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Toward Learning-Based Estimation of Strain Energy Density in a Fingertip from Surface Pressure*

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I. Introduction

Human mechanoreceptors are activated by skin deformation, producing cutaneous sensations. Merkel cells (SA1) are thought to be particularly responsive to strain energy density (SED). Thus, knowledge of subcutaneous SED is important not only for analyzing skillful actions based on cutaneous sensation, but also for achieving convincing haptic displays.

There have been several attempts to present tactile sensations based on SED in the fingertips. Sato et al. [1] calculated SEDs within the skin using offline finite element simulations and used the results to achieve real-time SED-based electrotactile stimulation. In that study, the skin was represented by a simple 2D model. Sase et al. [2] developed a 3D finite element model of a fingertip and performed real-time calculations to obtain the SED distribution within the skin. However, the 3D model of the finger was simplified to enable real-time simulation, which likely reduced the accuracy of the SED estimation.

Therefore, this study aims to develop a learning-based method to estimate subcutaneous SED distributions from surface pressure data, by utilizing a high-fidelity 3D fingertip model and deep learning techniques. The results of this study are expected to be beneficial for SED-based haptic displays in situations where only skin surface pressure can be computed in VR simulations, and for the analysis of mechanoreceptor activity when pressure distribution measurements in real-world environments are available.

II. Method

A. Overview

To estimate the subcutaneous SED using machine learning, a large amount of data must be collected. Since measuring subcutaneous SED directly is extremely difficult, simulation software is employed for data collection. To obtain valid data, a finite element (FE) model that accurately reproduces the mechanical properties of the human finger is required. Using this FE model, we collect pairs of surface pressure and subcutaneous SED distributions under various contact conditions.

The collected data pairs are then preprocessed and converted into image pairs, which are subsequently used to train machine learning algorithms. This task can be formulated as an image-to-image regression problem, allowing the application of existing deep learning-based methods.

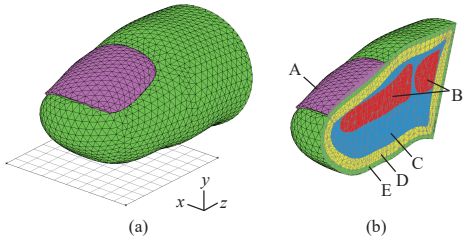
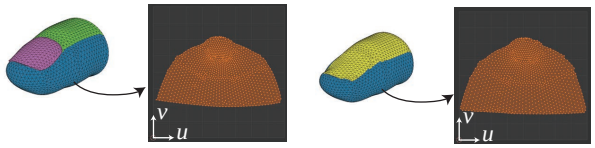


Fig. 1. Finite element model of the finger. (a) The finger model and a rigid plane. (b) Cross-sectional view of the model (A: nail, B: bone, C: subcutaneous tissue, D: dermis, E: epidermis).



(a) Pressure measurement area (b) SED measurement area

Fig. 2. UV mapping of the measurement areas for pressure and SED. The blue regions indicate the measurement areas. Pressure is measured on the surface (epidermis), while SED is measured at the dermis–epidermis interface.

B. Data Collection

We first constructed a fingertip FE model that considers the anatomical structure. The shape of the fingertip was extracted from a commercially available 3D human model (Zygote, Inc., adult male solid model). The internal volume of the fingertip was meshed into tetrahedral elements using Altair SimLab. Fig. 1 shows an overview and a cross-sectional view of the developed model. The model consists of the epidermis, dermis, subcutaneous tissue, bone, and nail. The thicknesses of the epidermal and dermal layers, as well as the material properties, were determined based on the work of Maeno et al. [3].

The nonlinear finite element analysis software Marc (Marc Mentat 2024.2, Hexagon) was employed for data collection. A rigid square plate measuring 20mm $\times$ 20mm was pressed against the finger pad from various angles. The maximum displacement of the plate was approximately 2.0mm. Simulations were conducted using frictionless static large strain

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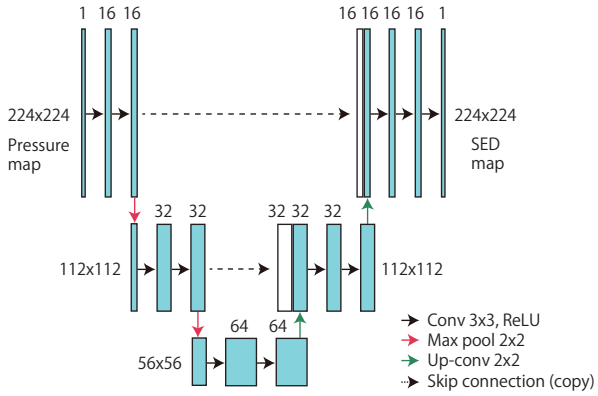

Fig. 3. Simplified U-Net architecture.

analysis. Among the analysis results, particular attention was given to the pressure values within the pressure measurement area and the SED values within the SED measurement area (both indicated as blue regions in Fig.2). The SED measurement area corresponds to the interface between the epidermis and dermis, where mechanoreceptors are located.

The two measurement areas were each unwrapped into 2D representations as UV maps. Angle-based unwrapping, as implemented in the software Blender, was employed. The pressure and SED values were mapped to each vertex of the mesh in the UV map. The vertex values were then linearly interpolated to represent continuous distributions over the mesh. Each value was stored as the intensity of a pixel, and the data were converted into 224 $\times$ 224 grayscale images. Pixels outside the mesh region were assigned an intensity value of zero. All image intensities were normalized by the maximum value across the entire dataset.

C. Machine Learning Method

For the image-to-image regression task, we employed a simplified implementation of U-Net [4]. U-Net consists of an encoder–decoder structure with skip connections between corresponding layers. The input and output images are of the same size, and it is reported that high performance can be achieved even with a relatively small dataset. Although the original network may be too large for practical use in haptic displays, a simplified version of U-Net was adopted in this initial study due to its high accuracy.

The simplified U-Net architecture consists of two encoding and two decoding stages, each comprising two 3$\times$3 convolutional layers followed by ReLU activations (Fig. 3). Downsampling is performed using max pooling, while upsampling is achieved via transposed convolution. Skip connections link the encoder and decoder at each corresponding level. The network takes a single-channel 224$\times$224 input image and outputs a single-channel prediction of the same resolution. The mean squared error (MSE) is used as the loss function, and the network parameters are optimized using the Adam optimizer with a learning rate of 1×10^{-3}.

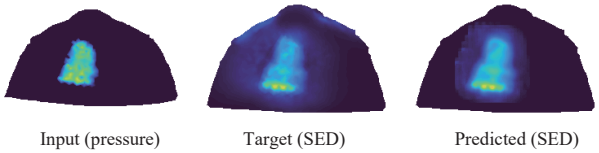

Fig. 4. Example of SED distribution prediction.

III. Results

We collected 1000 data samples, converted them into grayscale images, and conducted U-Net training. Eighty percent of the samples were used for training, and the remaining 20% were used for testing. A steady decrease in losses was observed, indicating that the network possesses sufficient learning capability. Fig. 4 presents an example of the prediction results. Note that in this image, the background has been replaced with white for better visibility, and the intensity values are represented using a color map.

As an overall trend, the predictions reproduced the target images well. Because the SED measurement points are located subcutaneously, surface pressure deformations result in a more widespread subcutaneous SED distribution. This tendency was generally well captured by the model. However, in some cases where the true SED distribution extended broadly toward the nail base, the predicted distribution did not adequately reproduce the overall spread.

IV. Conclusion

In this study, we developed a method to predict the subcutaneous SED distribution from the surface pressure distribution of the finger, with the aim of facilitating the prediction of mechanoreceptor responses during object manipulation. Data were collected using finite element analysis (FEA) software, and SED was estimated through image-to-image regression employing a simplified U-Net implementation. Although the learning model demonstrated sufficient learning capability, challenges remain in accurately reproducing SED distributions over a wide area.

Future work will focus on enhancing the diversity of the collected data and optimizing the model for real-time inference to further improve prediction accuracy.

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