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Multi-class biological tissue classification based on a multi-classifier: Preliminary study of an automatic output power control for ultrasonic surgical units

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A B S T R A C T

Ultrasonic surgical units (USUs) have the advantage of minimizing tissue damage during surgeries that require tissue dissection by reducing problems such as coagulation and unwanted carbonization, but the disadvantage of requiring manual adjustment of power output according to the target tissue. In order to overcome this limitation, it is necessary to determine the properties of *in vivo* tissues automatically. We propose a multi-classifier that can accurately classify tissues based on the unique impedance of each tissue. For this purpose, a multi-classifier was built based on single classifiers with high classification rates, and the classification accuracy of the proposed model was compared with that of single classifiers for various electrode types (Type-I: 6 mm invasive; Type-II: 3 mm invasive; Type-III: surface). The sensitivity and positive predictive value (PPV) of the multi-classifier by cross checks were determined. According to the 10-fold cross validation results, the classification accuracy of the proposed model was significantly higher ($p<0.05$ or <0.01) than that of existing single classifiers for all electrode types. In particular, the classification accuracy of the proposed model was highest when the 3 mm invasive electrode (Type-II) was used (sensitivity=97.33–100.00%; PPV=96.71–100.00%). The results of this study are an important contribution to achieving automatic optimal output power adjustment of USUs according to the properties of individual tissues.

1. Introduction

Ultrasonic surgical units (USUs) that are used in laparoscopic and thoracoscopic surgery have been developed to overcome problems such as spark, charring, and inefficient coagulation associated with electrosurgical units [1–5]. However, USUs have the limitation that the surgeons have to manually control the optimal output power according to properties of the tissue [6,7]. This subjective procedure could lead to a process of trial and error and might delay the operation time [7]. Therefore, it is necessary to develop a method to control the optimal output power of USUs automatically.

To develop such a method, *in vivo* tissues must be automatically distinguished, preferentially. The impedance that refers to the electrical characteristics of the tissue, which are dependent on the properties of the cells that make up the tissue at the molecular level and differ from tissue to tissue, can be used to classify the type of tissue. To date, impedance characteristics of tissues have been investigated in various medical fields, including dentistry [8] and internal medicine [9], mostly to classify normal and lesion tissues in conditions such as ischemia [10–12] and tumors [13–15]. Åberg et al. analyzed impedance data of normal tissue and denatured tissue (birthmarks, melanomas, and other human skin cancers) using a binary classification algorithm to determine the presence of disease [14]. More recently, Kalvøy et al. classified heterogeneous tissues for

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drug administration. They applied a partial least-squares discriminate analysis (PLS-DA) algorithm to the impedance data in order to classify two tissue types: muscle and fat [16]. However, the tissues encountered during laparoscopic and thoracoscopic surgeries are more diverse, not only muscle and fat tissues but also liver or lung tissues. Moreover, because the impedance values of tissues were reported to have a non-linear distribution [16,17], a higher order polynomial should be needed to classify the class of tissues. The impedance characteristics of muscle, fat, liver, and lung tissues extracted from pigs (Fig. 1(A)) showed non-linear distribution by each other as shown in Fig. 1(B) in this study. Therefore, the methods used in previous studies, such as binary classification, linear classification, and statistical analysis, have limitations for the classification of more than three types of tissue with a non-linear distribution of impedance.

In order to classify the intrinsic impedance value of multiple classes of tissue with a non-linear distribution, we applied a machine learning algorithm-based classification method that uses the inherent unique properties of the multi-dimensional input data. This approach has been applied in the fields of behavior pattern analysis [18], biometrics [19], and even in clinical areas such as prediction and diagnosis of disease [20,21]. However, previous studies have reported that there are differences in classification performance among each classifier with the same data set and limitations in the accuracy of multi-dimensional class classification with a single classifier [22]. For these reasons, recent studies have used a multi-classifier as a method of combining the results of several single classifiers; this approach has resulted in a higher classification rate than that achieved using single classifiers [20,21,23,24].

The goal of this study was to introduce a multi-classifier with increased accuracy of multi-class tissue classification based on the intrinsic impedance values of each *in vivo* tissue, with the ultimate aim of automatic optimal output power adjustment of USUs used in surgery. For this purpose, the classification performance of previously introduced single classifiers was analyzed using the electrical properties of tissues measured with the newly developed impedance measurement device. A multi-classifier that effectively classifies the multi-class tissue was introduced by combining the best single classifiers, and its performance was compared and analyzed with that of the former single classifiers. The results of this study are expected to be an important contribution toward performing tissue cutting and coagulation with minimum *in vivo* tissue damage during surgery using USUs.

2. Methods

2.1. System setup

This study aimed to increase the classification rate of multiple tissues using the unique impedance characteristics of different *in vivo* tissues. By applying a waveform of a particular frequency through the electrodes, the newly developed device obtained a feedback signal passing through the tissue using another electrode, as shown in Fig. 2(A). The impedance values of each tissue were calculated by the device and stored in the storage memory as a database. The paired subdermal electrodes (Medtronic Inc., Minneapolis, MN, USA) were distinguished as invasive (6 mm and 3 mm) or non-invasive (surface) types, which can be attached to the end of the ultrasonic surgical knife to analyze the classification rate of multiple tissues according to the invasion depth. The distance between the electrodes was 2.5 mm (Fig. 2(B)). To summarize, Type-I (6 mm invasive), Type-II (3 mm invasive), and Type-III (surface) paired subdermal electrodes were used to measure the impedance of the tissues, and the tissue classification rate for each electrode type was analyzed.

The main hardware structure for tissue classification consisted of a MSP430 microcontroller unit (MCU) (Texas Instruments Inc., Dallas, TX, USA) and an AD5933 analog circuit (Analog Devices Inc., Norwood MA, USA). The AD5933 module has a maximum frequency range of 100 kHz, and has both a fast response and high accuracy [25]. The MSP430 MCU was implemented for AD5933 module operation, data acquisition, and PC communication, and included a noise prevention shielded cable, communication cable, and power supply (Fig. 2(C)). Real-time hardware control and data storage were performed by PC software LabVIEW2012 (National Instruments Inc., Austin, TX, USA).

2.2. Data acquisition

The target tissues used in this experiment including fat and muscle which account for a large percentage of the human body, the liver which is the major intrathoracic organ in which laparoscopic surgery is performed, and the lung which is the major organ in the abdominal cavity and the site of thoracoscopic surgery [26,27]. Additionally, muscle and fat tissue were extracted from both the abdomen and neck regions because there is a possibility of heterogeneity according

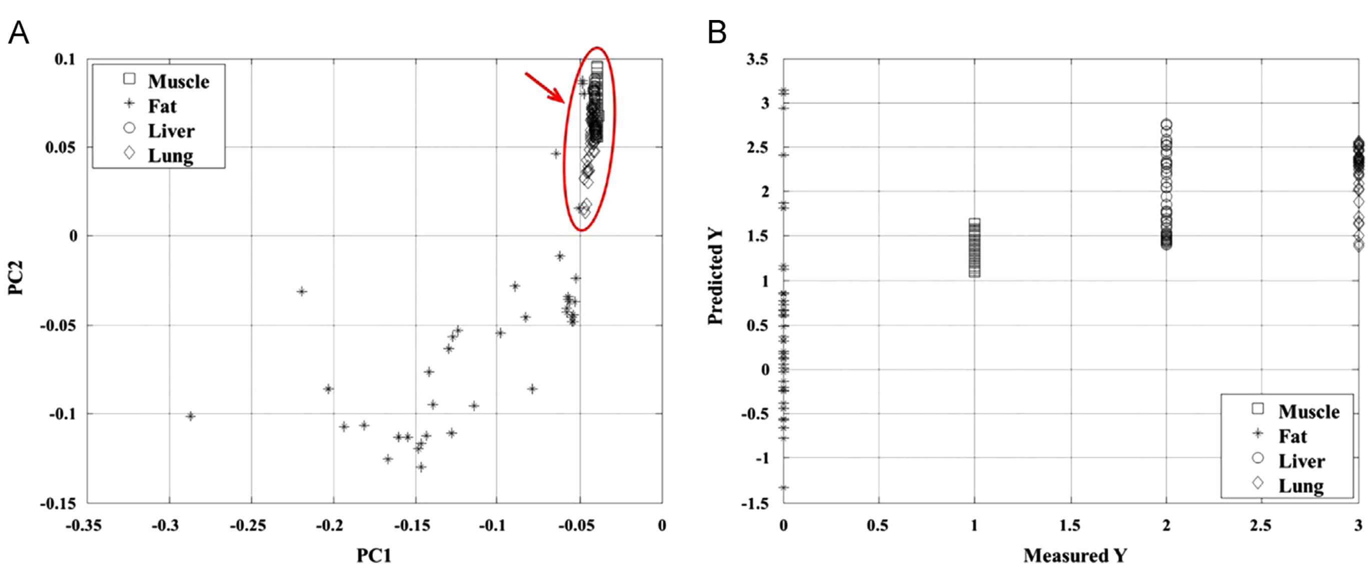

Fig. 1. PLS-DA application result on 4-class (muscle, fat, liver, and lung) model (6 mm invasive electrode); (A) scores plot of PLS analysis by the two principal components (PC1, PC2), (B) regression analysis utilizing the PLS analysis result.