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Data-driven electrical resistance tomography for robotic large-area tactile sensing

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Tactile sensing plays a crucial role in enabling robots to safely interact with objects in dynamic environments [1]. Given that potential physical contact can occur at any location during robot interaction, there is a need for a tactile sensor that can be deployed extensively across the robot's body. Some large-area tactile sensors based on sensing arrays have been proposed, but deploying many sensing units remains a challenge in practical applications. Recently, electrical resistance tomography (ERT) has been implemented in tactile sensing in order to overcome the restrictions of traditional array-type tactile sensors. It has already demonstrated its utility in some application scenarios.

Although ERT-based tactile sensors show unique advantages in large-area sensing, they face the challenge of low spatial resolution. Recently, some deep learning methods have been proposed to solve the imaging problem in ERT sensors and have shown promising results compared to traditional numerical methods. However, these methods mainly achieve the ERT images by training deep networks to directly learn the nonlinear relationship between boundary voltage and conductivity distribution [2]. In these methods, the physical model of ERT is not explicitly considered and the neural network needs to learn the basic physical model from scratch. This learning task is often difficult or even impossible for ERT-based sensors.

In this work, we present a novel data-driven resistance tomography (DDERT) sensing method for large-area tactile sensing. In particular, the method utilizes a generative model to reconstruct the boundary measurement voltage of the ERT sensor into a tactile image. By combining a generative model with a traditional imaging algorithm, introducing a spatial attention mechanism, and applying a mask constraint, the proposed method aims to enhance the imaging quality of ERT-based tactile sensors, ultimately improving the sensing performance.

Sensor fabrication. In order to take advantage of the multilayer structure in piezoresistive sensing, a multilayer configuration is selected to design the tactile sensor, which mainly includes a base layer and a conductive layer. The base layer of the sensor is a 20 × 20 cm^2 flexible printed circuit, where 16 electrodes are evenly arranged on the boundary. Following our previous work [3], the sensing domain is fabricated by spray-coating it with carbon black (CRAMOLIN 1281411) on the layer, whose conductivity is controlled to be around 0.006 S/m.

The conductive layer consists of discrete pieces of highly conductive fabric (silver fiber, YSILVER82, China) instead of using a single piece of conductive fabric. This design prevents current from flowing through the sensing layer between different touch points, thereby enhancing the sensor's multi-touch point detection capability. In particular, this layer is constructed by pasting 24 × 24 conductive fabric patches with dimensions of 7.5 × 7.5 mm^2 onto the neoprene foam.

Subsequently, the base layer and the conductive layer are carefully assembled and firmly secured using tape. With the aforementioned fabrication process, the tactile sensor exhibits good flexibility, making it highly suitable for deployment on a large area on the robot's surface. The details of sensor fabrication are provided in Appendix A.

Methods. The framework of the DD-ERT model is shown in Figure 1. It is structurally divided into two cascaded modules: an initial imaging module and an image reconstruction network. First, the initial conductivity image is reconstructed from the measured boundary voltages by the initial imaging module. After initial reconstruction, the image is fed into a reconstruction network to generate an enhanced conductivity image. This is an end-to-end model, and the modules are jointly trained.

The initial imaging module consists of a fully connected layer that is responsible for generating the conductivity image from the boundary voltage data. Unlike existing data-to-image methods, we initialize the initial imaging module using the sensitivity matrix obtained by traditional reconstruction algorithms in this work. Due to incorporating the physical model, the network is easier to converge during training, and the performance of the model can be improved. Compared with methods that use a fixed initial reconstructed image, our proposed method can effectively eliminate errors caused by ill-posedness, thereby improving the reconstruction quality of tactile images.

The goal of the image reconstruction network is to generate high-quality conductivity images from low-resolution initial images to effectively describe tactile information about physical interactions. The U-Net architecture's ability to

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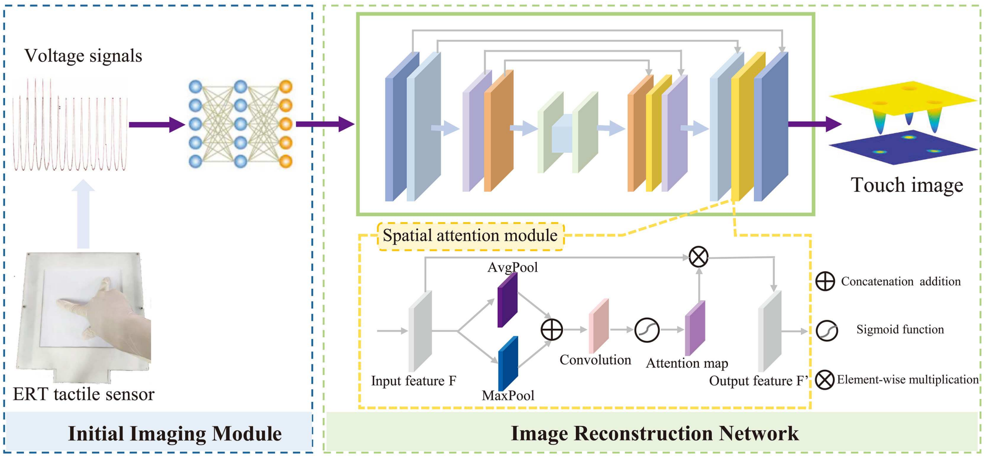

Figure 1 (Color online) Framework of the proposed method DD-ERT.

preserve detailed spatial information through skip connections has made it a popular choice in image-to-image translation tasks. However, in our experiment, we observed that the standard U-Net network does not explicitly focus on the regions that represent the effective contact area, which greatly limits the performance of the model. To this end, we propose a novel generative model for the ERT-based tactile sensor, which follows the basic structure of U-Net, as shown in Figure 1.

To improve the quality of tactile images, a spatial attention mechanism is incorporated into the model. This mechanism enables the model to have the ability to dynamically focus on the areas of contact, allowing for more accurate imaging of those regions. This adaptability is critical for the network to accurately capture and understand tactile data, especially when dealing with complex or dynamic tactile interactions.

In ERT-based tactile sensors, a tactile image can be divided into two distinct parts: the background and the foreground. The background region refers to the untouched area where no tactile information related to object contact exists. Conversely, the foreground region represents the interaction area between the sensor and the object, containing vital information about the contact and interaction. Therefore, a mask constraint is introduced as prior information to guide the model focus on the foreground region, enhancing the quality of the tactile images in areas of contact. The details of our method are provided in Appendix B.

Experiments. To verify the effectiveness of our proposed method, it is quantitatively compared with seven widely used reconstruction algorithms using four evaluation metrics. Through a qualitative comparison, it can be observed that our model outperforms in all four metrics. This suggests that the method is effective in ERT tactile image reconstruction. Detailed information on these datasets and metrics can be found in Appendix C.

Moreover, a series of physical experiments were conducted to evaluate the sensing performance of the sensor in terms of localization performance and sensitivity. The experimental results show that the sensor can achieve good localization accuracy and spatial sensitivity. Detailed information on these datasets and metrics can be found in Appendixes D.1 and D.2.

To validate the feasibility of the proposed tactile sensor in real applications, the proposed sensor is applied in tasks of static contact target detection and dynamic continuity touch tracking. In addition, the developed sensor is integrated onto the UR5 robotic arm to perform obstacle avoidance experiments. Experimental results show that the sensor exhibits good sensing performance in different application scenarios. Detailed information about the experiment can be found in Appendixes D.3–D.5.

Conclusion. In this article, a novel DDERT sensing method is proposed for large-area tactile sensing. In particular, the method utilizes a generative model to reconstruct the boundary measurement voltage of the ERT sensor into a tactile image. To improve the quality of tactile imaging, a spatial attention mechanism is incorporated into the model. Additionally, a mask constraint is introduced as prior information to ensure that the generated images contain more accurate tactile information in areas of contact with objects. Experimental results validate the proposed method is effective for the large-area robotic tactile sensing. Furthermore, the prototype of the ERT-based tactile sensor is fabricated and the sensing performance is evaluated in real robotic applications.

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Supporting information Appendixes A–D. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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