Supplementary Materials

Zichen Wang, Tao Zhang, Xinyu Zhang, Qi Wang

In this material, we give the details of the training datasets and the model configurations of SWU-Net proposed in this paper.

(1) Details of training datasets: The simulation datasets are utilized for training and fine-tuning our method, and the real-world measured signals acquired by the physical tank are utilized to validate the robustness and generalization of the method. In this paper, we consider the two applications including multi-phase distributions in industrial scenarios and lung imaging for medical task, respectively. The forward problem of EIT is solved by finite elements method (FEM) using COMSOL Livelink MATLAB software, the observation domain is discretized into a triangular mesh and then solved. For the 16-electrode EIT measurement model, a total of 208 voltages are obtained for all electrodes excitation-measurement at one time. In order to avoid the problem of 'inverse crime', the observation domain is divided using square grids into 256×256 pixels to adequately represent information about inclusions with complex boundary shapes. Overall, the total number of simulation samples, including multi-phased distributions, complicated shapes, and lung-shaped phantoms, is 62,530, where the 80%, 10%, and 10% are split as the training sets, validation sets, and test sets.

The observation area is set a circular shape with the diameter of 0.19 m, and there are 16 electrodes uniformly attached on the outside boundary of the domain. The protocol of data acquisition is 'adjacent current excitation-adjacent voltage measurement', where the current is utilized with the amplitude of 4.5 mA and the frequency of 50kHz. The NaCl solution with 0.06 S/m is set up as background in the homogeneous field.

(a) Multi-phase regular inclusion datasets: One to four circular inclusions with random position are simulated in database. The radius is set as the range of 0.02—0.08m, and inclusions do not intersect each other. The mediums are set to a different conductivity, whose value are in the range of 10-6-106 S/m. A total of 42,430 simulation samples are obtained. The training, validation and test samples are set to be 80%, 10% and 10% of the total database respectively.

(b) Complex shape inclusion datasets: The shapes of the inclusions include squares, triangles, and circles. There are also some mixtures of all three shaped inclusions. Among them, the squares and triangles having different angles of rotation and the inclusions not overlapping each other. The conductivity is set as in (1) and a total of 10,000 simulation samples are generated, setting the training, validation and test samples to be 80%, 10% and 10% of the total database.

(c) Healthy/injured lung-phantom datasets: The procedure of lung-shaped data mainly includes four steps: CT image selection, lung region segmentation, lung shape establishment, and model augmentation. The lung CT images are selected from the Lung Image Database Consortium image collection (LIDC-IDRI) provided by the Cancer Imaging Archive (TCIA). Eighty patients from the database are selected and randomly divided into two groups, in which the chest CT images of 70 patients are used as training samples and the CT images of the remaining 10 patients are used as test samples. For each patient, we only study the CT slices within 8-cm vertical distance to the central slice, which leads to 350 and 50 slices in the training and testing data sets, respectively. The global thresholding image segmentation algorithm is applied to extract the lung contours. The approximate conductivity parameters for the internal organs (subcutaneous tissue, lungs, heart/aorta and spine) are set to as: body fluid 1.5042 (S/m)/98.553, lung (Inflation) 0.30569 (S/m)/4239.9, heart 0.1957 (S/m)/16844, aorta 0.31688 (S/m)/1619.5, spine 0.003123 (S/m)/179.18. The lung injury is simulated by randomly removing a portion of the lungs and replacing the missing portion with the other medium, where the conductivity of the injured lungs ranged from 0.165 to 0.285 S/m. For augmenting the simulation data, the Gaussian white noise is added into the measurements with a signal-to-noise ratio (SNR) of 65 dB. Finally, the number of simulated lung phantoms is 9,100 for training and 1,000 for testing, respectively.

(2) Model configurations: The implementation details are illustrated as follows: The resolution of initial reconstructions and final results is set as 256×256. we set the iteration step as 100 for multi-phase inclusions reconstruction and 75 for lung-shaped distribution reconstruction. The number of Encoder and Decoder is set as 5 in SWU-Net, and the number of bottlenecks is 4. The number of channels of each Encoder and Decoder is $C_k=[8,\ 16,\ 32,\ 64,\ 128]$. Moreover, the configuration of Omni-Convolution in Encoder is: the reduction ratio of fully-connected layer is $r=1/8$. For four head branches (spatial-wise α_s, input channel-wise α_c, output channel-wise α_o, kernel-wise α_w), the parameters are set as $k\times k\,(k=3)$, $c_{in}\times1$, $c_{out}\times1$, $a\times1\ \ (a=1)$. In the bottleneck, the size of the image patch is 4, the number of rswFormer in each bottleneck is 1. For CrossHL, the point-wise convolution $1\times1\times2C_k$ and deep-wise convolution $3\times3\times2C_k$ are introduced for obtaining latent features, and the reshape operation is utilized to change the tensor to matrix with $\hat{\mathcal{Q}}\in\mathbb{C}^{\left(\frac{N}{2^k}\times\frac{N}{2^k}\right)\times2C_{in}}$, $\hat{\mathcal{K}}\in\mathbb{C}^{2C_{in}\times\left(\frac{N}{2^k}\times\frac{N}{2^k}\right)}$ and $\hat{\mathcal{V}}\in\mathbb{C}^{\left(\frac{N}{2^k}\times\frac{N}{2^k}\right)\times2C_{in}}$. In cross attention, the size of image patch is 4, the number of CrossHL is set as 1. The training procedure of SWU-Net is: the boundary voltages U are fed into the CvNR iterative algorithm, and the initial imaging results $\hat{X}_{LQ}$ are obtained. These pre-reconstruction results $\hat{X}_{LQ}$ are taken as the input of the SWU-Net, and the final reconstructions X_{HQ} are obtained by forward information propagation. The X_{HQ} and the true medium distribution X_{Label} are taken as independent variables of the loss function, which is used to constrain and monitor the training process. After calculating the loss, the reverse gradient flows are backpropagated to update the weights in the SWU-Net. In SWU-Net, the input is the measured voltages, and the output is the predictions of the complex-valued admittivity distribution.