# Sensor Design and Model-based Tactile Feature Recognition

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*Abstract* — **This paper[1] presents the design of a flexible tactile sensor and a model-based approach for the pose estimation and surface reconstruction of objects in a gripper. We show that the proposed sensor composite can be easily attached to almost all object shapes, while still achieving a high spatial sensor resolution and a high force sensitivity. Since machine learning algorithms require a large data base and do not offer the scalability of training data, the approach that we prefer here uses model-based feature classification. In order to improve the accuracy of our approach, we investigated fundamental sensor properties and applied sustainable correction methods to the data processing. Finally, the sensor's operability and the evaluation results have been verified in a pick-and-place application for two different grippers.**

***Keywords—tactile sensor; dexterous object manipulation; tactile gripper; tactile feature recognition; pose estimation***

## I. INTRODUCTION

One of the most important and challenging application areas of tactile sensors is the flexible and dexterous manipulation of objects with robots. In such cases, the spatially resolved pressure feedback in the gripper can be used in flexible handling strategies like *reactive grasping* [1], grasp monitoring [2] or object classification in the gripper [3] which increase the reliability of autonomous pick-and-place application. Inaccurate sensor data pose strong requirements on the use of model-based and image recognition algorithms like the Iterative-Closest-Point-Algorithm [4]. Machine learning approaches like deep learning [6] can be used to overcome these limitations, however, they cannot cope with the large scalability and adaptability of model-based feature recognition. There are already some use cases which present sufficient results on the tactile based feature classification [5] but could be improved through proper consideration of immanent sensor properties. The reliable implementation of model-based dexterous handling strategies depends on the accurate correction of uncertain, mostly time variant material properties like drift, hysteresis and inhomogeneous sensitivity properties of the sensor. In this paper, we present the design of a flexible tactile sensor array and its immanent sensing properties. We apply correction methods like the equilibration to improve the accuracy of our approach. The paper is structured as follows: Section □ gives a short overview of unique sensor properties and the conceptual design of the tactile sensor array. Section □ presents the results of the model-based pose estimation for two different gripper applications. Finally, section □ draws the main conclusion from the outlined approach, followed by a short summary of the experimental results.

## II. PIEZORESISTIVE SENSOR

### *A. Material Properties of Piezoresistive Sensors*

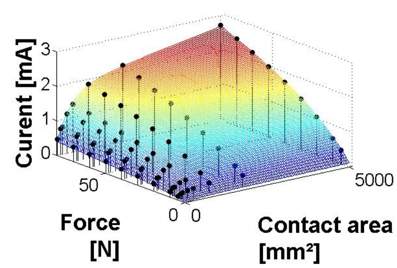


Fig. 1. Experimentally determined current from different loadings and sizes of pressurized sensor area.

The most popular tactile sensor principles base either on the capacitive, optical, piezoelectric or the piezoresistive effect. Piezoresistive sensors which are used here feature unique sensor properties ranging from a high force sensitivity to low-cost fabrication methods. The main conductivity effect bases on the change of electrical resistance due to the applied stress on the sensor. This can be achieved either through bending, stretching or exerting pressure on the sensor. Textile materials consist of unique sensing properties that, depending on the choice of material, can affect the signal processing. A reliable model-based feature classification, which is a goal in this work, requires a certain level of accuracy and reproducibility of signal processing. In et. al. Meier [5], a Kalman filter has been applied for that propose but it does not correct the exact quantities which, in some aspects, limits the performance of the pick-and-place operation. In general, material properties of piezoresistive sensors such as the inhomogeneous distribution of conductive elements, drift and hysteresis restrict the reliable implementation of classification algorithms. Drift and hysteresis arise from the deformation of viscoelastic material. The Voigt

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model can be used to compensate for signal drift during a loading sequence [7], thereby reducing impacts of hysteresis. Another aspect of these material properties is that the signal processing depends on the size of the pressurized area, as seen from Fig. 1. Therefore, we applied a $\mathrm{PIDT_1}$-element (1) as used in control feedback theory to approximate the area dependency (2) at a specific load:

$$\mathrm{h(t)} = \mathrm{K} * \left[1 + \frac{\mathrm{t}-\mathrm{T_1}}{\mathrm{T_I}} + \left(\frac{\mathrm{T_D}}{\mathrm{T_1}} + \frac{\mathrm{T_1}}{\mathrm{T_I}} - 1\right) * \mathrm{e}^{\frac{-\mathrm{t}}{\mathrm{T_1}}}\right] \tag{1}$$

$$\mathrm{Current}(A) = \mathrm{p_1} + \mathrm{p_2} * \mathrm{A} + \mathrm{p_3} * \mathrm{e}^{\frac{-\mathrm{A}}{\mathrm{p_4}}} \tag{2}$$

Based on Fig. 1 we can conclude that the sensor signal and thus the processing of data depends on the size of a pressurized sensor area and the applied load. However, since the sensor data represents a 1D information, only one physical quantity can be used for an accurate processing of data. Since we aim to determine the objects contour from the pressure distribution we consider that the summarized sensor output equals the applied load. As a consequence, we made the size of each taxel as small as possible, thereby increasing the spatial sensor resolution, in order to prevent errors from partially pressurized sensor areas.

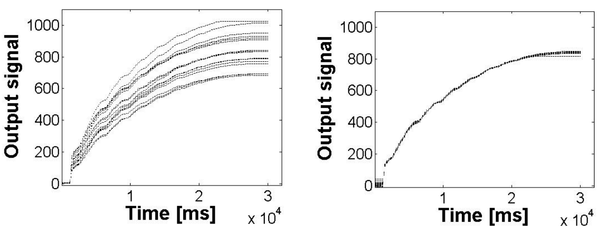


Fig. 2. Sensor output of 16 taxels for same force progression (left). Sensor output of all taxels after equilibration (right).

Another effect arises from an inhomogeneous distribution of randomly dispersed conductive fillers in the polymeric (non-conductive) material substrate which causes different force sensitivities of the tactile sensor array. For example: A maximum deviation of 55% from the minimum sensor output can be measured from a force of 40*N* applied to 10 different sensor cells, each of the size of 110$mm^2$. With respect to an accurate data processing, this fact at least requires the equilibration of the sensor array. The equilibration of tactile sensors is already done by e.g. TEKSCAN[2]. We experimentally determined the parameters of a second-order polynomial function for the approximation of the force sensitivity, namely the sensor output of each taxel. The results are shown in Fig. 2.

### B. *Design of Tactile Sensor Arrays and Electronics*

The tactile sensors that are used in the following consist of a matrix structure. The sensor arrays are made of crossing lines, namely rows and columns which are placed above and underneath piezoresistive material. The proposed tactile sensor composite bases on textile substrate material and thus provides a high flexibility. The sensor can be attached to almost every object surface (except e.g. holes and spikes). The spatial resolution of the presented tactile sensor arrays differ from 5mm (magnet gripper) to 1mm (2-jaw gripper). The sensor data of a taxel is read by connecting a voltage of 2.56V to a column and a row. The A/D converter provides the sensor data of each taxel by 10-bit resolution. The readout rate is within the range of 50*Hz*-200*Hz*, depending on the overall number of taxels.

## II. Tactile Sensor Application

### A. *Tactile Grippers*

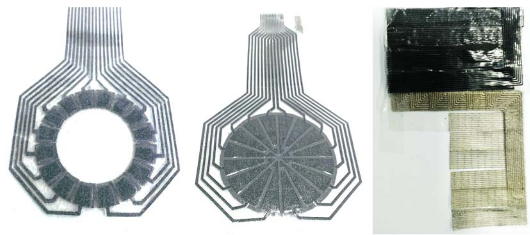

Fig. 3. Tactile sensor for vacuum gripper (left), magnet gripper (middle) and a jaw gripper (right).

For the proposed use case we designed three highly resolved, tailor-suited tactile sensor arrays (Fig. 3) and attached them to three different types of grippers, namely a vacuum gripper, a magnet gripper and a 2-jaw gripper (Fig. 4). The electronics are placed apart from the loaded gripper area, thus reducing wearing effects and increasing the durability of the proposed sensor concept. The sensor for the vacuum gripper consists of 16 radially arranged sensor cells, whereas the sensor of the magnet gripper has a radial arrangement of 72 taxels. Both grippers are flat, making it easy to design and apply the sensors. In order to demonstrate a tailor-suited design for a 3D shape, we also attached the sensor to a rigid jaw gripper. Here, the sensor covers the complete gripper surface with approximately 2000 sensor cells, while also achieving a spatial sensor resolution of 1mm, which is required for an accurate pose estimation and object classification.

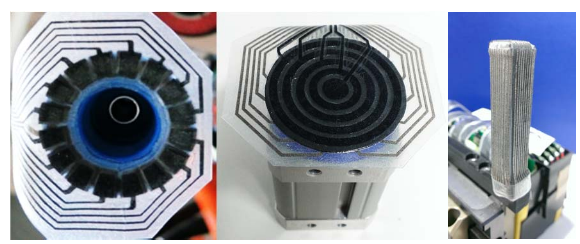

Fig. 4. Tailor-suited tactile sensor arrays attached to a vacuum gripper (left), a magnet gripper (middle) and one finger of a 2-jaw gripper (right)

### B. *Model-based Feature recognition*

As mentioned in the beginning, machine-learning algorithms are often applied to the classification of tactile sensor data [8, 9] since they can be used on uncertain and unstructured data. These methods are even capable of detecting object features like edges or holes without *a prior* specification of exact feature dimensions. However, they need to incorporate elaborate and mostly expert-based processes to create the necessary data base. This is why we'd like to present a method for the classification of sensor data which uses model-based feature recognition, thus

[2] https://www.tekscan.com/

allowing us to introduce new objects easily to a handling application.

Besides impacts from several material properties, there are two strong impacts on the model-based evaluation of sensor data mainly: the shape and the deformability of a gripper. Whereas rigid surfaces, equipped with a tactile sensor, allow for the determination of 2D-contour features (Fig. 4) like edges, recesses etc., deformable grippers are able to attain 3D-object information (Fig. 6) from the pressure feedback. Taking into account the location and the sensor output of each taxel, we are able to reconstruct the surface of an object that is gripped, as shown in the following. In case of loading *n* independent sensor cells we define the *Shape factor* (*SF*):

$$\mathrm{SF_i} = \frac{\mathrm{Deformation_i}}{\mathrm{SensorOutput_i}} \qquad ,\mathrm{i} = [1, \dots, \mathrm{n}]. \qquad (3)$$

The *Shape factor* (1D dependency for simplification) has been determined experimentally and provides a 1D-representation of the sensor deformation. The object's shape and the determined position in the gripper is given by the following 3D point cloud:

$$\begin{pmatrix} \mathrm{x_i} \\ \mathrm{y_i} \\ \mathrm{z_i} \end{pmatrix} = \begin{pmatrix} \mathrm{x_{0i}} \\ \mathrm{y_{0i}} \\ \mathrm{z_{0i}} \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \\ \mathrm{SF_i} * \mathrm{SensorOutput_i} \end{pmatrix}, \ \mathrm{i} = [1, \dots, \mathrm{n}]. \quad (4)$$

$[x_{0i}, y_{0i}, z_{0i}]^T$ is the vector of the original position of each taxel and $[x_i, y_i, z_i]^T$ is the corrected position which includes the 1D-deformation of the gripper. In the following, the 3D-surface reconstruction is shown for the suction cup. The magnet gripper, in contrast, does not provide any depth information on the object's shape. In this case, the *Shape factor* drops close to zero and only the pressurized area can be attained from the tactile feedback.

### C. *Tactile Modality for Pick and Place Operation*

The use of the pressure-sensitive vacuum and magnet gripper have been verified in different pick-and-place applications. The use of a 2D-contour recognition shows that our approach is capable of determining the pose of a washer in the magnet gripper (Fig. 5). As a consequence, the tested washers can be placed reliably (95%) in the appropriate stacks. For the vacuum gripper, the reconstructed 3D-shape information can be used to determine the orientation of the gripped angle tubes. This is done according to the modeled pressure feedback, as shown in Fig. 6 with a reliability of up to 100% (we tested the correct pose estimation for different part situations 20 times in a row).

## III. Summary and Conclusion

The proposed sensor design has been verified for a jaw gripper, a magnet gripper and a flexible vacuum gripper, while we could demonstrate that a high deformability of the substrate improves the proper feature classification of 3D-shape information as shown for cylindrical form primitives. The presented methods enable simple 2D-feature recognition, as shown for the magnet gripper and even a 3D-object shape reconstruction with the vacuum gripper. The sensors and applied methods have been verified in a pick-and-place operation. Herein, parts of known shape could be placed in the appropriate deposit. In our future work, we intend to evaluate the operability of the 2-jaw gripper for a similar pick-and-place operation.

Fig. 5. Magnet gripper with gripped washer (left). Tactile feedback from washer on magnet gripper and estimated object pose (right).

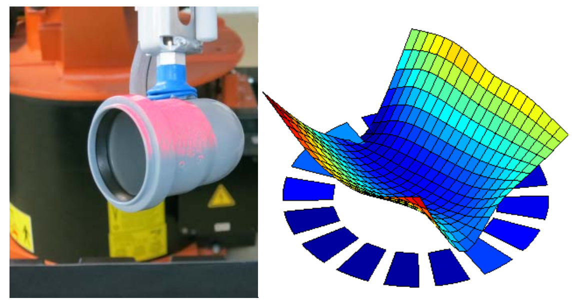

Fig. 6. Vacuum gripper with gripped angle tube (left). Tactile feedback and contour estimation of angle tube (right).

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