TACTILE GRAPHS FOR GRASP STABILITY PREDICTION

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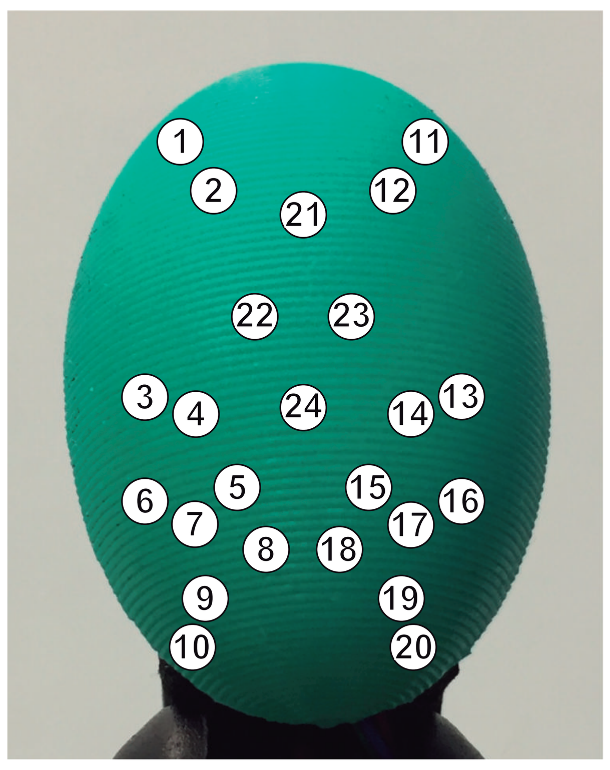
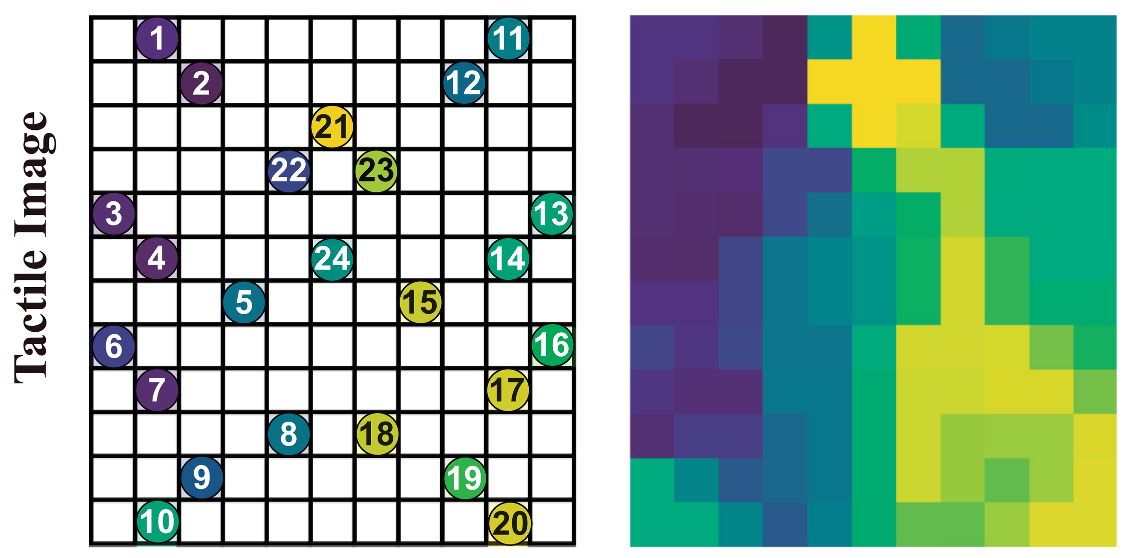
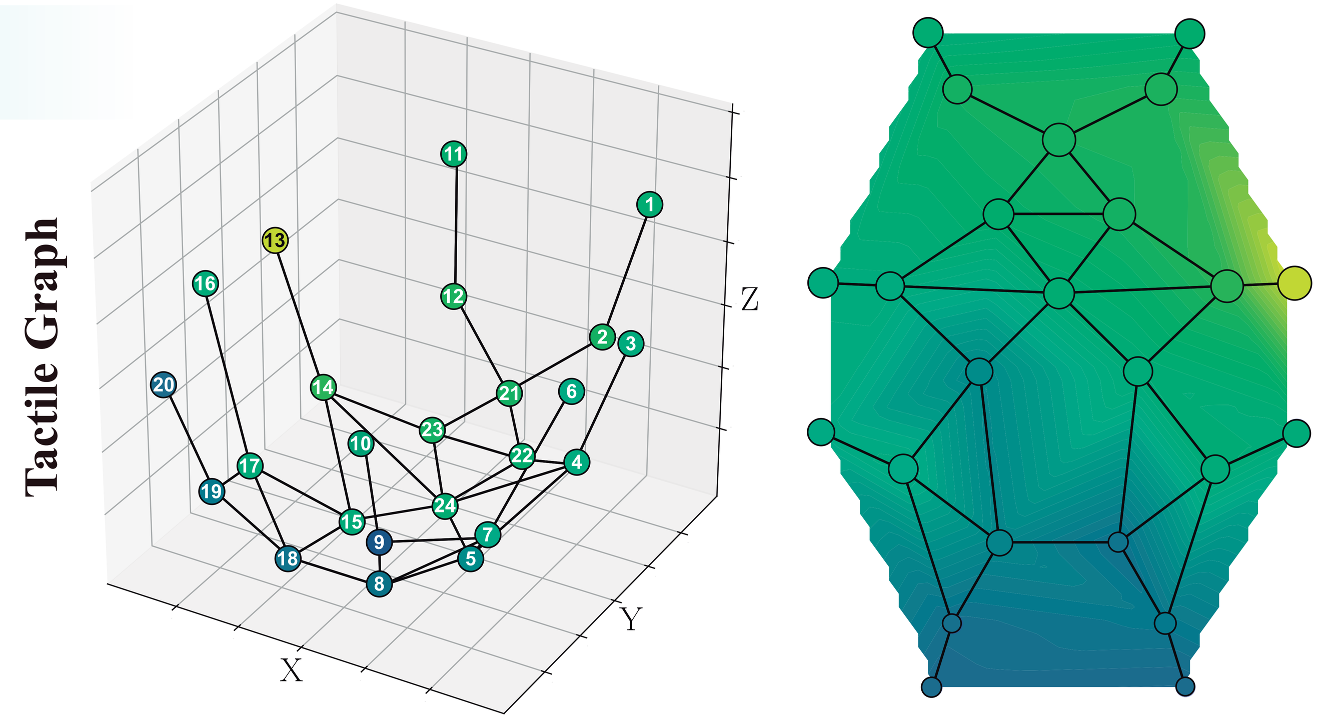
1 Problem Statement



BioTac SP tactile sensor

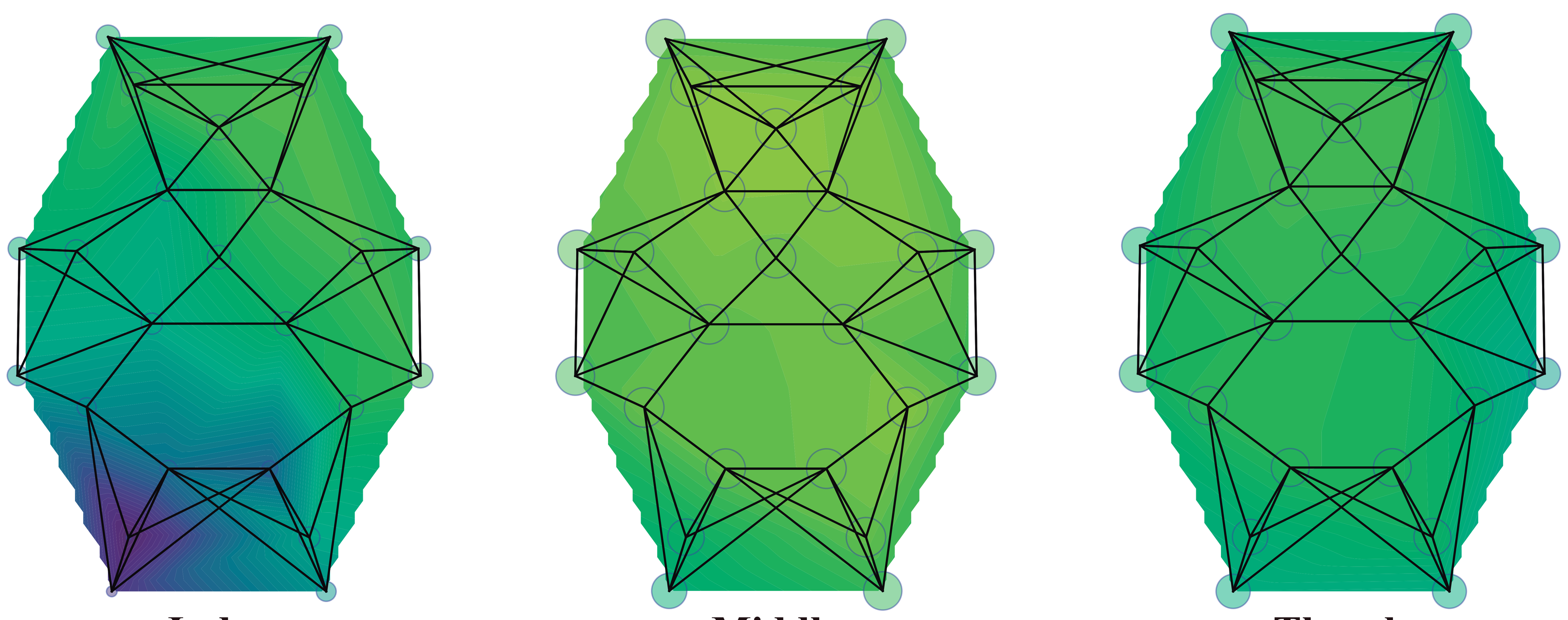




Robotic **tactile sensors** provide useful data for **predicting the stability of grasps**. That is, it is possible to predict whether a grasp will be stable before lifting the object using tactile perception. Previous works extracted the values from the taxels (sensing points) and calculated **custom features**. Modern approaches, re-interpret tactile data as **tactile images**. In this work, we explore the possibilities of **graph-like representations** which preserve the actual spatial arrangement of the sensor.

2 Methodology

We installed on a Shadow Dexterous hand **three BioTac SP tactile sensors** (index, middle and thumb). Our proposal consists on generating graphs `G = (N, E, Y)`, where `N` is a set of 24 nodes, `E` is a set of edges and `Y` is the label of the graph (`stable` or `unstable`). Each node `n` is characterized by the 3D position p_n `= (x, y, z)` of the sensing point inside of the real sensor and a feature vector $f_n = (f_{n0}, f_{n1}, f_{n2})$, where f_{ni} is the value of the `n-th` taxel on the `i-th` finger, being index f_{n0}, middle f_{n1} and thumb f_{n2}. Edges are generated following two approaches: **manual** or using the **k-Nearest Neighbours** (kNN). Graph on Section 1 displays manual connections. See below three graphs generated with `k = 4`.



Index Middle Thumb

	Training Set		Test Set	
Configuration	**Stable**	**Slippery**	**Stable**	**Slippery**
Palm Down	667	609	153	163
Palm Side	603	670	157	165
Palm 45º	1058	1075	250	261

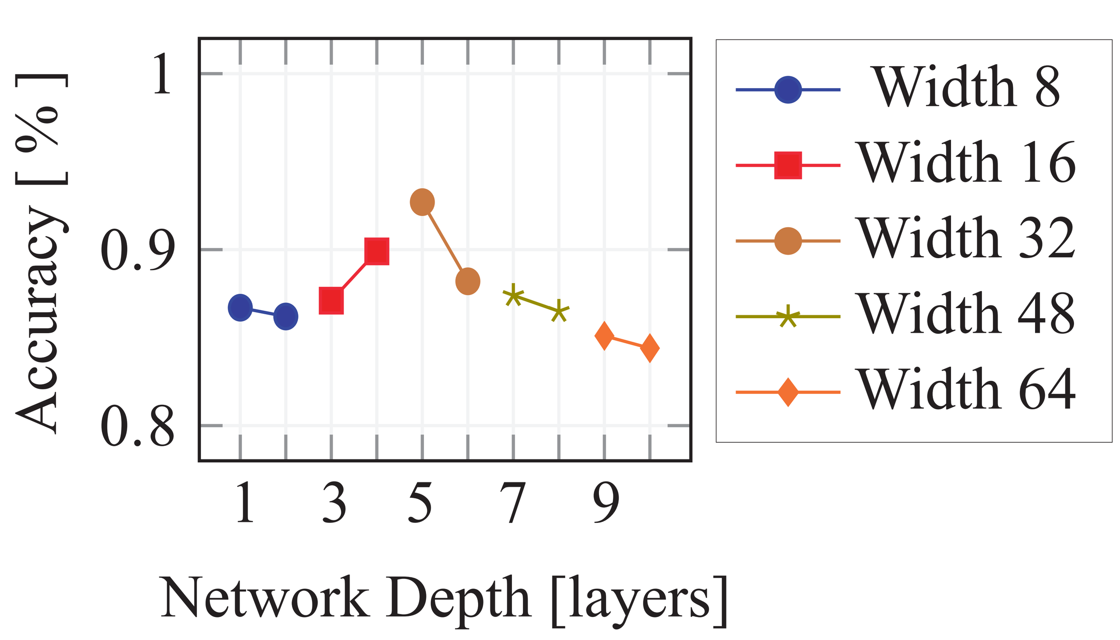
We trained **Graph Convolutional Networks (GCNs)** for testing our graphs. Besides, a **dataset of grasps** with three orientations was recorded, freely available at: `https://github.com/3dperceptionlab/biotacsp-stability-set-v2`

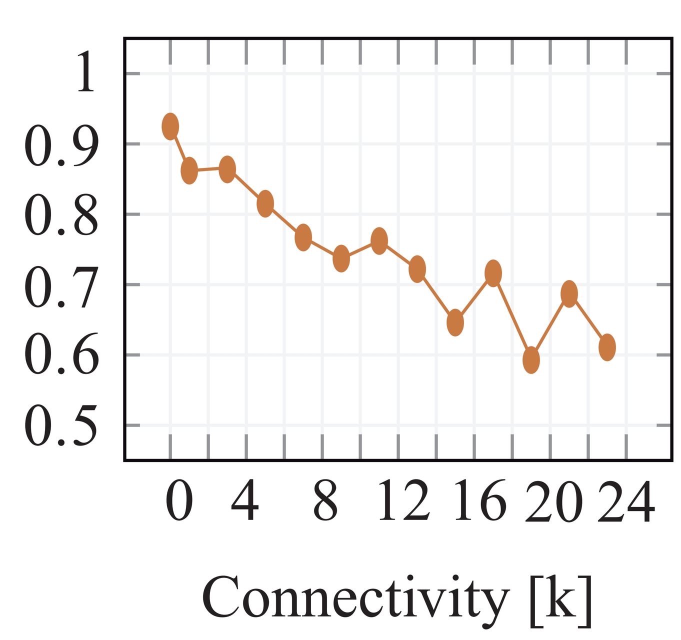
Training Set

Testing Set

3 Results

We investigated the impact of **network depth** (convolution layers) and **width** (amount of features per layer). To that end, we have tested **ten different models** ranging from one to ten **`GCNConv`** layers with increasing number of features (8, 16, 32, 48, 64). Rectified Linear Unit (ReLU) activations were used after each convolutional layer. Two fully connected layers were also placed at the end of the network (with 128 and 2 output features respectively) to produce the classification result. For this experiment, we used the manually defined graph connections (`k = 0`). In addition, we also compared the **manually specified edges** (`k = 0`) and the **k-NN strategy** with `k = [1, 23]`. Implementation of these architectures is open sourced at `https://github.com/3dperceptionlab/tactile-gcn`





	Accuracy		Precision		Recall		F1	
Test Set	**GCN**	**CNN**	**GCN**	**CNN**	**GCN**	**CNN**	**GCN**	**CNN**
Palm Down	0.741	0.829	0.741	0.936	0.751	0.717	0.745	0.812
Palm Side	0.751	0.708	0.785	0.858	0.709	0.515	0.745	0.643
Palm 45º	0.774	0.763	0.774	0.860	0.783	0.639	0.778	0.734

In order to prove the **generalization capabilities** of our system, we trained our best GCN (5 layers whose widths were `8-8-16-16-32` and `k = 0`) with our training set and evaluated it on the test sets. We carried out the same test with a **baseline CNN** (1 layer with 32 filters and a fully connected layer) but trained with tactile images.

4 Future Works

- **Decouple the GCN** so that each finger is processed as a different graph.
- Model the sensor's noise for **data augmentation**.
- Extend tactile graphs for approaching **temporal sequences** (i.e. direction of slip detection).

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