Tactile Sensor System Processing Based On K-means Clustering

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***Abstract*—Development of a touch-sensitive (sensate) skin for robotic manipulators would provide tactile feedback for fine-grained dexterous control of robots interacting with objects in their environments, a capability that has largely been missing with robotic systems developed to date. A sensate skin for robots would require integration of hundreds or thousands of minute force or pressure sensors, each producing a localized response. Interpretation and extraction of useful information from the sensate skin presents a key technical challenge. In this paper we present a technique for analyzing data from tactile sensor arrays based on K-means clustering. Using a simplified contact model, the procedure estimates both magnitude and location for impacts on the sensate skin surface. Furthermore, it robustly accommodates a variety of sensor array densities by interpolating across areas of sensor response, providing accurate results even between sensing elements.**

I. Introduction

In designing a touch-sensitive skin for a robotic manipulator, we would like to interpret the signals from an array of tactile sensors embedded within an artificial skin (not including finger-tips or hand areas). Given that the robotic manipulator physically interacts with an object, person, another robot, or itself within its operating environment, based upon sensor feedback we would like to determine the location of the contact on the skin resulting from the interaction, and the force magnitude of the contact. In this paper we present a new approach for processing data from a tactile sensor matrix based on K-means clustering.

The paper is organized as follows: Section II provides a description of the sensor hardware setup, and explains the problem at hand. Section III describes some of the related approaches used previously in tactile processing and provides comparisons to the current approach. Details of the algorithm are presented in section IV. Section V describes the mathematics used to convert localized pressure measurements to impact force and location estimates. Sections VI and VII cover the simulation results.

II. Target Hardware

We first provide a brief overview of the intended target hardware to give context to the design of the algorithm. The tactile sensor system consists of a sensing matrix with a polymer compliance layer placed over the matrix supported by stand-offs sitting over each sensing element. An acrylic sheet was placed under the sensor setup to provide the backing for the entire system. Shown in Fig. 1, the sensing matrix, a square with 5 cm edges, includes 16 individual sensing elements.

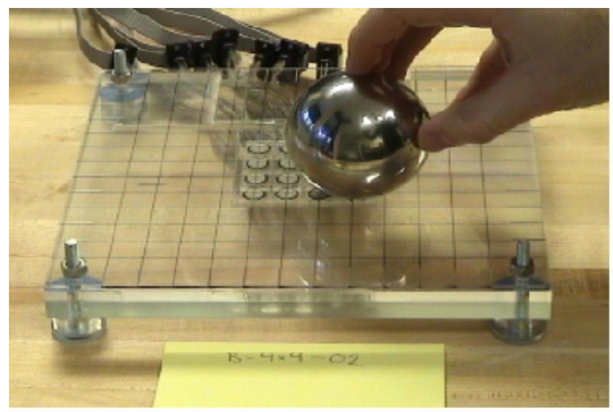

Fig. 1. Prototype Hardware Setup of the Tactile Sensor. At the very top is the compliance layer, the acrylic layer with grid marking. The sensor matrix sits underneath the compliance layer. The stand-offs provide spacing between the sensor matrix and the compliance layer.

Each sensing element was a piezoresistive pressure sensor. The sensor used was the Flexiforce A201-25 pressure sensor with a rated maximum input of 25 pounds; each sensor was circular, measuring 9.53 mm in diameter. The sensor output was resistance as function of the input pressure, where an increase in input pressure decreased the resistance of the sensing element (see Fig. 2). Polymer stand-offs were placed over each sensing element to increase the effective area of the sensor by channeling the pressure around the sensor onto the sensing area. The stand-offs also served as protection for the sensor by absorbing excess strain directed onto the sensor.

The polymer compliance layer covering the sensor matrix served to distribute an impact load over the surface of the entire sensing matrix, increasing the number of sensing elements registering the impact. The goal for the processing algorithm was to determine the presence of impacts, and estimate the location and magnitude of forces, on the surface.

The hardware setup was the primary motivation when selecting the method of processing. As indicated by the Nyquist-Shannon sampling theorem, an input signal must be sampled

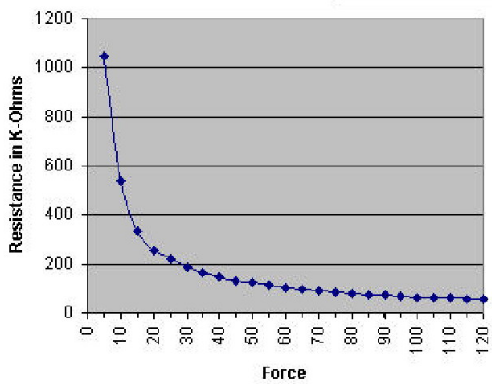

Fig. 2. The plot shows the factory sensor calibration curve for the A201-100 pressure sensor as output resistance versus input force. The force was measured in N.

at twice its maximum frequency to avoid aliasing and to reconstruct the signal correctly. Seen in Fig. 1, an area 5 cm by 5 cm is being sampled at only 16 discrete points, since the data transfer bandwidth limited the number of sensing elements. In addition, the physical size of each pressure sensor also limited the density of the sensor matrix. These hardware limitations made traditional signal reconstruction approaches infeasible, so an unconventional approach based upon K-means was chosen instead.

III. Previous Work

Tactile sensor arrays with a compliance layer have been extensively studied in the past three decades. The sensor arrays covered in [1], [2], [3] were significantly smaller; seen in Fig. 13 of [3], the spacing between each sensing element was 1.5mm, compared to 1 cm in the current hardware setup.

These small area tactile sensors were intended for mounting on the finger tips of manipulators, and used for the grasping control [1] [4]. For this purpose, the sensor needed to be able to distinguish different shape indenter [5]. This was accomplished primary through indentation modeling of stress features on the compliance layer. On a larger scale however, such as the one seen in Fig. 1, the stress feature for a point or a hemisphere indenter would be indistinguishable.

The main differentiating factor between these approaches and approach proposed here is the sensor size. The technique described in this paper is capable of interpolating between the tactile sensing elements (tactels), and thus produces sub-tactel resolution responses both spatially and in the overall resolved impact force.

IV. Algorithm Description

K-means is a data partitioning algorithm that sacrifices accuracy for fast and efficient computation. As described in [6], the general operation of K-means takes n samples $X = (x_1, x_2, x_3, ..., x_n)$ and finds the set of K partitions $S = (S_1, S_2, S_3, ..., S_k)$ of the samples X, where each partition S_i is the minimum distance partition

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x}_j \in S_i} \|\mathbf{x}_j - \boldsymbol{\mu}_i\|^2 \tag{1}$$

Here u_i is the centroid of S_j.

K-means uses an iterative method for data partitioning; each iteration consists of two steps, partition assignment and partition update. During partition assignment, the samples in X are partitioned amongst the K clusters, obtained from the previous iteration, by assigning each sample to the partition whose centroid was closest to that sample.

$$S_i^{(t)} = \mathbf{x}_j : \big\|\mathbf{x}_j - \mathbf{m}_i^{(t)}\big\| \le \big\|\mathbf{x}_j - \mathbf{m}_{i^*}^{(t)}\big\|, \quad i^* = 1, \dots, k \tag{2}$$

With all the samples partitioned, the cluster centroids are recalculated during partition update to accommodate the new data samples.

$$\mathbf{m}_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{\mathbf{x}_j \in S_i^{(t)}} \mathbf{x}_j \tag{3}$$

As an iterative algorithm where the previous partition configuration is used for the current iteration, an initial partitioning is needed to begin the partition refinement process. As suggested in [6], a randomized initial partition could be used as the starting case; at the start of the algorithm, K random data samples would be chosen from X to be the initial centroid locations for the starting partitions.

Applying the K-means partitioning algorithm here, the goal was to identify the sensor responses with impacts on the sensor surface. As stated in the hardware description, a polymer compliance layer was placed over the sensor matrix to distribute the force of any impact on the plate over a wide area; this stress distribution allowed the impact event to be registered by multiple sensing elements in the matrix. The pressure value registered at each sensing element is determined by the distance between the element and the location of the impact; sensing elements far away from the impact location register a smaller pressure. K-means clustering was used to cluster the sensor responses according to source impacts, thereby providing a mechanism to calculate total impact force and location for each contact.

Because the impact force is distributed outward in a circular fashion from the point of contact, the location of the impact can be determined as the centroid of the sensors registering the impact (see Fig. 3). Knowing the location of the impact, the force of the impact could be calculated as an inverse problem of the force distribution.

To extend this to the multiple impact scenario, when two impacts are applied to the sensor surface both impacts will exert forces radiating outward from each contact point. The sensor matrix will register the superposition of pressure readings, where each sensing element would return a pressure reading that is the sum of stresses from both impacts (see Fig. 4). So in order to determine the original impacts, the readings

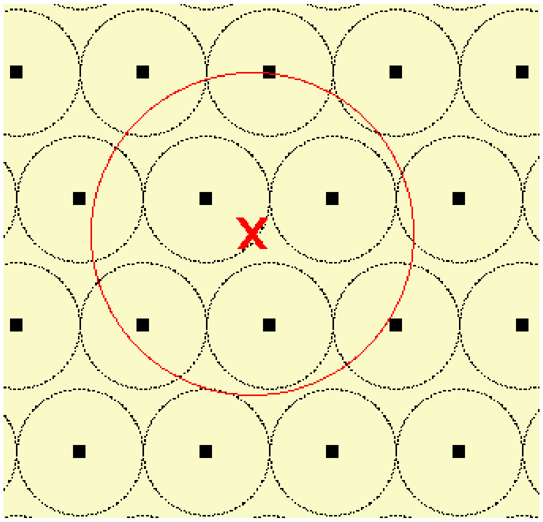

Fig. 3. Illustration of the centroid concept. An impact on the sensor surface, shown is in red, the location of the contact is marked by the red X, and the force distribution depicted by the red circle. The sensing elements overlapped by the force distribution will register the impact. Thus the approximate location of the impact can be found by calculating the centroid of responding sensing elements.

from each element must be categorized as originating from one of the two impacts.

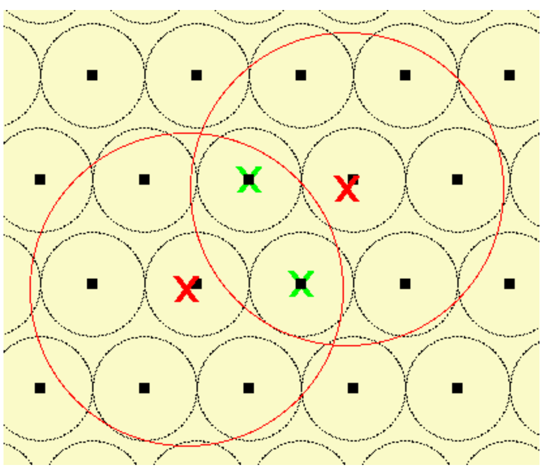

Fig. 4. Illustration of the overlapping impacts. The two impacts, here shown in red, produce two overlapping force distributions. The sensing elements marked by a green X would register a pressure that is the combination of the two impacts.

This problem could be viewed as a data partitioning problem, where each sensing element is a data point in two dimensional space; thus applying K-means, the sensor readings are partitioned, and an impact location is estimated for each partition.

One modification to the K-means was the calculation for the centroids in the partition update phase; the centroid for this application was calculated as a weighted centroid

$$\mathbf{m}_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{\mathbf{x}_j \in S_i^{(t)}} \mathbf{x}_j w_j \tag{4}$$

where the scaling factor, w_j, was related to the pressure value registered by the sensing element. This emphasized that the location of the centroid was determined by both the pressure reading at the sensing element and the element's location; if element A registered a larger reading than B, C, and D, then it is reasonable to assume that the impact location would be closer to element A.

V. Contact Modeling

While the weighted centroid calculation based upon K-means partitioning of the sensor responses provides the estimated location of the impacts, the magnitude of the impact force is calculated through inverse modeling of the force distribution. The model is created based on the concept of the impact force radiating outward from the point of contact with an ever decreasing magnitude, and is intended for modeling a point contact only.

As seen in Fig. 5, the model used for representing the force distribution of an impact was a cone. The volume of the cone, V, represents the total amount of force applied on the surface; the slope of the surface of the cone, S, gives the approximation of the decrease in the measured value as the distance from a sensing element to the point of impact increased. The radius of the base of the cone, R, given by

$$R(S) = \sqrt[3]{\frac{3V}{\pi |S|}} \tag{5}$$

demonstrates that the propagation distance is inversely related to the rate of drop-off in the force measured.

The height of the cone, H, also a function of S

$$H(S) = \sqrt[3]{\frac{3V}{\pi |S|}}\, |S| \tag{6}$$

or

$$H(S) = R\,|S| \tag{7}$$

represents the pressure value which would be measured at the center of the cone. In a continuous representation, the height of the cone can also be expressed as

$$H = \frac{dV}{dA} \tag{8}$$

where A is the area of the base of the cone. Because the volume of the cone is the total force applied on the surface, the first order derivative of the force over the area of the base would be an approximate representation of pressure.

For any point along the base of the cone, the pressure value is given by

$$p(\mathbf{X}) = S \times \|\mathbf{X} - \mathbf{C}\| + H \tag{9}$$

where $\mathbf{X}$ is a position along the base of the cone, $\mathbf{C}$ is the point of contact and $\|\mathbf{X} - \mathbf{C}\|$ is the distance from point $\mathbf{X}$ to the impact location (Fig. 5); this distance value depends on the result of K-means partitioning. Equation (9) provides the forward model for relating an impact force and location to the pressure value being registered by a sensing element anywhere on the sensor matrix.

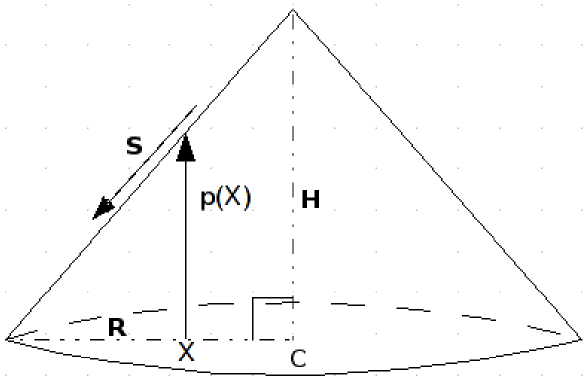

Fig. 5. A visualization of the contact model used for the forward modeling. Modeled as a cone, its volume is the total magnitude of force exerted by the contact on the surface. The slope, S, is the rate of decrease in magnitude as the force propagates outward. This demonstrates the forward modeling process. Given position $\mathbf{X}$, the force measured at this position is the perpendicular distance from base at $\mathbf{X}$ to side of the cone.

Given (9), the inverse model would be

$$H = p(\mathbf{X}) - S \times \|\mathbf{X} - \mathbf{C}\| \tag{10}$$

Once H is calculated, combined with (5) and (6), the force of the impact can be estimated relative to the sensor reading at one sensing element.

The cone representation for modeling the effect of an impact on the sensor surface offers a simplistic approximation of the behavior of the compliance layer under stress.

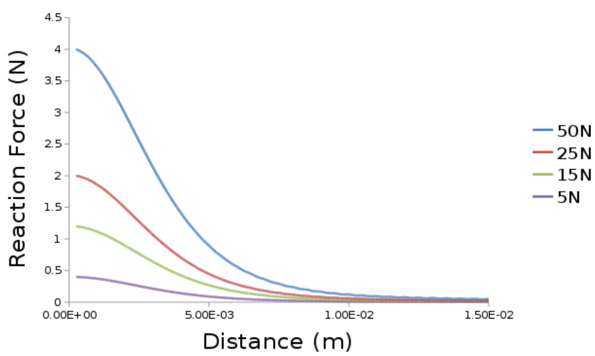

Fig. 6. Plot of the Finite Element Analysis simulation for a point contact on an elastic material, Kapton. The data shown is the force measured plotted against the distance between where the measurement was taken and the location of the contact

Fig. 6 plots the Finite Element Analysis result of an elastic material under a point load in two dimensions; the data plotted was the force measured versus the distance between where the measurement was taken and the impact location. The function shows a nonlinear decrease in the force measured compared to the increase in distance between the measurement point and the contact point. However, the goal of the model was not to provide an exact replica of elastic deformation and behavior, but to create a simple algebraic method of generating data for algorithm testing.

VI. Experiment Setup

The algorithm was analyzed for its accuracy in localization of impact, and the impact force resolution. The algorithm's performance was measured while varying the following parameters: sensor matrix density, impact force magnitude, and drop-off rate in force measurement (S in Fig. 5).

Sensor matrix density defined the number of sensing elements in the matrix. This was controlled by the spacing between each element; wider spacing makes for sparser matrix, and vice-versa.

Both the impact force magnitude and the drop-off rate directly varies the impact modeling. These two parameters control the distribution of force over the sensor surface, and force values registered by the sensing elements.

Verification was conducted in a simulated environment, where the simulation consisted of two portions: the compliance layer model, and the sensor model. The compliance layer model used the impact model described earlier to simulate the top compliance layer covering the sensor matrix; the sensor model simulated the sensor matrix made up of piezoresistive pressure sensors.

VII. Results

The localization of impacts on the sensor surface depends primarily on the accuracy of the K-means partitioning procedure. During the procedure, the location of an impact is estimated as the centroid of a partition; this produces a result similar to that of triangulation. Thus a major contributing factor to the accuracy of the localization is the percentage of sensing elements registering the impacts (i.e. the triangulation improves when more sensors are seeing an impact event). Thus one would expect from the results that situations where the force of impact was widely distributed over the sensor surface would produce higher accuracy. Of all the parameters tested, each parameter directly affected the number of available sensors for analysis.

A. *Effect of Sensor Grid Density*

By increasing the distance between sensing elements, the total number of available sensors decreased, and accuracy was reduced as shown in Fig. 7 and Fig. 8.

One of the major effects of decreasing density was the introduction of a null zone in the input range. Based on equation (5), the maximum force propagation distance has a direct relationship with the magnitude of the impact force; for the impact to be registered, the force propagation of the impact must reach at least one sensing element.

Relating to sensor grid density, the minimum impact force propagation distance must be at least half that of the distance between two adjacent sensing elements; any less and the impact may not be registered. Thus for a fixed drop-off rate in force measurement, the input null zone is an impact force magnitude value from zero to the magnitude needed to reach the minimum required propagation range.

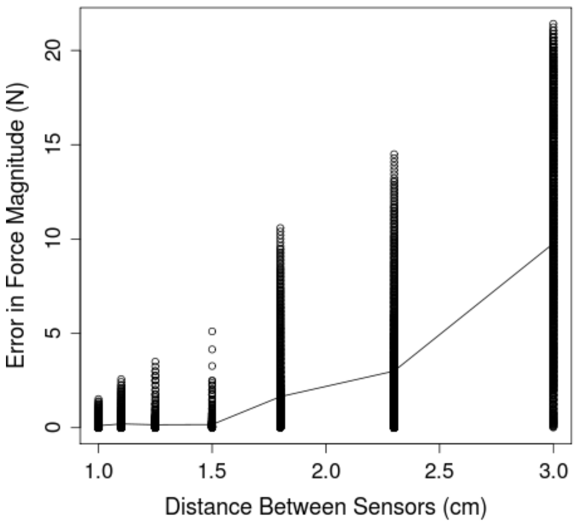

Fig. 7. Change in impact force estimation error as the sensor matrix density decreased. The line shows the mean values for each set of data.

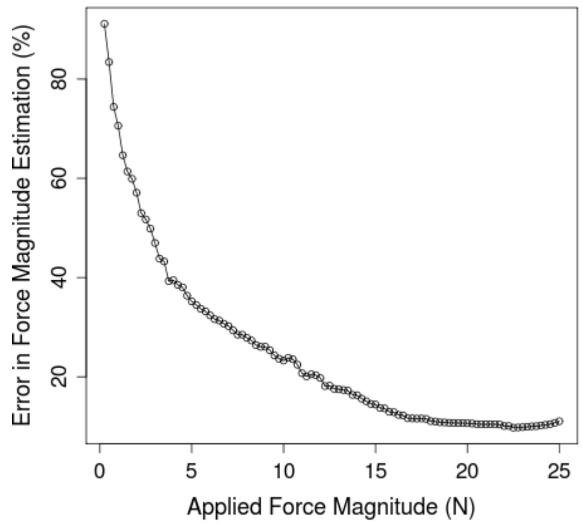

Fig. 9. Increase in accuracy of the estimated impact force as the input impact force was increased.

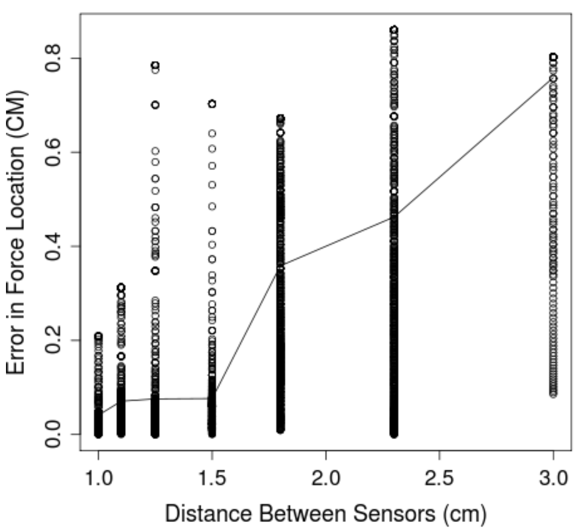

Fig. 8. Degradation in impact localization versus the decrease in sensor matrix density.

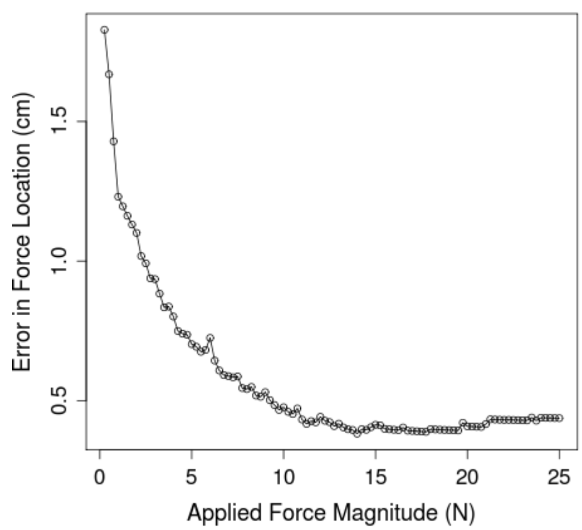

Fig. 10. Increase in impact localization accuracy as the input impact force was increased.

B. *Effect of Model Variations*

The impact force magnitude parameter has a more direct correlation to the force propagation distance. Fig. 9 and Fig. 10 demonstrated this clearly as the accuracy increased as a direct result of the increase in force.

The same could be observed in the error response when the drop-off rate in measured force was varied; the increase in drop-off rate decreased the force propagation distance, which increased the input null zone and reduced the accuracy (see Fig. 11, 12).

One side-effect of the slow drop-off rate was sensor saturation. With a slow drop-off rate, the propagation distance for a large impact force magnitude was considerably large, much larger than the sensor matrix dimensions.

Variance of the measurement readings throughout the sensor matrix was small. This does not affect the impact force magnitude estimation, but hampers the impact localization; because the modified K-means partition depends on the sensing element responses to calculate the weighted centroid, a situation where all the elements are giving relatively similar results would move the centroid to the center of the sensor

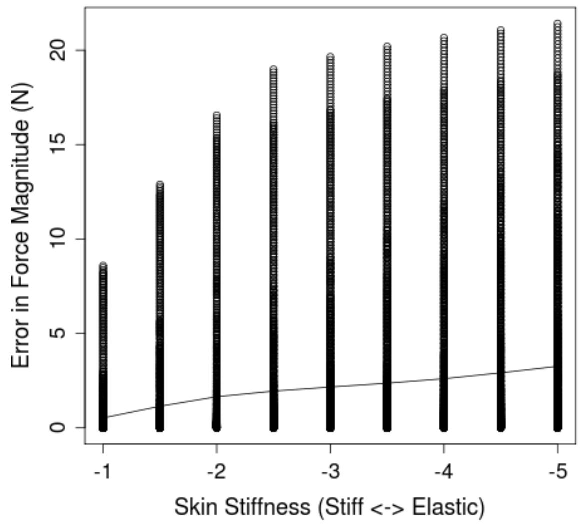

Fig. 11. Increase in drop-off rate increased the impact force estimation error as the force propagation distance decreased.

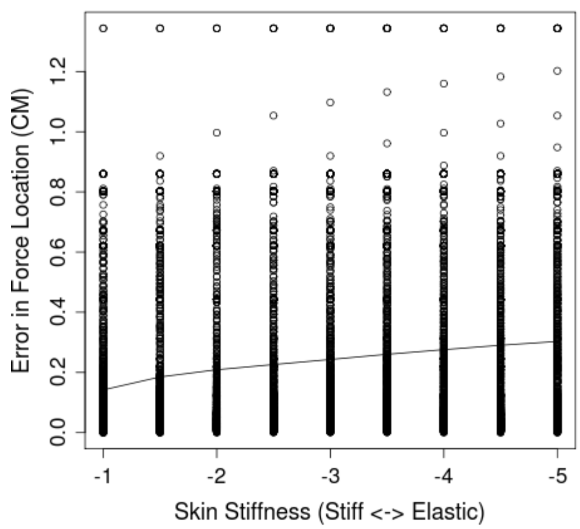

Fig. 12. Increase in drop-off rate increased the impact localization error as the force propagation distance decreased.

matrix regardless of where the impact was applied.

Shown in Fig. 13, for the slower drop-off rate, the increase in input force magnitude actually increased the localization error. Thus for optimal behavior, the property of the compliance layer which control the drop-off rate must be calibrated for a particular application in order to avoid sensor saturation at higher input force ranges.

VIII. Conclusion

In this paper we presented an algorithm for analyzing data from tactile sensor arrays. Based on K-means data partitioning,

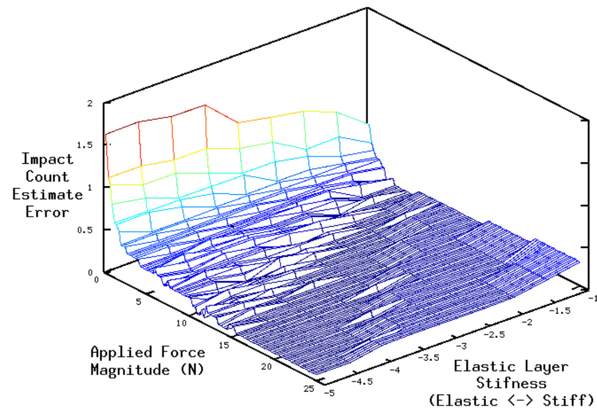

Fig. 13. The plot gives the effect of both the impact force magnitude and the drop-off rate on the force localization error. The feature which become apparent in this plot was the effect of sensor saturation. At the higher impact force range (15 25 N), the localization error increased as the drop-off rate was slowed.

the procedure estimates impact magnitude and locations on the sensor surface using a simplified contact model; this linear model provides an approximation for the stress model seen in the compliance layer during loading.

Through simulation, we determined that the driving factor behind the accuracy of the algorithm was the sensor matrix density, or the number of sensing elements which can register the impact on the sensor surface. Calibrations such as adjusting the sensor count, and the elastic properties of the compliance layer to fit a particular application would be needed so as obtain the optimal performance from the algorithm.

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