ELECTRICAL IMPEDANCE TOMOGRAPHY BASED
ABDOMINAL OBESITY ESTIMATION USING DEEP
LEARNING

Ariungerel JARGAL \(^1\) and Hyeuknam KWON \(^2\)

\(^1\) Department of Computational Science & Engineering, Yonsei University, Seoul, KOREA
\(^2\) College of Science & Technology, Yonsei University, Wonju, KOREA

Corresponding Author: Hyeuknam KWON, hyeuknamkwon@yonsei.ac.kr

ABSTRACT
We evaluate a learning-based method [1] of absolute electrical impedance tomography (EIT) to estimate a thickness of subcutaneous fat [2] and amount of visceral fat. The EIT is known to be a nonlinear and ill-posed inverse problem. Conventionally, penalty based regularization methods have been used to deal with the ill-posed problem. For difference EIT which uses data difference from reference data, the penalty based regularization method have been applied to animal experiments and clinical practice. However, in absolute EIT which does not have reference data, the conventional methods didn’t succeed on providing clinical useful image. The learning-based method which we use is completely different from conventional approaches; the used reconstruction method is developed based on the relation between data and image to generate a low dimensional manifold of approximate solutions, which converts ill-posed problem to a well-posed one. We use variational autoencoder to produce a compact and dense representation for absolute EIT images with a low dimensional latent space. The feasibility of the approach is validated through numerical simulations.

INTRODUCTION
Abdominal obesity is closely related to metabolic syndrome and cardiovascular disease [3–5]. There is a demand of estimate abdominal fats such as subcutaneous and visceral fats. The standard method uses computerized tomography (CT) which can quantitatively estimate the distribution of abdominal fat [6]. However, it is improper for use in the daily routine because it is relatively expensive and has a safety issue due to the radiation exposure [7]. Thus, it is required to have a cheaper and safer abdominal-fat-evaluation method for continuous self-monitoring in daily routine.

Electrical impedance tomography (EIT) [8–10] is a proper technique for abdominal-fat-evaluation for continuous self-monitoring in daily routine, because EIT is low economic burden, no-radiation, available in the daily routine. EIT aims to visualize the distribution of electrical conductivity (inside the human body) which distorts electric potential distribution generated by the injected electric current. The absolute imaging problem in EIT is nonlinear and severely ill-posed. Representative methods for the absolute imaging problem is the regularized least-square methods [8,11] which are based on the minimization problem \( \arg \min_{\sigma} \frac{1}{2} \| F(\sigma) - V \|^2 + Reg(\sigma) \) for finding conductivity distribution \( \sigma \) from given data \( V \) where \( F \) is the forward operator which
maps from $\sigma$ to the data $V$, i.e. $F : \sigma \mapsto V$, $\text{Reg}(\sigma)$ is the regularization term, and $\| \cdot \|$ is the Euclidean norm. These methods deal with the ill-posedness by enforcing the minimizer to have a desired property which is determined based on prior knowledge of $\sigma$ and incorporated in $\text{Reg}(\sigma)$. However, the performance of this approach is still not enough to apply to clinical applications.

To make the forward operator $F$, most of all conventional methods uses physics-model, specifically, Maxwell’s equation at low frequency [8,9]. The physics model deals with conductivity distribution and also geometry factors; body shape and electrode positions. Accordingly, errors or uncertainties in geometry factors distract the image reconstruction result. To handle these undesirable influence, the regularization term $\text{Reg}(\cdot)$ is introduced but the influence of geometry factors is severe that the regularization is not enough to provide absolute image.

To avoid of using physics-model which is the fundamental cause of difficulties in absolute imaging, we suggest to use deep-learning technique which uses a data-model. In this study, we use the variational autoencoder (VAE), one of the most popular approaches to unsupervised learning, because it can extract features (subcutaneous fat thickness) from complicated distributions (bunch of data) [1]. We establish the operator $f : V \mapsto \sigma$ which can be considered as backward operator using training data set. Here, we evaluate the feasibility of the approach through numerical simulations with 600 training images and 48 test images. The results reported confirm the feasibility of the technique to detect and estimate the thickness of subcutaneous fat.

**METHOD**

The inverse problem in EIT is to find the map $f : V \mapsto \sigma$ from measured data (electric impedance) $V$ to electric conductivity distribution $\sigma$ in human body. We aim to make a reconstruction map $f$ not using physics-based model so that there will be no geometry error but using data-based model so that it will be only determined by measured data and conductivity distribution. We adopt variational autoencoder (VAE), one of deep learning technique, to make $f$ from only training data $\{(V^i, \sigma^i) : i = 1, 2, \ldots, N\}$ where $N$ is the number of data.

The advantage of using VAE is that we can find low dimensional representation $z$, called latent, of image in measured impedance. The map $f$ is defined based on $z$:

$$f = \Psi \circ \Xi$$

where $\Xi$ is nonlinear regression map from measured impedance $V$ to the latent $z$ and $\Psi$ is generator from latent $z$ to conductivity distribution $\sigma$. The nonlinear regression $\Xi$ is defined by

$$\Xi = \arg\min_{\Xi} \frac{1}{N} \sum_{i=1}^{N} \| \Xi(V^i) - z^i \|^2$$

The generator $\Psi$ is defined with inference $\Phi$ as

$$(\Phi, \Psi) = \arg\min_{\Phi, \Psi} \frac{1}{N} \sum_{i=1}^{N} [\| \Psi(\Phi(\mu^i)) - \sigma^i \|^2 + \mathbb{KL}(\mathcal{N}(\mu^i, (\nu^i)^2) || \mathcal{N}(0, I))]$$

where $\mathbb{KL}$ divergence is difference between two distributions and it is equal to $(\text{tr}[(\nu^i)^2] + \|\mu^i\|^2 - \log|\nu^i|)$. The architecture of proposed method is illustrated in fig. 1. The detail of computation is following:

- $\Phi(\sigma) := (\mu, \nu) = W_\Phi(\eta(W_2^\Phi(\eta(W_1^\Phi(\sigma))))))$
\( z = \mu + e^{\epsilon \nu} \) where \( \epsilon \in \mathcal{N}(0, 1) \)

- \( \Psi(z) := \hat{\sigma} = s(W_3^{\Psi} (\eta(W_2^{\Psi} (\eta(W_1^{\Psi} z)))) \)
- \( \Xi(V) := \hat{z} = W_2^{\Xi} (\eta(W_1^{\Xi} V)) \)
- \( \eta(x) = \max(0, x) \) and \( s(x) = 1/(1 + e^{-x}) \)
- \( W \) is linear transformation.

We use several types of body but here we present 2 kinds of different body with different subcutaneous and muscle layer thickness. The size of images \( \sigma_i \) and EIT data \( V_i \) are \( 64 \times 64 \) and \( 256 \times 1 \), respectively. The proposed method successively reconstruct absolute image as shown in fig. 2.


