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Adaptive Optimal Electrical Resistance Tomography for Large-Area Tactile Sensing

Wendong Zheng, Huaping Liu, Di Guo, Wuqiang Yang

***Abstract*— It is critical to perceive physical contact for intelligent robots to safely interact in dynamic, unstructured environments. As physical contacts can occur at any location, a well-performing tactile sensing system should be able to deploy a large area on robotic surface. Some researchers have implemented large-area tactile sensors by using sensing arrays, but it is challenging to deploy many sensing elements. Electrical resistance tomography (ERT) has recently been introduced into tactile sensing to overcome some of the limitations with conventional tactile sensing arrays, and good results have been achieved for some robotic applications. However, a particular challenge is that spatial resolution is low. Although various attempts have been made to improve the performance of ERT-based tactile sensors, the intrinsic resolution issue remains unsolved. In this paper, we propose a novel adaptive optimal drive strategy for efficient ERT-based large-area tactile sensing for robotic applications, which can adaptively select the current injection and voltage measurement pattern for optimal tactile stimulus. In particular, regions of tactile contacts are preliminarily detected and localized by a base scanning pattern with only a few measurement data. According to this detected region, the adaptive strategy can select the optimal current injection and voltage measurement pattern to improve the sensing performance by maximizing the current density. To verify the effectiveness of the proposed strategy, the proposed method is comprehensively evaluated by simulation and experiments. The results revealed that the optimal strategy can effectively improve both spatial and temporal resolution.**

I. INTRODUCTION

Tactile sensing is important in the field of robotics, especially when complex physical interaction is involved in unstructured environments [1], because tactile sensing can directly measure the various attribute information related to physical contact with surrounding environment [2]. By utilizing this information, robots can perceive their surroundings better and effectively perform various operations [3] [4]. Therefore, tactile sensing has attracted significant attention in robotics over the last decades [5] [6]. Various types of tactile sensors based on different sensing mechanisms or sensing materials have been proposed for robotic applications [7]. Although these tactile sensors have achieved promising performance in some occasions, most of them were designed for fingertips only, and are not suitable for the distinct goals of large-scale tactile sensing [8].

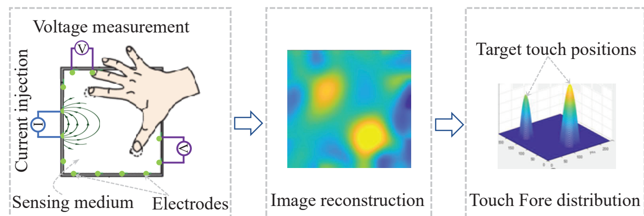

Fig. 1. Principle of ERT-based sensor for tactile sensing.

As the deployment of robotics has rapidly expanded to challenging dynamics scenarios in industry, it is required for robots to have the ability to interact safely with physical environment as well as humans [9] [10]. To achieve this goal, deploying large-area tactile sensors on the entire or most of a robot body is indispensable to detect a wide range of potential physical contact and sense over an area [11] [12]. Nowadays, there is an increased interest in developing large area or whole body tactile sensors that allow a robot to safely perform a task while maintaining physical contact. Currently, the most widely used large-area tactile sensing system is array-type tactile sensor, which consists of a series of discrete sensing elements, each responsible for a small region. This method is feasible and effective when the number of required sensing units is small, because of the practical issue that wires connecting the sensing elements usually needed to be arranged inside the sensor and the number of wires increases with the number of sensing units. Also, distribution of wires not only reduces the flexibility and stretchability but also causes electromagnetic noise [13]. Therefore, deploying large-scale array sensing units is not realistic in practical applications in terms of manufacturing, cost-efficiency, and durability [14].

Recently, non-invasive electrical resistance tomography (ERT) was introduced to provide a new solution for pressure sensing over a large area. The reconstructed images can be used to estimate the internal conductivity distribution of an sensing medium by using measurements from a few electrodes attached to its boundary only as shown in Fig. 1 [15]. Because of its advantages of continuous sensing, simple structure and low-cost, ERT seems promising in implementing large-scale robotic tactile sensing [16]. ERT was first applied for tactile sensing by Kato et al. [17]. They placed a few electrodes on the boundary of a rubberized material to obtain the internal conductivity distribution. S-

Wendong Zheng and Huaping Liu are with the Department of Computer Science and Technology, Tsinghua University, Beijing 100084, China, and also with the State Key Laboratory of Intelligent Technology and Systems, Beijing National Research Center for Information Science and Technology, Tsinghua University, Beijing 100084, China (Corresponding author: Huaping Liu, hpliu@tsinghua.edu.cn).
Di Guo is with School of Artificial Intelligence, Beijing University of Posts and Telecommunications, Beijing, China.
Wuqiang Yang is with the Department of Electrical and Electronic Engineering, The University of Manchester, Manchester M13 9PL, U.K.

ince then, various ERT-based tactile sensors with different conductive materials have emerged [18] [19]. Most of them have been adopted for tasks of human-robot interaction or gesture recognition [20] [21].

While conventional ERT-based tactile sensors show unique advantages at large-area deployment, they pose a particular challenge of relatively low spatial resolution due to the ill-posed nature [22]. This makes them difficult to meet the requirements of most practical applications. To overcome this drawback, many solutions have been proposed. As an intuitive method, increasing the number of boundary electrodes may improve imaging quality, but its efficacy is saturated when the number of electrodes reaches a threshold [23]. Moreover, it mainly improves the performance near the boundary and the central region still shows poor performance. To improve sensing resolution in the central region, some researchers suggested to deploy a limited number of electrodes within the sensing domain [9] [8]. While the results exhibited that the method can provide improvement in spatial acuity and noise rejection, they rely on a heuristic search strategy to select current injection patterns of internal electrodes, reducing the real-time efficiency required for robotic applications.

Some studies have demonstrated that choosing an optimal drive pattern would allow the sensor not only to effectively improve sensing performance but also to reduce the number of measurements [24] [25] [26] [27]. Ma et al [28] proposed a feature selection based optimal driving pattern for electrical impedance tomography, and the proposed method was demonstrated effective in hand gesture recognition. However, it is only limited to classification tasks specified in advance. Therefore, the method is not suitable for robotic tactile sensing. Recently, an adaptive optimal measurement method have been proposed for ERT-based large-area tactile sensor, which can adaptively select a set of local patterns near the pressed region for acquiring more detailed information [14]. Even if the measurement strategy was carefully designed, it is still limited to the implemented patterns when physical contacts occur simultaneously at multiple locations or contact area is large.

In this paper, we propose a novel adaptive optimal drive strategy for efficient large-area ERT-based tactile sensing in robotic applications, which can adaptively select the optimal current injection pattern for the current tactile stimulus. To verify the effectiveness of the proposed strategy, a prototype large-area ERT-based tactile sensor is developed. The major contributions are as follows.

1) We propose a novel adaptive optimal electrical resistance tomography for large-area tactile sensing, which aims to maximize sensitivity to regions of the present contact without increasing computational and time cost.
2) The prototype of a large-area ERT-based tactile sensor is developed and fabricated, where a few internal electrodes are introduced to improve spatial resolution, and a corresponding algorithm is developed to improve the temporal resolution.
3) The adaptive optimal strategy is comprehensively evaluated by simulation and experiments, and the results demonstrated that the optimal design have effectively improved spatial and temporal resolution.

II. Electrical Resistance Tomography

ERT is an inferential imaging technique that can infer the resistance distribution throughout a sensing medium by injecting currents and measuring voltages from a small number of electrodes. It has been utilized for medical imaging, industrial monitoring, and geophysical exploration. Recently, it has been used in the field of robotic tactile sensing.

There are two problems to be solved for ERT, which are forward problem and inverse problem. The forward problem is solving the voltage distribution based on given mediums conductivity and boundary conditions, and the inverse problem is to reconstruct the conductivity distribution from the measured voltages. For better elaboration, the remainder of this section briefly describes the forward problem and inverse problem.

A. Forward Problem

For a sensing domain Ω of conductivity distribution σ, the forward problem aims to predict boundary potential ϕ on its boundary $\partial\Omega$, where the current is injected through the boundary electrodes. According to Kirchhoff's Law, the relationship between ϕ and σ can be determined by solving the partial differential equation

$$\nabla \cdot (\sigma \nabla \phi) = 0 \quad \text{in } \Omega \tag{1}$$

For a given conductivity σ, its potential can be calculated according to the boundary condition on $\partial\Omega$:

$$j = \sigma \nabla \phi \cdot n = 0 \quad \text{on } \partial\Omega \tag{2}$$

where j denotes the current density and n represents the unit vector normal to $\partial\Omega$.

This is a typical Dirichlet-Neumann boundary value problem, of which the numerical solution can be achieved through the finite element method (FEM). Here, FEM is considered as resistor network to form a discrete domain. The electrical behavior of the sensing domain is described by a transfer resistance matrix $S(\sigma) \in R^{L \times L}$

$$v(.;\sigma, i) = S(\sigma) I \tag{3}$$

where $I \in R^L$ is the current injected to two electrodes and $v \in R^L$ is the resulting voltages on other electrodes.

B. Inverse Problem

Inverse problem refers to reconstruct the conductivity distribution within the sensing domain from the measured boundary voltages. For robotic applications, the sensor should have ability to reconstruct the dynamic conductivity distribution in real time. The time-varying distribution $\Delta\sigma$ of conductivity changes can be determined by the potential difference Δv between time t and initial time t_0.

In general, the mapping between the boundary voltages and the conductivity changes distribution is approximately described by linear equation:

$$\Delta v = \mathbf{J}\Delta\sigma + w \tag{4}$$

where $\mathbf{J}$ is the Jacobian matrix, $\Delta v = v_2 - v_1$ is the difference between two potential measurements v_1 and v_2 in times t_1 and t_2, and w is a measurement noise vector.

The above processes can be numerically implemented by exploiting an open-source software package, EIDORS for EIT based on MATLAB. The more detail information about EIDORS can refer to [29].

III. ADAPTIVE OPTIMAL DRIVE PATTERN

Because tactile contacts typically occur locally, a large-scale tactile sensing system should dynamically change to maximize sensitivity to local region of targets, rather than maintaining uniform sensitivity on the entire sensing area. As above mentioned, the imaging performance of the ERT-based tactile sensor strongly depends current injection and voltage measurement, which are also termed drive pattern. If the drive pattern can be adjusted according to the contact situation, the sensing performance can be improved and the data acquisition time can be reduced. Thus, adaptive optimal drive pattern is critical for ERT-based tactile sensor especially when the sensing area is large.

We propose an adaptive optimal drive pattern method to improve the sensing performance of a large area ERT-based tactile sensor. In particular, the proposed method can dynamically select an optimal drive pattern according to the location of the present tactile stimuli to maximize its sensitivity. The proposed method is shown in Fig.2, which contains a base scanning pattern and an optimal drive pattern.

A. Base Scanning Pattern

Base scanning pattern aims to rapidly detect local tactile contact on the entire sensing area with a small number of measurements. In this pattern, we only consider 12 electrodes attached at the boundary of the sensing domain. For efficient implementation, we adopted the most commonly used adjacent drive pattern. In this pattern, current is sequentially injected by two adjacent electrodes while the resulting potentials are measured at all remaining electrode. Considering that real-time efficiency plays a crucial role in an ERT-based tactile sensor, we use one-step Gauss-Newton method for basic implementation to solve the inverse problem. To solve the ill-conditioned inverse problem, a regularization term $\mathbf{R}$ is introduced to provide a prior information as physical constraint. In ERT-based sensing, a smoothing prior is commonly used. Here, the Laplacian prior [9] is selected as regularization constraint, which is expressed as:

$$R(i,j) = \begin{cases} d+1, \text{if } i = j \\ -1, \text{if } i \neq j, \;\; elements\, i,j\, is\, adjacent \\ 0, \text{otherwise} \end{cases} \tag{5}$$

where i denotes an index for FEM elements, d is 2 in our case corresponding to the two dimensional model.

The Laplacian regularization method would make transitions between elements be smooth. This counteracts the coarse nature of the mesh and produces a smoother image that distributes the Region of Interest (ROI) more evenly. It would reduce position errors due to discrete models. Nevertheless, this may also make it more difficult to accurately distinguish contact edges during reconstruction.

In robotic applications, only conductivity change in the sensing domain is required for ERT-based tactile sensors. To obtain distributions of conductivity changes, we use dynamic imaging method to realize real-time image reconstruction.

B. Optimal Drive Pattern

From Fig.2, it can be found that there are artifacts in tactile images reconstructed from the based scanning patter, which would affect pressure profile. The main reason for these artifacts is the low sensitivity of the contact region. Our previous work have demonstrated that the sensitivity is highly related to the current density in this region. To improve the sensitivity to the region of physical contact, it is necessary to select a set of current injection pairs that maximize current density to concentrate in the contact region in real time, instead of the entire sensing domain.

To realize the above goal, it is necessary to deploy a few internal electrodes within the sensing domain. Meanwhile, an appropriate electrode selection strategy is needed. For robotic applications, ERT-based tactile sensing is highly desirable to have a generalized reconstruction ability to measure tactile contact of unknown and complex forms. This strongly demands the sensor to dynamically change corresponding to the location of the tactile stimuli with the internal electrodes. To this end, we proposed an adaptive optimal method to dynamically select the injection current pattern according to the location and size of the contact region.

To maximize the current density in the contact regions, we firstly need to detect the location of the local contact regions. To detect tactile contact, the blurred image obtained by based scanning pattern is subjected to threshold segmentation, which can be described by

$$\gamma(k) = \begin{cases} \gamma(k), \text{if } \gamma(k) > \gamma_0 \\ 0, \quad \text{otherwise} \end{cases}, \forall k \in [1, K] \tag{6}$$

where γ_0 is a predefined threshold. Because local conductivity may change many times, the predefined threshold is determined by average conductivity change without contacts in the base pattern.

By the above threshold segmentation, the position of the target contact area can be preliminarily determined. The current density concentrated in ROI is determined by the current injection pair. We propose an optimal electrode addressing protocol that intends to select a set of injection patterns by considering the importance of each possible pair, maximizing the current density in the determined area.

To assign weights individually to all possible electrode pairs, the mean of the distribution in the contact regions is

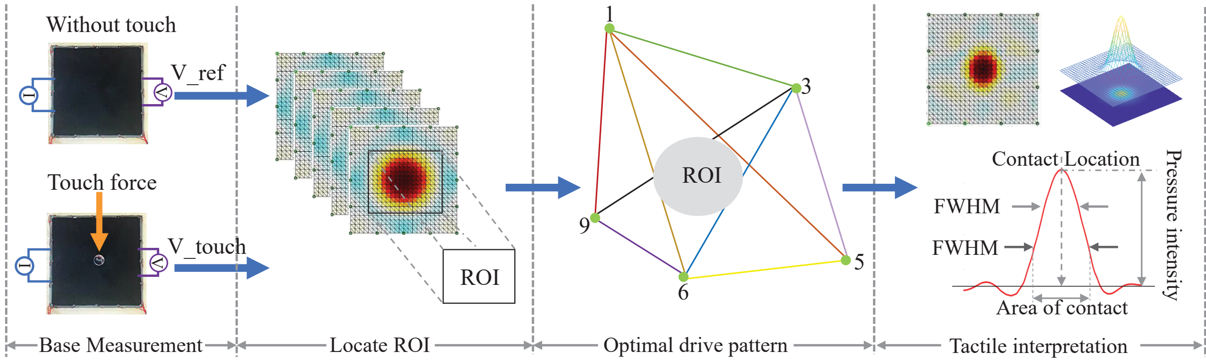

Fig. 2. Framework of the proposed method.

calculated and the three elements that are the closest to the mean are identified. Then, the areas of the triangles formed by two electrodes and the three points are computed for all possible pairs of electrodes. The areas of the three triangles that share the same electrode pair are summed. All electrode pairs are operated as described above, resulting in an array with the areas sum for each combination. The pair with a smaller area sum would be assigned a larger weight, making more current pass through the target contact area. The weight w_i assigned to the electrode pair is define as:

$$w_i = \sum_{i=1}^{N} S(i)/S(i) \tag{7}$$

where i is the index of the all possible electrode pairs in the sensor, and $S(i)$ is the areas sum of the all triangles formed by the electrode i and the corresponding three mean points.

For simplicity, we use point electrode method in this work, where electrodes are treated as single nodes in the FEM mesh. Moreover, the contact impedance between electrodes and the conductive fabric are ignored.

IV. ERT-BASED TACTILE SENSING SYSTEM

This section describes the sensor fabrication procedures and ERT system electronics.

A. Sensor Fabrication Procedures

One of the main components of an ERT-based tactile sensor is the sensing material, which is crucial to its performance. Considering the advantage of the multiple layer structure on sensing large range of forces, the tactile sensor is constructed with multiple layers. Following Park et al's work [30], we firstly fabricate a $20 \times 20cm^2$ conductive area by spraying with carbon black CRAMOLIN 1281411) on an epoxy resin board, which is used as the base layer of the sensor. The spraying on the base layer contributes to forming a sensing domain on any shape surface of robots. The measured the conductivity of the sprayed base layer is 0.00183 S/m. Sixteen electrodes are placed evenly on the base layer in a regular 4×4 grid by screwing in.

To detect multiple pressure points simultaneously, the conductive layer is made of unconnected discrete squares of fabric. In particular, the layer is fabricated by attaching an array of 24×24 highly conductive fabric patches (Silver fiber, YSILVER82, China) on the neoprene foam. These conductive fabric patches are set in size $7.5 \times 7.5mm^2$ and cut by laser cutters. The adopted lattice structure can reduce the risk of current flowing between the different contact points through the highly conductive fabric. By the above-mentioned fabrication process, the conductive layer is soft and slightly stretchable.

Finally, the base layer and the conductive layer are assembled to construct the completed tactile sensor. The sensor is mainly sensitive to normal forces. When normal pressure is applied to the neoprene foam, the combined conductivity between the highly conductive fabric and the based layer sprayed with carbon black would change. As the intensity of the contact pressure increases, the conductivity of the corresponding local region also increases.

B. ERT System Electronics

To realize tactile sensing on the above fabricated sensor, electronics are required to control a set of digital channels to select electrodes for current injection and voltage measurement.

The system consists of a commercial data acquisition card (NET6024-S) and a customized multiplexing board. For efficient implementation, we use current injection. A constant voltage source is used as the excitation source because it is a simple and effective way to provide a stable power supply. The electrodes are connected to two multiplexers (MAX306), and the current driver and the data acquisition card. During the operation, the electrodes are selected by the multiplexers, which is controlled by a microcontroller STM32F107.

In the process of voltage measurement, the parallel acquisition is adopted, which not only reduces data acquisition times, but also ensures no time difference between data from different channels. The obtained data is then transmitted to the host PC through universal asynchronous receiver transmitter communication, where further image reconstruction and visualization is performed.

V. EXPERIMENTS

To evaluate our proposed method, performance analysis is performed by both simulation and experiments.

A. Simulation Analysis

For quantitative evaluation, we assume that tactile stimulus are simplified as some solid circles, as shown in Fig.3 and Fig.4, where 12_Electrodes_B and 16_Electrodes_B represent 12 electrodes and 16 electrodes uniformly distributed on the sensor boundary. 16_Electrodes_I represents 12 boundary electrodes and 4 inner electrodes uniformly deployed on the sensor in the form of a 4×4 grid, where it adopts the typical adjacent drive pattern. Different from 16_Electrodes_I, an adaptive optimization drive pattern is employed in 16_Electrodes_O.

Fig.3 shows the simulation results of single target touch at different positions. From the results, it can be seen that the proposed method give the best performance of tactile imaging, indicating the effectiveness of our proposed adaptive optimization algorithm. From the comparison of 16_Electrodes_B and 12_Electrodes_B, it can be seen that adding boundary electrodes can improve the reconstruct performance of the proposed sensor, but it mainly improves the performance near the boundary and the central region still shows poor performance. Moreover, the results demonstrated that adding internal electrodes within the sensing domain can significantly improve imaging performance, particularly in the central areas of the sensor.

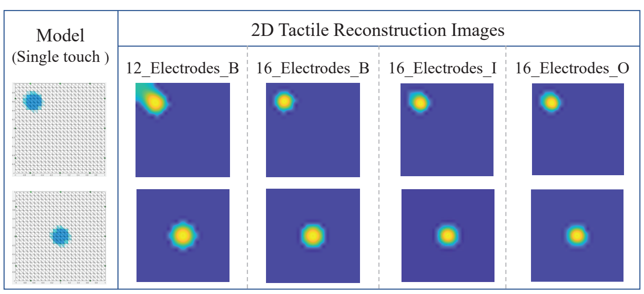

Fig. 3. Simulation results of tactile reconstructed images of single touch at different positions.

For further evaluation, multiple touches at various positions are simulated. The simulation results of tactile reconstructed images are shown in Fig.4, showing that our proposed method gives correct tactile images. It is clear that tactile images of our proposed method contain fewer artifacts and are clearer.

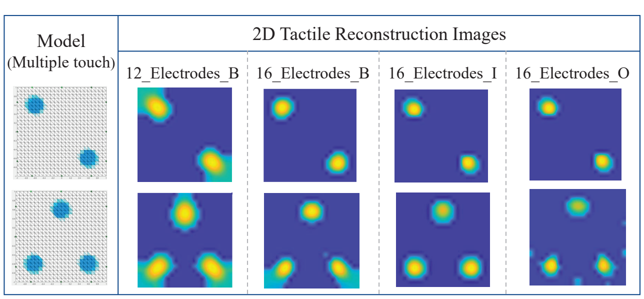

Fig. 4. Simulation results of tactile reconstructed images of multiple touch at different positions.

To analyze the performance of imaging, cross-sections across the center of reconstructed images are shown in Fig. 5, where the peak position denotes the location of the touch, and the width represents the contact area. According to the magnitudes, the proposed method can achieve maximum value. This indicates that our method achieves good sensitivity. By comparing the widths of the curves, it can be seen that the proposed method can detect the pressure profile effectively.

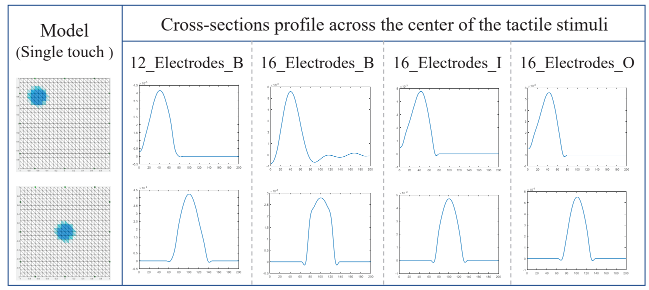

Fig. 5. Cross-sections profile of reconstructed images along the center of the tactile stimuli.

In order to quantitatively analyze the performance of the sensor, we employ Position Error (PE), Amplitude Response (AR), Shape Deformation (SD) and Ring (R) to evaluate the quality of the reconstructed images. The detail defines of the these metrics can refer to [31]. In this experiment, the contact position is selected in the upper left of Fig.3. The results obtained from the different methods are summarized in Table I.

TABLE I
PERFORMANCE COMPARISON OF TACTILE IMAGING

Methods	AR	PE	SR	SD	R
12_Electrodes_B	0.0006	-0.29	0.309	1	1.960
16_Electrodes_B	0.0027	-0.253	0.469	0.732	1.401
16_Electrodes_I	0.0035	0.242	0.320	0.676	1.2282
16_Electrodes_O	**0.00475**	**0.173**	**0.275**	**0.573**	**0.917**

Table I shows that our proposed method achieves the highest AR and smallest PE. It means that the proposed method is superior to other methods and it can detect tactile contact sensitively. These results demonstrate that the sensitivity of the tactile sensor can be improved by maximizing the current density of touch region.

B. Physical Experiment

In this section, the performance of the sensor is analyzed from the image reconstruction, localization performance and spatial resolution of the sensor.

1) Contact Shape Performance Analysis: To verify the performance of the proposed sensor for different contact shapes, we perform the five different touch experiments. The reconstruction results are shown in Fig.6. The reconstructed image of the typical adjacent drive pattern has relatively large artifacts, and the shape of the reconstructed target is different from the applied pressure profile. In the image reconstructed from the adaptive drive pattern, the artifacts around the target are reduced, and the shape of the object can be reflected.

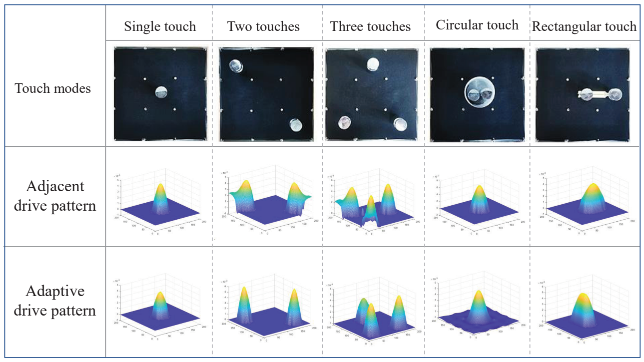

Fig. 6. Experimental results of image reconstruction of the proposed tactile sensor.

2) Location Performance Analysis: To verify the location performance of the sensor, we conduct experiments on 81 different location on the sensor surface, where pressure is applied through point contact. The target in an image is segmented and the centroid position is extracted. The actual pressure position and the centroid in the reconstructed image are compared. The results are shown in Fig. 7. The average positioning error of the typical adjacent drive pattern is 1.301cm, while the average positioning error of the adaptive drive pattern proposed in this paper is 1.023cm. It indicates that the adaptive drive pattern significantly improves the accuracy of localization.

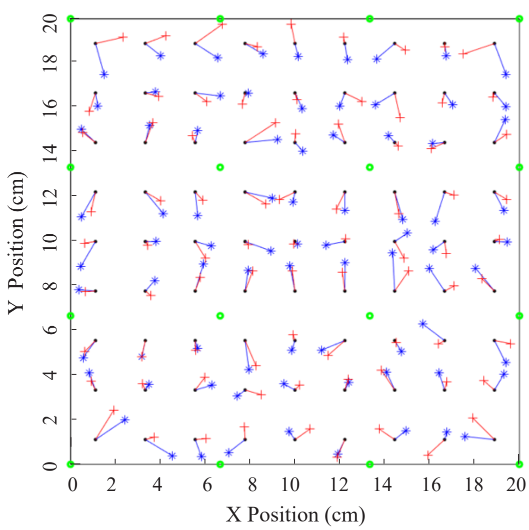

Fig. 7. Experimental results of true touch positions and their corresponding estimated positions, where green circles represent electrodes, black dots indicates the location of the centroid, blue asterisks indicate contact locations estimated by typical adjacent drive pattern, and red cross represent the positions estimated by the adaptive drive method.

3) Spatial Resolution Analysis: In the above experiment, we analyzed the localization performance of the sensor under a single touch. In addition to location performance, spatial resolution is another important performance for tactile sensors. We use two-point touch to evaluate this performance. We randomly select three areas on the sensor surface to conduct the two-point touch experiments, where two weights of 100g is applied to press on the sensor surface. During the experiment, the initial value of the distance d between the two weights is 60mm, and the distance d decreases by 5mm for each experiment. The experimental results are shown in Fig. 8. With the typical adjacent drive pattern, it is difficult to distinguish the two pressure points when the distance between two points is less than 17mm, while the adaptive drive pattern can distinguish the two pressure points when the distance is larger than 12mm.

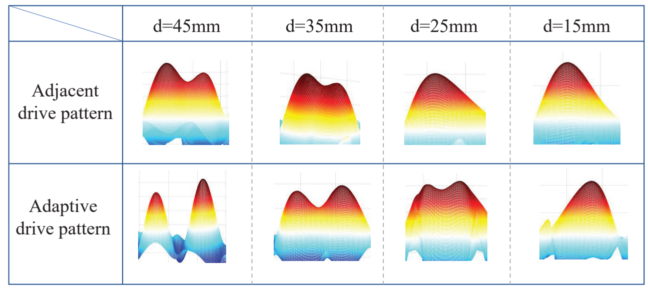

Fig. 8. Experimental results of spatial resolution of the different methods

VI. CONCLUSIONS

In this paper, a novel adaptive optimal drive pattern method is proposed for large-area ERT-based tactile sensing for robotic applications. By maximizing current density, this method can adaptively select the optimal current injection pattern for the present tactile stimulus, with the aim of improving the the imaging resolution and enabling the sensor more precisely detect and localize contact locations and shapes. Simulation and physical experiments validate the effectiveness of the adaptive optimal measurement strategy, demonstrating that the optimal design has improved both spatial and temporal resolution. The method proposed in this work has potential to enable robots have whole-body tactile sensing abilities with high-resolution.

Our focus in this work is on the study of an adaptive optimal drive method, where we employ linear approximation and a regularization strategy to solve the imaging problem. In the future, we plan to investigate a nove data-driven ERT imaging method with the aid of a deep learning-based algorithm, which aims to further enhance sensing performance. Moreover, we intend to quantitatively evaluate the performance of the sensor in real robotic applications.

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