Efficient and Robust Detection of Local Impedance Changes Using Selected Electrical Excitation Conditions

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ABSTRACT Bioelectrical impedance method is useful for evaluating tissue state such as muscle injury but there is a trade off between efficiency and robustness in detection of various local impedance changes. To solve this problem, we proposed a method using compressed electrical impedance sensing and discrimination analysis. We employed multiple excitation conditions like electrical impedance tomography, and investigated the effective excitation conditions. We then used both simulation and measurement data for efficient training process. In our experiment, we implemented a simulator and a measurement system with 16 electrodes and biological phantoms, and evaluated the discrimination rate for various impedance distribution by assuming muscle injury. As a result, we found that 6/120 excitation conditions are sufficient for detection of local impedance changes in a simple model and sufficient blending ratio of the measurement data to simulation data was 10.6% to perform 90% discrimination. The experimental result also indicated that the proposed method was robust for injury size, injury position, and body shape and 90% discrimination was achieved using 13/120 excitation conditions for complex models including skin, bone, and muscle area.

INDEX TERMS Electrical impedance, compressed sensing, potential distribution, muscle injury.

I. INTRODUCTION
Detecting local changes in body composition is important for understanding body function, evaluating tissue state, finding tumors, and so on. For example, earlier detection of the onset of skeletal muscle injury by measuring tissue composition is useful to prevent progression [1], [2], especially in inspecting tiny muscle injury in ubiquitous environment. When muscle injury occurs, blood vessels near the injured muscle tissue cause hematomas and blood concentration of creatine kinase increases when muscle cells are destroyed [3]. These phenomena are related to the local changes in body composition and used for detecting injuries.

Different technologies for detecting local changes in body composition are available. For example, nuclear magnetic resonance (MR) and ultrasound (US) imaging are used to visualize tissue composition based on the hydrogen densities and the elasticities, respectively [4]. Although MR imaging provides accurate classification of the muscle states and US imaging contributes to ubiquitous sensing, these technologies have limitations. The measurement environment in MR imaging is restricted due to the strong magnetic field requirement, and in US imaging, it is difficult to discriminate tiny muscle injury from the normal muscle [5]. Spectroscopy is highly accurate for detecting injury by measuring the blood concentration of creatine kinase [2], but it involves the collection of blood sample, which is an invasive procedure. Bioelectrical impedance method [6] and electrical impedance myography [7] are effective methods to detect the local changes in bioimpedance due to the muscle injuries. Freeborn et al. investigated the local changes in bioimpedance due to the eccentric exercise [8]. However, in these electrical impedance sensing methods, high reproducible positioning of the electrodes is required. Specifically, the positions of the electrodes were determined based on the location of the injury which is difficult to be determined in advance. Therefore, a robust
electrical impedance sensing system for detecting impedance changes in various locations is required. It is also important to reveal the effects of the injury locations on the detection performance.

Recently, electrical impedance tomography (EIT) is focused on as a ubiquitous sensing method of body composition. EIT is a technology for visualizing 2D/3D electrical impedance distribution of a conductive object using potential data from the surface electrodes surrounding the object for various excitation conditions [9]–[13]. As EIT is noninvasive, low cost, and highly portable, it has been applied to ubiquitous measurements, including the diagnosis of pulmonary embolism [14], monitoring of pleural effusion clearance [15], imaging of electrical activity in the brain [16], and hand gesture recognition [17]. EIT enables visualization of tissue composition based on conductivity and permittivity and is expected to be applied for the detection of local impedance changes such as muscle injury based on the electrical properties of the tissues. However, it is difficult to detect small local changes in tissue composition using EIT because of its low spatial resolution [18], [19].

Recent advanced technologies for high spatial resolution EIT include: structure-aware sparse Bayesian learning [20], frequency difference EIT [21], and statistical shape-constrained reconstruction [22]. On the other hand, EIT requires a temporal division measurement to switch the excitation conditions, in order to obtain sufficient data for solving an ill-posed inverse problem [23]. Compressed sensing (CS) is an efficient method to reduce the number of electrodes and the excitation conditions and useful for high speed and low power consuming measurement [24]–[26]. However, it is difficult to drastically reduce the excitation conditions without losing the high spatial resolution. Furthermore, little is known about the effects of CS on the detection of local impedance changes.

In this study, we focus on the efficient and robust detection of the local impedance changes in a target body by using an electrical impedance sensing device. To this end, we propose a classification method using the potential data obtained by compressed electrical impedance sensing. Unlike the conventional EIT [9]–[13], our method employs direct classification process using potential data obtained through selected excitation conditions rather than impedance visualization using numerous excitation conditions as shown in Fig. 1. Moreover, the potential data from simulation and measurement are used for optimizing the parameters of the classification to enhance the robustness of the discrimination using small number of measurement data. We investigate the performance of the proposed method using biological phantom and simulation model by assuming muscle injury. Although the simplified model used in this article is different from the human body, we focus on the fundamental analysis of the proposed method. The main contributions of this article are as follows.

1) To reveal the sufficient excitation conditions for an efficient detection of local impedance changes using the simulation data.

2) To propose an efficient learning process using both simulation and measurement data.

3) To demonstrate an efficient and robust classification by using biological phantoms and simulation model under various impedance conditions.

II. METHOD

A. SYSTEM OVERVIEW

As shown in Fig. 2, the proposed system comprises electrodes, switching and sensing circuits, and a classifier to detect local impedance changes based on the potential data. To select sufficient excitation conditions, we introduce the proposed compressing method based on the redundancy of the simulated potential data. To develop an efficient data collection framework for the learning process, we used the simulation data for various impedance distribution besides the actual measurement data. To realize a robust detector, we considered the reproducibility of the electrode attachment by data augmentation using random noise for the electrode position in the simulation model.

B. ELECTRICAL MODEL

1) ELECTRICAL PROPERTIES OF TISSUES

In this study, we focus on muscle injury in the femur muscle as local impedance changes for the future application of the proposed method. The tissue of the femur comprises the skin, fat, skeletal muscle, bone, and blood vessel. It is reported that the tissue conductivity depends on the cytoplasm and extracellular fluid, while its permittivity depends on the insulating cell membrane [27]. The muscle fiber has a large anisotropic conductivity. The conductivity of the muscle fiber in longitudinal direction is approximately seven times larger than that in transversal direction [27].

When the muscle is injured, its conductivity in transversal direction increases because of the increase in blood amount around the tissue. On the contrary, the conductivity of the target body decreases when the blood coagulates due to platelet aggregation [28]. Because it takes time to coagulate the blood, the change in conductivity due to blood coagulation seems to
FIGURE 2. Overview of the system. The system scans electrical potential on the target body with the selected excitation conditions and detects muscle injury using the potential data. The parameters for the discrimination analysis are optimized using the measurement data for the normal muscle and the simulation data for the normal and injured muscle with random noise in the electrode positions.

have a small effect on short-period measurement. Therefore, we used the impedance of blood for injured muscle detection. At a 10 kHz frequency, the conductivity and permittivity of the muscle in longitudinal direction were 0.55 S/m and $7.1 \times 10^{-7}$ F/m, those in transversal direction were 0.085 S/m and $6.2 \times 10^{-7}$ F/m, and those of the blood were 0.68 S/m and $2.3 \times 10^{-8}$ F/m, respectively [29], [30].

FIGURE 3. Typical schematic of electrical impedance sensing with a 3D domain.

2) POTENTIAL SIMULATION

In this study, we considered a typical 3D cylindrical domain, as shown in Fig. 3. For each data acquisition cycle, the AC voltage was applied using the two electrodes mounted at the domain boundary. According to Maxwell’s electromagnetic equations, the potential distribution on a conductive body $\Omega$ is subjected to the Laplacian elliptic partial differential equation:

$$\nabla \cdot (\sigma(x) \nabla u(x, t)) = 0 \quad x \in \Omega,$$

(1)

where $x \in \mathbb{R}^3$ is the 3D spatial variable, $t$ is the time, $\sigma(x)$ is the second-order impedance tensor, and $u(x, t)$ is the potential. The impedance tensor is represented using a complex electrical conductivity $\sigma^e = \sigma + j\varepsilon$ with an imaginary unit $j$ and second-order conductivity and permittivity tensors $\sigma, \varepsilon$.

As the muscle is an anisotropic conductor, unique parameters for each component of the impedance tensor are needed for practical application.

Let us assume that a total of $L$ electrodes are attached to the boundary $\partial \Omega$, whose locations are denoted as $\partial \Omega_l \in \partial \Omega, l = 1, 2, \ldots, L$. Using the shunt model [31], the excitation conditions of the driving and grounding electrodes, $\partial \Omega_d$ and $\partial \Omega_g$, are expressed as follows:

$$\begin{align*}
u(x, t) &= V \exp(j\omega t) \quad x \in \partial \Omega_d \\
u(x, t) &= 0 \quad x \in \partial \Omega_g \\
 \cdot (\sigma^e(x) \nabla u(x, t)) &= 0 \quad x \in \partial \Omega \setminus \partial \Omega_l,
\end{align*}$$

(2)

where $V$ the amplitude, $\omega$ is the angular frequency of the applied AC voltage, and $n$ is the normal vector. In this study, we used a linear finite element method (FEM) to solve the equation. To obtain the amplitude at a certain frequency, we transformed the equation into the frequency domain by Fourier transformation and solved the forward problem. We implemented the simulator using C++ and CPPLapack library.

C. POTENTIAL SCAN

The voltage application to a conductor causes potential distribution related to the impedance distribution and to how voltage is applied. Unlike the impedance scan used in the conventional EIT [9]–[13], our system switched the driving and grounding electrodes and measured the potential at the electrodes to obtain the change in the potential pattern due to a small change in the impedance distribution. As shown in Fig. 2, the circuit comprises a switching circuit (MUX), a lock-in amplifier, and a controller (MCU). Although a current source is widely used for the driving, a voltage source was used for the ease of implementation.

It is known that biological tissues have a specific impedance and the difference in the impedance between the skeletal muscle and fat is large (within the frequency range of 1-1000 kHz) [29], [30]. As detection sensitivity is related to the difference in impedance, we used an AC signal with a frequency of 1-1000 kHz for the excitation. The amplitude
of the AC signal was detected using a lock-in amplifier that comprises a high-path filter (HPF) to eliminate the offset voltage, an analog synchronous multiplier, and a low-path filter (LPF).

As for the excitation condition, possible combinations of the driving and grounding electrode pairs are the two combinations from a set of $L$ electrodes. Therefore, the number of combinations is $L(L-1)/2$. However, most conventional EIT systems use only adjacent electrode pairs to reduce the scanning time with high sensitivity [32]. On the other hand, little is known about the sufficient excitation conditions for the detection of local impedance changes. Since our target is detection of the local impedance rather than visualization of impedance distribution, most combinations might have redundant information. Therefore, in the following section, we introduce a novel method to select excitation conditions.

D. SELECTION OF EXCITATION CONDITIONS

In our compressing method, the sufficient excitation conditions are selected from the possible $K = L(L-1)/2$ conditions. The strategy is to eliminate the excitation conditions that produce the similar potential distribution. To this end, we define a selecting metrics as the correlation coefficients of the potential data between the normal and injured muscle states. Because the potential data of the injured muscle are difficult to obtain, we use the simulation data for calculating the selecting metrics. For the $L$ potential data for each excitation condition, the selecting metrics using the Pearson product-moment correlation coefficient $r_k$ is represented as

$$r_k = \frac{\sum_{l=1}^{L}(\phi_{k,l}^{nm} - \bar{\phi}^{nm})(\phi_{k,l}^{im} - \bar{\phi}^{im})}{\sqrt{\sum_{l=1}^{L}(\phi_{k,l}^{nm} - \bar{\phi}^{nm})^2} \sqrt{\sum_{l=1}^{L}(\phi_{k,l}^{im} - \bar{\phi}^{im})^2}}$$

where $\phi_{k,l}^{nm}$ and $\phi_{k,l}^{im}$ are the potentials at electrode $l$ for the excitation condition $k$ of the normal and injured states, and the overline represents the mean value for the potential dataset.

If the correlation coefficient is small, the excitation condition has a large contribution for detecting the impedance changes. Therefore, we define the selected excitation condition $k_s$ as follows:

$$k_s = \left\{ k \in \left\{1, \ldots, \frac{L(L-1)}{2}\right\} \mid r_k < r_{th}\right\},$$

where $r_{th}$ is the threshold of the correlation coefficient, which can be determined based on the detection performance. Because the detection performance depends on the simulation model, we investigate the appropriate thresholds for simple and complex models in experiments. The number of selected excitation conditions $K_s$ is represented by $\text{dim}(k_s)$ and the selection rate is represented by $K_s/K$, where $K$ is the total number of conditions. The measurement time is represented by $LK_sT_m$ with scanning time $T_m$ for each excitation condition. There is a trade-off between detection performance and measurement time, which will be investigated in Section III-C.

E. DETECTION OF IMPEDANCE CHANGES

We used Fisher’s linear discrimination analysis (LDA) [33] to classify the potential data into two classes: normal muscle (initial impedance distribution) and injured muscle (impedance distribution with local changes). By using Fisher’s LDA, the distance between the means of two classes in the potential data was maximized by the projection whereas the variance was minimized within each class. Using the potential vector $\phi$ obtained by the selected excitation conditions, the classifier is represented as

$$y = \text{sgn}(w^T \phi + b),$$

where $w$ is a constant weight vector and $b$ is a constant value.

The dimension of the weight vector and potential data is $LK_s$. The parameters need to be optimized to classify the normal and injured states appropriately.

1) TRAINING

To obtain optimal parameters, we use both the measured and simulated potential data. Because the potential data of injured muscle is difficult to obtain, we use the measurement data for the normal muscle state and the simulation data for normal and various injured muscle states. The simulated potential data for the normal and injured muscle states were calculated using the model introduced in Section II-B2. To develop a robust classifier, we introduced the data augmentation method [34], [35]. A Gaussian noise $N(0, \sigma^2)$ with the standard deviation $\sigma$ was superimposed to each electrode position of the FEM to implement random position noise for data augmentation. An effective combination of the dataset for the training process will be investigated in Section III.

2) TESTING

To assess the classification performance, we prepared a testing dataset using the simulation and measurement potential data for various conditions, including the normal and injured muscles. Note that the selection of injury conditions is important to evaluate the robustness of the method which will be explained in Section III. The two classes, normal and injured muscles, were known and used to calculate the discrimination rate $DR$ defined by the following equation:

$$DR = \frac{TP + TN}{TP + TN + FP + FN},$$

where $TP$ indicates the true positives, $TN$ indicates the true negatives, $FP$ indicates the false positives, and $FN$ indicates the false negatives.

III. EXPERIMENT

The key features of our method are selection of the excitation conditions and an efficient training using both the simulation and measurement data, to develop an efficient and robust detection system. To reveal the sufficient excitation conditions and robust noise used in the simulation, we investigated the $DR$ against the random position noise and selection rate.
To reveal an efficient and accurate training dataset, we investigated the detection accuracy against the blending rate of the simulation and measurement datasets. For practical use, the system is required to have more than 90% detection accuracy. In the following section, we will explain the experimental setup, parameter search (EX1), effective blending rate (EX2), and performance evaluation using complex simulation models (EX3).

A. EXPERIMENTAL SETUP

1) IMPLEMENTATION

To assess the performance of the proposed method, we implemented a measurement system using biological phantoms that mimicked the skeletal muscle of the femur. We prepared a cylindrical phantom with a diameter of 70 mm and height of 10 mm for EX1 and 2. The diameter was similar in size to the muscle of the femur and the height was based on the possible size of hematoma [36]. The phantom was located on the base of the sensing device and \( L = 16 \) copper electrodes were contacted at equal intervals on the bottom surface of the phantom. Although the electrodes need be attached to the side surface in practical application, we controlled the contact state of the electrode by the phantom’s own weight. The electrode base and phantom are shown in Fig. 4(a). Each electrode was connected to three multiplexers (ADG732BSUZ) for switching the driving, grounding, and sensing modes, and a 4-bit digital control signal generated by a multi-function instrument (Analog Discovery 2, DIGILENT) was used. We used a switching period of 20 ms, which is longer than the time constants of the tissues and measurement circuit, to obtain a steady signal from the target body. We used a sinusoidal driving signal for the excitation and set the amplitude and frequency to 2 V and 10 kHz, respectively. The calculated current for the setup was less than 0.2 mA, which allowed the safety guideline in the human body [37].

2) BIOLOGICAL PHANTOM

In this study, we design the experiments by assuming the evaluation of injury at the femur muscle. The target body area included various tissues, such as the epidermis, dermis, fat, skeletal muscle, blood vessel, and bone. To assess the fundamental performance of the proposed method, we focused on the skeletal muscle. Considering the composition of biological phantom presented in the literature [38], we used a mixture of sodium chloride, agar, polyethylene powder, glycerin, and pure water to mimic the electrical properties of the skeletal muscle and blood due to injury. The composition of the phantom is shown in Table 1. The conductivity and permittivity can be adjusted by changing the mass ratio of sodium chloride. Although the skeletal muscle has anisotropy of the electrical property, the phantom has isotropic electrical property. The conductivity and permittivity of the muscle phantom were 0.037 S/m and \( 2.5 \times 10^{-8} \) F/m and those of the blood phantom were 0.14 S/m and \( 4.0 \times 10^{-8} \) F/m, respectively. These values are similar to those of the actual tissue [29], [30] and valid for the evaluation.

3) CONDITIONS AND DATA RECORDING

We developed phantoms for muscle injury by embedding the blood phantom into the muscle phantom at a certain position, with the size based on the injury conditions. In this experiment, six types of phantoms were prepared: normal muscle (M1), tiny muscle injury (2.5% of the cross-section at the center) (M2), small muscle injury (5% of the cross-section at the center) (M3), moderate muscle injury (10% of the cross-section at the center) (M4), small muscle injury with small bias (5% of the cross-section at 13.5 mm distant from the center) (M5), small muscle injury with large bias (5% of the cross-section at 27.0 mm distant from the center) (M6). Each measurement was repeated 50 times, and a total of \( 6 \times 50 = 300 \) datasets were prepared. The phantom was relocated on the electrode base every 10 recordings. We conducted the measurements for all conditions in one day after the production of phantom. The temperature of the phantom was not strictly controlled but the phantom was placed in the room where the temperature was around 25 °C for one day to ensure the steady state.

As for the potential simulation, we prepared two models to investigate the effect of the model shape: a cylinder volume mesh of the same shape as that of the actual phantom and an elliptical cylinder model with a minor diameter of 66 mm. The cylinder model had 3462 nodes and 14247 tetrahedral elements, and the elliptical cylinder model had 4140 nodes and 17852 elements. The size of the element was sufficiently smaller than that of tiny muscle injury. We prepared two types of mesh: a normal muscle phantom (S1) and a muscle phantom with 10% injury at the center (S2). The bottom and top views of the cylinder mesh with small injury and the typical potential distribution are shown in Fig. 4(a). To investigate the effect of random position noise, we used 10 standard deviations \( \sigma = 0.03, 0.06, \ldots, 0.30 \) mm for noises of the electrode position. The simulations for S1 and S2 were repeated 10 and 30 times, respectively, and a total of \( 2 \times 10 \times 10 \times 2 \times 10 \times 30 = 800 \) datasets were prepared. The details of the training and testing datasets are shown in Table 2. Fig. 4(b) and (c) show

| Material        | Muscle phantom Mass ratio [%] | Blood phantom Mass ratio [%] |
|-----------------|-------------------------------|-----------------------------|
| Pure water      | 44.2                          | 44.1                        |
| Glycerin        | 44.2                          | 44.1                        |
| Polyethylene powder | 8.8                           | 8.8                         |
| Agar            | 2.7                           | 2.6                         |
| Sodium chloride | 0.1                           | 0.4                         |

TABLE 1. Composition of the phantom to mimic the electrical properties of the living muscle and blood.
FIGURE 4. Experimental setup and typical potential data. (a) Measurement and simulation environments. (b) Absolute potential data for S1, S2, M1, and M3. (c) Potential difference between S1 and S2, M1 and M3, S1 and M1, and S2 and M3. The simulation result is with a position noise of 0.24 mm.

TABLE 2. Number of data in the training and testing datasets.

|        | S1  | S2  | M1  | M2  | M3  | M4  | M5  | M6  |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|
| Grade [%] | 0   | 10  | 0   | 2.5 | 5   | 10  | 5   | 5   |
| Bias [mm]  | 0   | 0   | 0   | 0   | 0   | 13.5 | 27  |
| Training | 30-\(K_m\) | 30-\(K_m\) | 0   | 0   | 0   | 0   | 0   | 0   |
| Test A   | 0   | 0   | 30  | 10  | 10  | 0   | 10  | 0   |
| Test B   | 0   | 0   | 30  | 10  | 10  | 0   | 10  | 0   |

examples of typical potential data and comparison between the normal, injury, simulation, and measurement data.

B. EX1: PARAMETER SEARCH

1) PROCEDURE

In EX1, we investigated the discrimination rate against the position noise and selection rate. We used different datasets for training and testing to verify the robustness of the proposed method. As shown in Table 2, we trained the model using \(K_m = 20\) measurement datasets and tested the model as follows: First, the effect of position noise was evaluated to find the best noise parameter with the datasets of tests A and B. Second, the effect of selection rate was evaluated for the cylinder and elliptic cylinder models with the best parameter. Then, the sufficient excitation conditions were assessed based on the relation between the discrimination rate and selection rate. For cross-validation [39] purposes, we randomly selected data from the datasets to train and test the system, and repeated 10 times.

2) RESULTS

The resulting plots by the parameter search are shown in Figure 5. Fig. 5(a) shows that the correlation threshold increases with the selection. The result suggests that most of the potential distribution between normal and injured conditions are correlated. Therefore, we selected 10 excitation conditions providing 10 lowest correlation thresholds, and used them for analyzing the position noise. For each excitation condition, we normalized the DR among the position noises. The relation between the normalized DR and position noise for the test A and B datasets is shown in Fig. 5(b). The result showed that the maximum discrimination rate exists at a position noise of 0.24 mm regardless of the testing datasets. Figure 5(c)(d) shows the relation between the discrimination rate and the selection rate with (c) test A and (d) test B. The relation between the discrimination rate and selection rate with (c) test A and (d) test B. Error bars represent standard deviations for the testing data.

FIGURE 5. Results of parameter search. (a) The relation between the correlation threshold and selection rate using S1 and S2. (b) The relation between the normalized DR and position noise. The relation between the discrimination rate and the selection rate with (c) test A and (d) test B. Error bars represent standard deviations for the testing data.
conditions are sufficient for the cylinder and elliptical cylinder models, respectively. A typical combination of the excitation conditions for the minimum number \( K_s = 6 \) is shown in Table 3.

### C. EX2: EFFECTIVE BLENDING RATE

1) PROCEDURE

It would be efficient if we could reduce the number of the measurement data for the training process. In EX2, we investigated the relation between the discrimination rate and blending ratio of the measurement data to simulation data. Although the sufficient blending rate seems to be related to the selection rate, we used 6 and 16 excitation conditions and a position noise of 0.24 mm obtained through EX1, and calculated the detection rate using dataset for test A. The blending rate \( \alpha \) was defined by the ratio of that of measurement data \( K_m \) to the number of simulation data \( 30 - K_m \). The dataset shown in Table 2 was used for the training and testing in EX2. We obtained the discrimination rate for the number of measurement data \( K_m = 0, 1, \ldots, 20 \).

![FIGURE 6. Plots of discrimination rate against the blending rate. (a) with 6 excitation conditions and (b) with 16 excitation conditions. Error bars represent standard deviations for the testing data.](image)

2) RESULTS

The resulting plots are shown in Fig. 6, where the discrimination rate increases with a change in the blending rate. To find a sufficient blending rate, we fitted the model to the experimental data and found the saturation blending rate providing a discrimination rate of 90%. We defined the relation between the discrimination rate \( DR \) and blending rate \( \alpha \) as follows:

\[
DR = \frac{1}{1 + \exp(-p_1\alpha + p_2)},
\]

where \( p_1, p_2 \) are constant parameters. We estimated the constant parameters by fitting the model to the experimental data and calculated the saturation blending rate \( \alpha_{90} \). The resulting parameters and saturation blending rates for the 6 and 16 excitation conditions (ECs) are shown in Table 4.

![TABLE 3. Typical combination of the excitation conditions for \( K_s = 6 \).](table)

| Electrode type   | Electrode index |
|------------------|-----------------|
| Driving electrode| 1, 3, 4, 4, 9, 11|
| Grounding electrode| 5, 15, 8, 16, 13, 15|

![TABLE 4. Estimated parameters and the saturation blending rates for the 6 and 16 excitation conditions.](table)

| Number of ECs | \( p_1 \) | \( p_2 \) | \( \alpha_{90} \) |
|---------------|----------|----------|-----------------|
| 6             | 11.8     | -0.939   | 0.106           |
| 16            | 16.6     | -0.848   | 0.081           |

### D. EX3: PERFORMANCE FOR COMPLEX MODELS

1) PROCEDURE

It is important to show the feasibility of the proposed method for an arbitrary injury location in a complex body composition. To this end, we prepared a simulation model which includes skin, bone and muscle area with various injury sizes and locations. The model had 3743 nodes and 14430 tetrahedral elements. The conductivity and permittivity for each component were set based on the biological characteristics [40], [41] and shown in Table 5. In order to evaluate the robustness for the impedance distribution, we used different positions (0 - 20 mm distant from the center) and sizes (20.4 - 24.4 mm diameter) of bone and positions (45 - 70 mm distant from the center) and sizes (11.0 - 22.2 mm diameter) of injured muscle. The diameter and the height of the model were 170 mm and 10 mm respectively, and the electrodes of 6 mm diameter were located on the side of the model. 120 simulation models including 60 injury and 60 normal conditions were prepared and examples of the models are shown in Fig. 7. In order to investigate the effect of the noise on the discrimination, we added Gaussian noise with 0.005, 0.05, and 0.25% standard deviation to each potential data. We used a leave-one-out cross validation method and calculated average discrimination rate for each selection rate.

2) RESULTS

The resulting plot is shown in Fig. 8, where the discrimination rate increases with a change in the selection rate. The result suggests that the lower noise rate is more efficient for
compressing excitation conditions but the discrimination rate with the lowest noise rate 0.005% decreases at the higher selection rate. Therefore, the setting of the appropriate noise level is important for efficient and robust detection of the local impedance changes. With the 0.05% noise rate, 90% discrimination was achieved by using 13/120 excitation conditions and the maximum discrimination rate was 95%. The result suggests that the more complex model requires the more excitation conditions.

IV. DISCUSSION

The experimental results suggest that the proposed method exhibits great performance on discrimination of the local impedance changes in biological phantom. In this section, we address the following research questions:

- How efficient, accurate, and robust is the method?
- How to select the effective excitation conditions?
- How to prepare the training dataset efficiently?

3) EFFICIENCY, ACCURACY AND ROBUSTNESS

The results suggest that the system performed accurate discrimination with 6/120 excitation conditions for the simple models and 13/120 excitation conditions for the complex models. Because the switching time for each scan was 20 ms in our experimental setup, the sensing time was reduced from 38.4 to 1.92 s for the simple models and to 4.2 s for the complex models. The achieved sensing time to detect localized impedance changes is shorter than that in the conventional methods [3]–[5]. Compressed impedance sensing is also expected to reduce the motion artifact.

We found that the system can detect local impedance changes in biological phantom with various sizes and positions, which are not used in the training dataset. Specifically, it was possible to detect local impedance changes of 11 mm diameter that was difficult to detect using the conventional EIT and US imaging technologies. A comparison of the plots in Fig. 5(c)(d) shows that the system has an accurate detection performance regardless of the size and position of impedance changes. Therefore, the proposed system is robust against injury size and position factors. The contrast of the impedance between normal and injured muscles is also important factor. But we didn’t investigated the factor because it is reported that there is a detectable difference in the impedance between the normal muscle and the muscle in grade I injury [6].

It was also revealed that the model trained using the elliptical cylinder model enabled accurate discrimination of the local impedance changes in the cylinder phantom. Although the number of selected excitation conditions \( K_e = 20 \) was larger than that of the cylinder model, the number was sufficiently smaller than the total excitation conditions \( K = 120 \). The proposed method was also effective for the complex model including skin, bone, and muscle. On the other hand, the difference between the simulation model and actual body had a large impact on the accuracy of EIT reconstruction [42]. Liu et al. revealed that a 0.1% change in the length of the short axis of the elliptical model trebles the estimated conductivity in EIT [10]. Therefore, the direct use of potential data in the discrimination is effective to overcome the mismatch between the simulation model and target body.

4) SUFFICIENT EXCITATION CONDITIONS

The results shown in Table 3 indicate that in the sufficient excitation conditions for the cylinder model, an interval phase of 45 degrees (three electrodes) between the driving and grounding electrodes was used. The improvement from the reconstruction using electrodes at interval has also been reported for the conventional EIT [23]. To obtain the potential data related to the impedance in the deep area from the surface electrode, it is important to increase the current density in the deep area. Therefore, the results suggest that the electrode interval phase of 45 degrees is effective for focusing the current in the deep area. It has also been reported that the trigonometric current patterns has more impacts on the electrode contact impedance than the current pattern using the adjacent electrodes [43].

5) BLENDING EFFECTS

As shown in Fig. 6, the use of measurement data in the training data is important to achieve a high discrimination rate, by considering the error factors that are not introduced in the simulation model. The differences between the potential data obtained from the measurement and simulation are shown in Fig. 4(b)(c). The potential differences between M1 and M3, and S2 and M3 are similar to the potential difference between S1 and S2. The average of the potential difference between S1 and M1 was 0.02 V (1% of the maximum potential). Possible factors include an uneven shape, heterogeneity of impedance distribution, electrical contact impedance, and noise in the sensing circuit. Because the system enabled 90% discrimination with the blending rate \( \alpha_{blend} = 0.106 \), the proposed method drastically reduced the measurement data for the training process.

In the clinical use, it is important to prepare the gold standard for the learning data. As shown in the previous literature [4], MRI can be used for evaluating the muscle injury state. However, it is difficult to obtain the potential
and MRI data for various injury conditions from patients. The experimental results suggest that the effectiveness of the substitution of simulation data for a part of measurement data to reduce the measurement cost. It is also important to prepare a standard model of the impedance distribution of the target body.

6) LIMITATIONS AND PERSPECTIVES

The experiments conducted herein revealed great performance of the proposed method. However, it has some limitations due to the following factors: (1) composition distribution of the tissues, such as the epidermis, dermis, fat, skeletal muscle, blood vessel, and bone; (2) effects of changes in body composition, such as weight, vessel pulsation, and body motion; and (3) individual differences in the participants. Therefore, the sufficient excitation conditions are only effective for the phantom model used in this study. For the practical application of the proposed method, the potential data need to be collected from various participants and evaluated to reveal the sufficient excitation conditions. Finally, we used a simple injury condition in the training and testing processes. Therefore, the proposed method would gain medical acceptance only if the effectiveness were proved by compared with present standard measurement such as MRI and ultrasound. To detect various types of injuries, more complex injury conditions, such as injuries at multiple positions and various shapes of body should be investigated. Investigation of the performance of the proposed system with human participants and evaluation by clinical tests for detecting muscle injury are expected in the future.

V. CONCLUSION

In this study, we proposed an efficient and robust method for detecting local impedance changes by using the selected excitation conditions. We then conducted an experiment using biological phantoms that mimic human tissues and evaluated the discrimination rate for various parameters. The summaries of our findings are as follows: (1) The compressed sensing was effective and the selected excitation conditions were 6/120 conditions for a simple model and 13/120 conditions for a complex model. (2) It was possible to maximize the effect of an electrode position error guided by Gaussian distribution with 0.24 mm standard deviation. (3) Sufficient blending ratio of the measurement data to simulation data was 10.6% to perform 90% discrimination. (4) The system was robust against injury size, injury position, and body shape but more excitation conditions are required for more complex model. Further investigation on the effects of the changes in body composition and subjective study to consider more complex tissue would be beneficial for considering a clinical use in a ubiquitous environment.

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