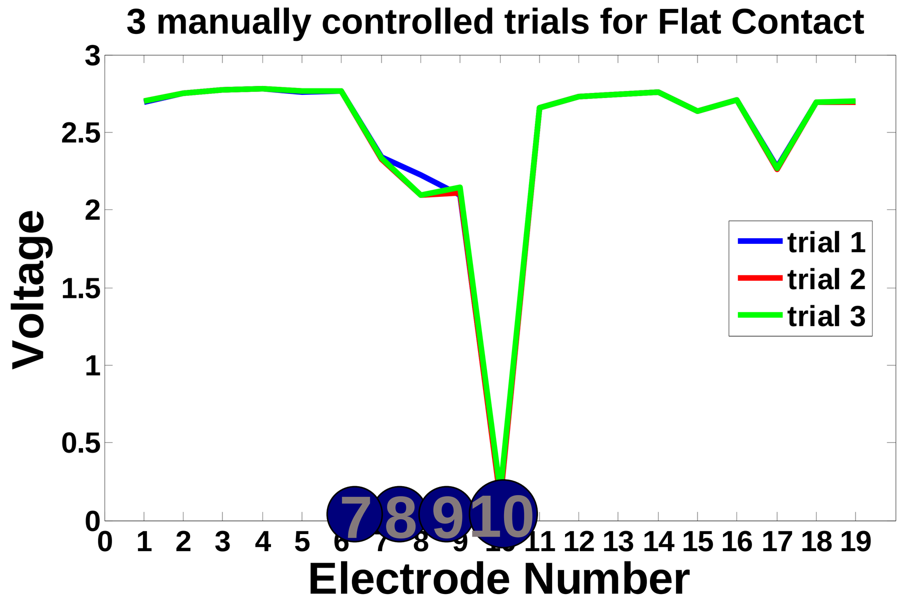
Corner



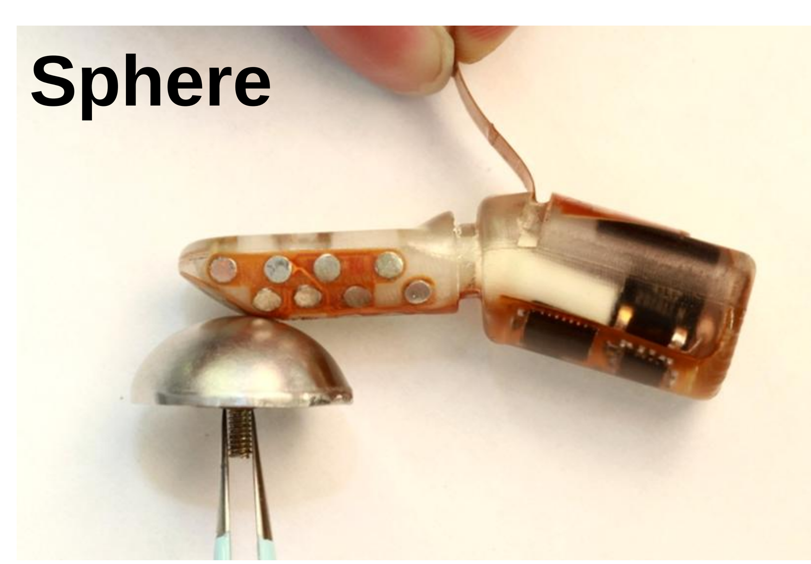


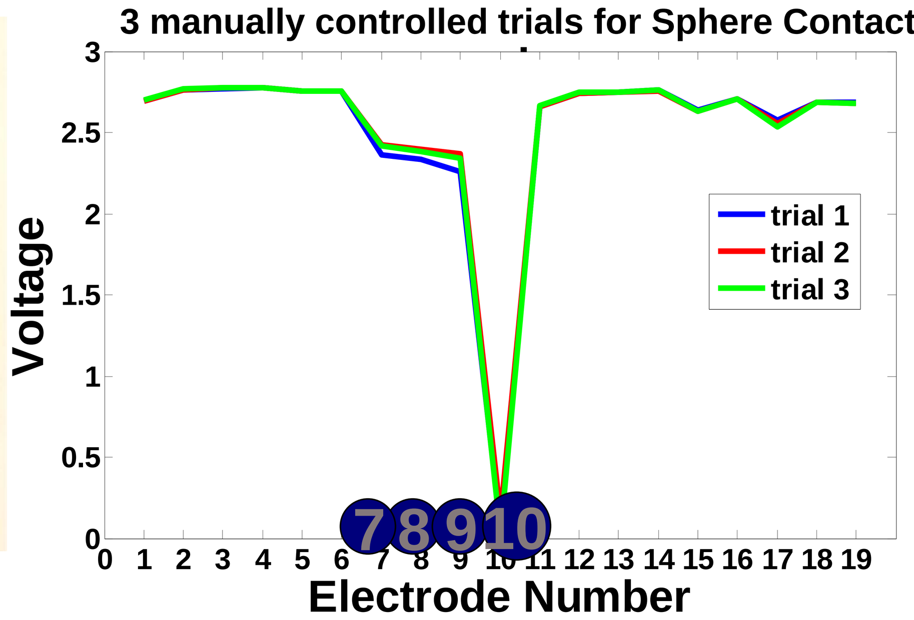
Flat



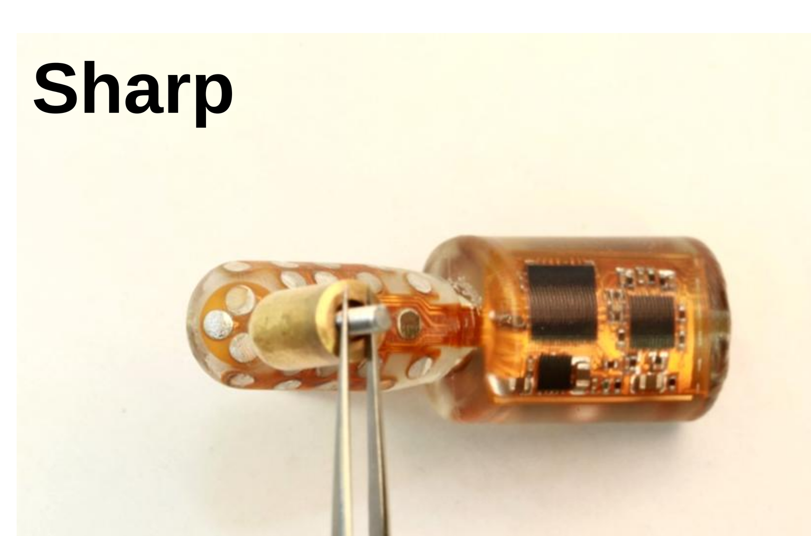


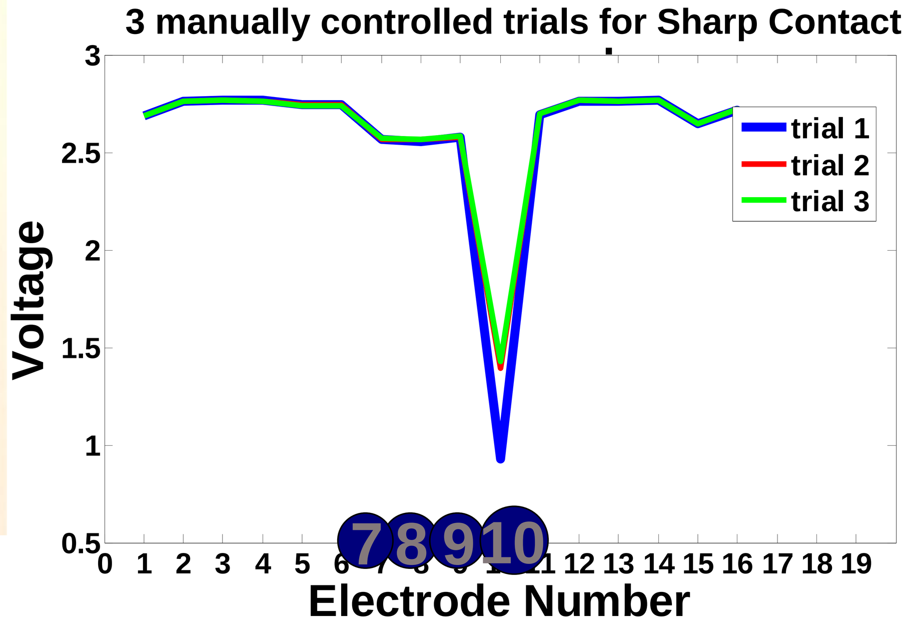
Sphere



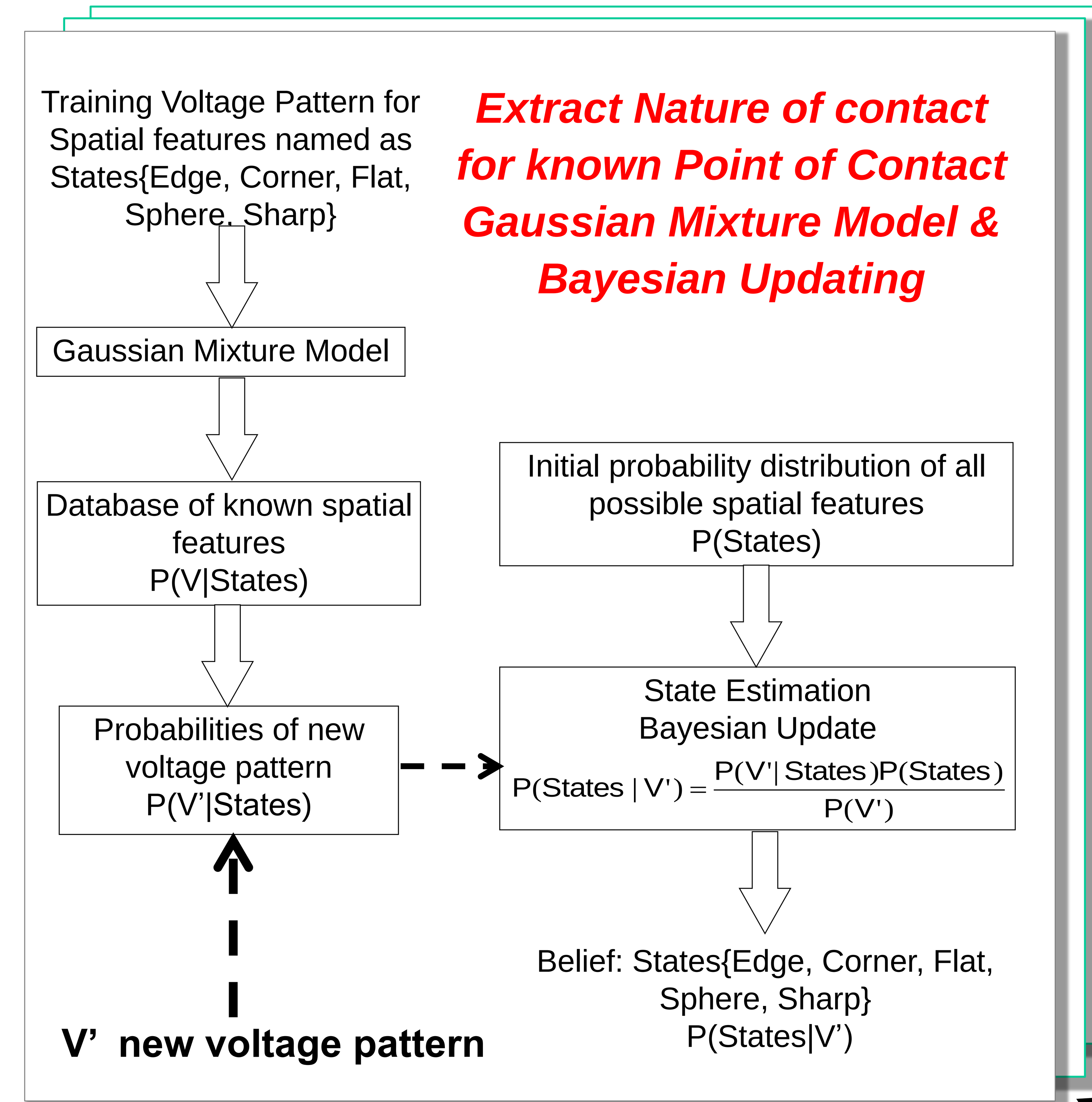


Sharp





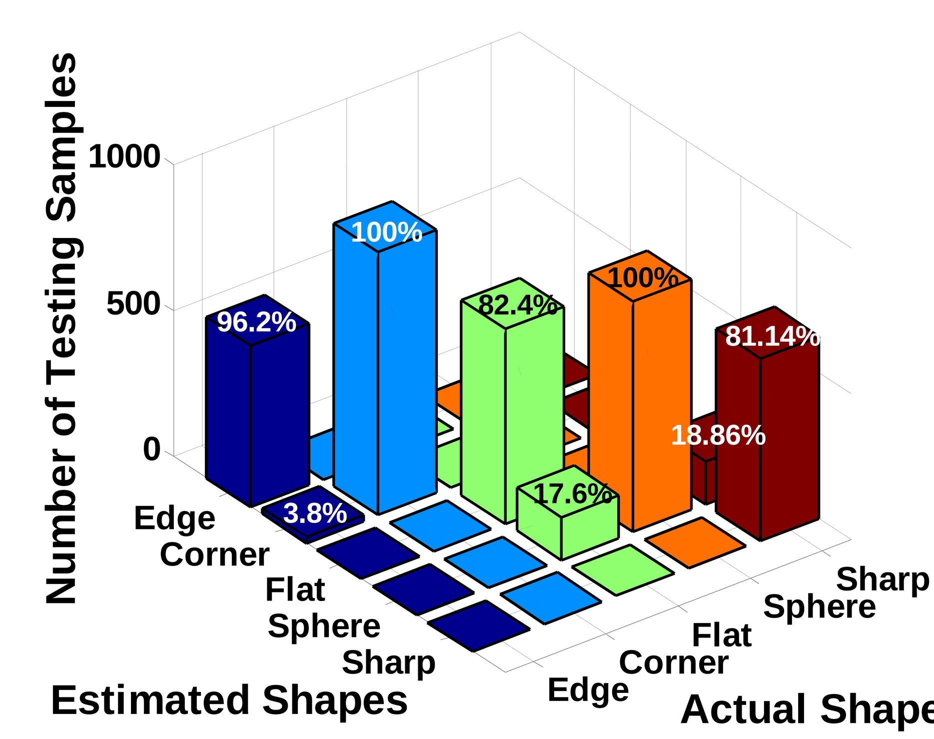
Classification Algorithm



Train for Multiple Point of Contact (POC)

Select Estimator for Each POC

Results



Future work

Expand to multiple point of contact

Facilitate robots to learn exploratory movement (contour following)

Apply Bayesian decision rule to recognize and classify objects