PRECLINICAL REPORT

Toward optoacoustic sciatic nerve detection using an all-fiber interferometric-based sensor for endoscopic smart laser surgery

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Abstract

Objectives: Laser surgery requires efficient tissue classification to reduce the probability of undesirable or unwanted tissue damage. This study aimed to investigate acoustic shock waves (ASWs) as a means of classifying sciatic nerve tissue.

Materials and Methods: In this study, we classified sciatic nerve tissue against other tissue types—hard bone, soft bone, fat, muscle, and skin extracted from two proximal and distal fresh porcine femurs—using the ASWs generated by a laser during ablation. A nanosecond frequency-doubled Nd:YAG laser at 532 nm was used to create 10 craters on each tissue type's surface. We used a fiber-coupled Fabry–Pérot sensor to measure the ASWs. The spectrum's amplitude from each ASW frequency band measured was used as input for principal component analysis (PCA). PCA was combined with an artificial neural network to classify the tissue types. A confusion matrix and receiver operating characteristic (ROC) analysis was used to calculate the accuracy of the testing-data-based scores from the sciatic nerve and the area under the ROC curve (AUC) with a 95% confidence-level interval.

Results: Based on the confusion matrix and ROC analysis of the model's tissue classification results (leave-one-out cross-validation), nerve tissue could be classified with an average accuracy rate and AUC result of 95.78 ± 1.3% and 99.58 ± 0.6%, respectively.

Conclusion: This study demonstrates the potential of using ASWs for remote classification of nerve and other tissue types. The technique can serve as the basis of a feedback control system to detect and preserve sciatic nerves in endoscopic laser surgery.

KEYWORDS
acoustic shock signal, artificial network machine, laser ablation, principal component analysis, sciatic nerve tissue, tissue classification

INTRODUCTION

Laser surgery offers numerous advantages to both patients and surgeons, such as ablating organic tissues with high precision and achieving a functional cutting geometry with minimal trauma. Additionally, contact-free ablation of the laser allows an advanced level of sterility compared to the use of mechanical tools in surgery.1,2 Combining laser osteotomy with endoscopy (minimally invasive surgery) will additionally push the restrictions of possible applications for the benefits of the patient—in the field of maxillo-facial-, neuro-, and orthopedic surgery.3 However, these advantages are somewhat diminished by a lack of information on ablated tissue type and this is an open access article under the terms of the Creative Commons Attribution-NonCommercial License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes.

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depth. During laser ablation, it is crucial to preserve vital tissues, such as the sciatic nerve to preserve collateral damage. Preservation is particularly challenging when operating on body parts with complex tissue types, such as a femur, including hard and soft bone, muscle, fat and skin, and most importantly, the sciatic nerve.5-7

The sciatic nerve is the largest in the human body, measuring up to 2 cm in diameter. Originating from the lumbar and sacral spine, the sciatic nerve travels through the greater sciatic foramen below the piriformis muscle. Surrounded by a fatty sheath, it follows the upper thigh's back, from the pelvis to the knee. At the popliteal fossa, which serves as a conduit for blood vessels and nerves in the leg, the sciatic nerve divides into the common peroneal nerve and the tibial nerve. Both are responsible for motor and sensory function in the lower leg and foot.6,7 Nerves are embedded in various other tissues, making it challenging for surgeons to discriminate between them, mostly smaller diameter nerves. Damaging the sciatic nerve's anatomical structure or the subsequent common peroneal and tibial nerves can drastically affect sensation over the sole, the back of the femur, part of the lower femur and the knee. 8-10

Fractional damage to the nerve can cause weakness of foot movements, weakness of knee flexion (bending), trouble bending the foot down (plantar flexion), or bending the foot inward (inversion).11 Different approaches have already been proposed in the literature to detect nerves during laser ablation. For example, electrical stimulation, diffuse reflectance spectroscopy, optical spectroscopy, and mass spectroscopy have been proposed to detect the nerve tissue during laser ablation or surgery; however, no one has investigated it in a minimally invasive setting.4,12

Depending on the laser's parameters (i.e., pulse duration, wavelength, and output energy), superficial or deep ablation can occur with minimal temperature dissipation. In other words, when using lasers at a wavelength of 2940 nm, deep ablation can occur; this is not the case at 532 nm, where only superficial ablation is possible. To achieve deep ablation, different lasers have been compared and the results suggest that microsecond duration, wavelength, and output energy), supercontinuum erbium-doped yttrium aluminum garnet (Er:YAG) lasers can provide high ablation rate with high efficiency, mainly because the operation wavelength of the Er:YAG laser corresponds to the highest absorption peak of water and hydroxyapatite, the main component of bone.13,14 In contrast to the Er:YAG, the Nd:YAG (neodymium-doped yttrium aluminum garnet) laser source operating at 532 nm is transparent in water and seems well suited for tissue ablation in a liquid environment, such as knee arthroscopy.15,17 Additionally, by using a nanosecond (ns) pulsed laser at 532 nm, we fulfill the thermal confinement condition in biological tissues. Therefore, a ns-pulsed Nd:YAG laser at 532 nm could be alternatively used to avoid thermal damage, producing superficial ablation.17-19 Moreover, since the ablation rate is less than that of Er:YAG lasers, the risk of ablating more than one tissue at the same time is also less, leading to an in increase the possibility of preserving vital tissues.

Furthermore, when ns-pulsed lasers interact with biological tissues, acoustic shock waves (ASWs) from plasma-induced ablation are generated and can propagate through the air.20 The propagated ASW can be measured using piezoelectric transducers, air-coupled transducers (microphones), and free-space Mach–Zehnder interferometer sensors, which convert the spherical wavefront into electrical signals.21-24 ASW signal parameters mainly depend on the type of tissue ablated.21 Therefore, feedback of these parameters can be used for real-time tissue differentiation.24,25 The previously proposed bulky sensors to measure ASWs had limited bandwidths (typically <1 MHz) and were not suitable for minimally invasive setting.26 The need for both a broadband and compact sensor led to new optical sensors, with extended bandwidths and small designs sufficient for endoscopic applications.27

Interferometric-based methods detect variations in the optical interference patterns generated by the ASWs. Interference pattern variation is due to the ASW pressure that can interact directly with the interrogating beam, vary the resonance frequency, or cause reflector vibration. Depending on how the interferometer is configured, interference pattern variations are triggered by changes in the mean free path, the optical wavelength, or the optical phase.24 The resulting variations in intensity or frequency of the interferometer output are measured by a photodiode and generate information about the ASW signals.5,27

Also, according to the literature reviews, support vector machine (SVM) and artificial neural network (ANN) are effective and practical solutions for biomedical signal recognition.28-30 The ANN behavior mostly depends on weights and transfer function. The output of the transfer function is multiplied weights connecting the hidden layer and the output layer to generate the network output.31 Consequently, in our previous study, we compared the performance of PCA combined with either a quadratic and Gaussian VMs or an ANN method.32 The ANN was composed of a pattern network function combined with the Tan-Sigmoid activation function in the hidden layers. The main advantage of the Hyperbolic Tangent Function (Tanh) is that it generates a zero-centered output, thus strengthening the backpropagation process. The multilayer networks can use the Tan-Sigmoid function and the output neurons are often used for pattern recognition problems. Softmax activation function which was also known as a normalized exponential function was further employed to the output layer to predict the label.33,34 Furthermore, ANN is a nonlinear model that is easy to use and understand compared to statistical methods, because ANNs are nonparametric models while most of the statistical methods are parametric models that need higher
background of statistics. That is why ANN with back-propagation learning algorithm is widely used in solving various classification and forecasting problems. In addition, it has been found in our previous study that the ANN showed the best performance in terms of classifying all tissues during ablation. Thus, ANN was also used for this optoacoustic data.

In this study, we used our custom-made fiber-coupled Fabry–Pérot etalon system to measure ASWs during laser ablation. Among the advantages of using etalon sensors are their compactness and broad usable bandwidths (exceeding 2.5 MHz). We used a frequency-doubled, Q-switched Nd:YAG laser at 532 nm to produce craters on the surface of hard bone, soft bone, muscle, fat, skin, and nerve tissue. We measured the ASWs emitted and then assessed the measurements by looking at the frequency band that delivered the best accuracy and area under the curve (AUC). We used principal component analysis (PCA) and an ANN to reduce the dimensionality of data points and to classify sciatic nerve from among other tissue types, respectively.

**MATERIALS AND METHODS**

**Sample preparation**

In the experiments, we used samples from two fresh porcine proximal and distal femurs. Figures 1A–F and 1G–L show pictures of six tissue types (hard bone, soft bone, muscle, fat, skin, and nerve) which were obtained from porcine proximal and distal femurs, respectively. The connective tissues were carefully separated with scalpels. The samples were then rinsed in distilled water before undergoing the laser experiments.

**Experimental setup**

We ablated the samples using a Nd:YAG laser (Q-smart 450; Quantel) with 5 ns-long pulses at 532 nm. The pulse energy was 200 mJ, with a repetition frequency of 10 Hz. The laser beam was focused at a 7.5 cm focal distance (LA5042; Thorlabs), using an antireflection coated biconvex lens. A detailed explanation of the experimental setup, including calibration steps, was reported in previous work. The focal point was positioned 2 mm under the sample surface to achieve deeper ablation. Using a Gaussian distribution, whereby maximum irradiance is reached at an amplitude of $e^{-2}$, the laser spot size was estimated to be 15.6 μm. A sequence of 180 laser pulses was applied to the fresh porcine femur. Ten craters, each 4 mm apart, were created on the surface of each sample.

In the optical sensor system, we used a single-frequency laser source (SFL1550S; Thorlabs) that emits continuous coherent light at a center wavelength of 1550 nm, with an output power of 40 mW. The laser contains a single-mode (SM) output fiber tail (CLD1015; Thorlabs). The output of the fiber tail is coupled into Port 1 (P1 in Figure 2) of the single-mode fiber-optic circulator (FOC) (6015-3-APC; Thorlabs). A single-mode 50:50 partial reflector fiber (P5-SMF28ER-50-1; Thorlabs) is connected to Port 2 (P2 in Figure 2) of the FOC to split the incident beam into two spectral bands: one transmitted and one reflected. The reflected light from the coated facet of the fiber is routed to Port 3 (P3). The transmitted light is collimated at the surface of an antireflection coated biconvex lens (67-593; Edmund Optics). The coated double-convex lens with a focal length of 9 mm is embedded in the 4 × 20 mm optical cavity to focus the collimated light onto the surface of a flat mirror. The propagating beam in the optical cavity is
retroreflected by a protected gold mirror (PF1011-M01; Thorlabs) and coupled back into the 50:50 partial reflector fiber. The FOC also routes the retroreflected beam to P3. The FOC’s P3 connector is mounted to an InGaAs detector with a fixed amplifier gain (PDA20C2; Thorlabs) to sense the variation in light intensity.

During laser tissue ablation, the ASWs generated cause spatiotemporal variations of the air refractive index in the optical cavity. Thus, changes in the light intensity of the probing laser beam in the optical cavity correspond to the ASW pressure, which can be accurately measured by an InGaAs detector. The custom-made all-fiber Fabry–Pérot sensor is illustrated in Figure 2.

**Data acquisition**

During laser tissue ablation, we measured the ASWs emitted using the custom-made optical sensor (Figure 2). Acoustic data acquisition was triggered by an external CMOS trigger from the laser. The time gate window of each measurement was 82 μs. The measured analog signals were digitized using a PCI Express x8 (M4i.44xx-x8; Spectrum Microelectronic GmbH), with a 16-bit transient recorder and a sampling rate of 10 MS/s.

**Classification matrix**

Statistical analysis and calculations were performed with MATLAB (version R2018b). We suppressed each ASW signal's phase shift by characterizing the amplitude spectrum, using the fast Fourier transform. We improved the contrast of the visualization of each ASW using the logarithm of the amplitude spectrum. We split the amplitude spectrum into six equal frequency bands (F1–6). We normalized each frequency band value by subtracting the mean of all frequency bands measured to enhance classification performance. Therefore, a mean of zero was obtained for each frequency range. Each frequency band was used as an input for PCA, which was applied to reduce the dimensionality while maintaining the patterns and trends of the ASW field.38 In other words, PCA decomposes the data by generating orthogonal and, thus, independent linear combinations of the variables known as principal components (PCs) or PCA scores.

To classify tissue, we investigated the post-processed acoustics by looking at the spectral band in which we achieved the best average classification accuracy and the area under the ROC curve for nerve detection. We combined PCA scores with an ANN to carry out the classification (Figure 3).

We used the pattern network function combined with the Tan-Sigmoid activation function for hidden layers and the SoftMax activation function for the output layer available in MATLAB. To build the network, we used an input, one hidden, and an output layer. The input layer was made of three neurons for the first three PCA scores. The single hidden layer and output layer were made of 10 neurons and 6 output neurons, respectively (Figure 4).

Only a few PCA scores are needed to describe the large variability of the data points. Thus, by using only three PCA scores, we were able to reduce the dimensionally of the frequency band while keeping most of the variance of the selected frequency band for classification (Figures 5 and 6A,B).

A total of 7200 ASWs were measured for each type of tissue extracted from two femurs—each femur has a proximal and a distal. During the classification phase, we used a set of 3600 data points measured from 10 craters in one proximal and distal femur as training data. During the validation phase, 1800 data points were used from the
second proximal femur, and the remaining 1800 data points from the same femur were used as testing data. We performed a leave-one-out cross-validation by using the second femur as training data and the first one as validation and testing data. From the two confusion matrices and the receiver operating characteristics (ROCs), we calculated the mean accuracy of the testing-data-based scores for sciatic nerve classification and the AUC with a 95% confidence-level interval. We evaluated the performance of our models fairly on a single
computer with a specification of 2.4 GHz Intel Core i7 processor, 16 GB 1867 MHz DDR3 memory.

RESULTS

ASWs measured in the time and frequency domains for each ablated tissue are shown in Figure 5. Hard tissue (hard bone) produced higher peak amplitude values in the time and frequency domains than did the soft tissues (soft bone, muscle, fat, skin, and nerve). We used each frequency band as input for the PCA (see Appendix A for results at frequency bands, except for FR4).

The analysis of the training and testing data scores from frequency range FR4 are shown in Figures 6A and 6B, respectively. Results from other frequency bands are in Appendix A (Figures A1–A5 and Tables A1–A5). The first three PCs selected for differentiation were responsible for 87.5% of the variation around the data point where the first contributed 85.28% (PC1) followed by 1.89% (PC2) and 0.33% (PC3) to the cumulative variance. From the confusion matrix and the ROC analysis (Figure 4C), the average classification accuracy (with leave-one-out cross-validation) between nerve tissue and other tissues was more than 95.78 ± 1.3% (Table 1). The corresponding AUC was more than 99.58 ± 0.6%, for nerve, against other tissues (Table 1). Backpropagation was used for training with a learning rate of 2.4 ms. The computation time for testing was of the order of 0.46 ms.

DISCUSSION

Based on the confusion matrix and the ROC analysis of the model’s tissue classification results, nerve tissue could be classified with an accuracy rate and AUC results of

![FIGURE 6](image-url) First three principal component (PC) scores from (A) the training data for hard and soft bone, muscle, fat, skin, and nerve (FR4 = 1.25–1.67 MHz), using the artificial neural network (ANN) models combined with the nanosecond (ns)-Nd:YAG laser. First three PC scores from (B) the testing data for hard and soft bone, muscle, fat, skin, and nerve (FR4 = 1.25–1.67 MHz), using the ANN models combined with the ns-Nd:YAG laser. The receiver operating characteristic curve (C) to multiclass using the ANN models combined with the ns-Nd:YAG laser. Note that the curve of hard bone, skin, muscle, and nerve tissues versus other tissues overlaps.
TABLE 1  Confusion matrix for hard bone, skin, muscle, fat, soft bone, and nerve tissues (FR4 = 1.25–1.67 MHz) during laser ablation at 0.2 J pulse energy

| Tissue       | Classified as  |
|--------------|---------------|
|              | Hard bone     | Skin | Muscle | Fat | Soft bone | Nerve | Accuracy with leave-one-out cross-validation (%) | Area under ROC curve (%) |
| Hard bone    | 1800          | 0    | 0      | 0   | 0        | 0     | 100                                               | 100                      |
| Skin         | 0             | 1734 | 0      | 0   | 0        | 66    | 99.33                                             | 99.91                    |
| Muscle       | 0             | 0    | 1712   | 7   | 0        | 81    | 95.11                                             | 99.83                    |
| Fat          | 0             | 0    | 9      | 1593| 198      | 0     | 88.50                                             | 98.90                    |
| Soft bone    | 0             | 0    | 0      | 198 | 1602     | 0     | 89                                                | 98.98                    |
| Nerve        | 0             | 43   | 33     | 0   | 0        | 1724  | 95.78                                             | 99.58                    |

Abbreviation: ROC, receiver operating characteristic.
As already mentioned, the Er:YAG laser at 2940 nm is generally used for deep ablation accompanied by a water-cooling system, while the Nd:YAG laser at 532 nm can be used to ablate surfaces in a wet environment. Depending on the laser pulse parameters, such as laser energy, pulse duration, and focusing conditions, the ASW properties can be slightly different. Therefore, for more application, investigating tissue classification using the Er:YAG at 2940 nm combined with the Nd:YAG laser at 532 nm in vivo is an essential next step.

CONCLUSION

The results of this study show the potential of using ASW for remote classification of nerve and other types of tissue (hard and soft bone, muscle, fat, and skin). The average classification accuracy and AUC result with leave-one-out cross-validation was more than 95.78 ± 1.3% for distinguishing nerves from other tissues. This technology can be used to develop a control system capable of identifying nerve tissue during endoscopic laser surgery to prevent sensation and motor function loss in the lower body. Future work should focus on tissue classification and carbonization detection with sufficiently short computational time when ablating a wide range of tissue types in vivo, using Nd:YAG and Er:YAG at 532 and 2940 nm, respectively.

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CONFLICT OF INTERESTS

The authors declare that there are no conflict of interests.

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### APPENDIX A

#### Tables A1–A5

**Figures A1–A5**

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#### TABLE A1

Confusion matrix for hard bone, skin, muscle, fat, soft bone, and nerve tissues (FR1 = 0–0.42 MHz) during laser ablation at 0.2 J pulse energy

| Tissue       | Hard bone | Skin | Muscle | Fat | Soft bone | Nerve | Average classification accuracy with leave-one-out cross-validation (%) | Area under ROC curve (%) |
|--------------|-----------|------|--------|-----|-----------|-------|---------------------------------------------------------------------|--------------------------|
| Hard bone    | 1798      | 2    | 0      | 0   | 0         | 0     | 99.88                                                               | 100                      |
| Skin         | 0         | 1800 | 0      | 0   | 0         | 0     | 100                                                                 | 100                      |
| Muscle       | 0         | 0    | 1797   | 3   | 0         | 0     | 99.83                                                               | 100                      |
| Fat          | 0         | 0    | 321    | 1479| 0         | 0     | 82.17                                                               | 98.65                    |
| Soft bone    | 0         | 0    | 0      | 259 | 1541      | 0     | 85.61                                                               | 98.66                    |
| Nerve        | 0         | 0    | 0      | 0   | 0         | 1800  | 100                                                                 | 100                      |

Abbreviation: ROC, receiver operating characteristic.

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#### TABLE A2

Confusion matrix for hard bone, skin, muscle, fat, soft bone, and nerve tissues (FR2 = 0.42–0.83 MHz) during laser ablation at 0.2 J pulse energy

| Tissue       | Hard bone | Skin | Muscle | Fat | Soft bone | Nerve | Average classification accuracy with leave-one-out cross-validation (%) | Area under ROC curve (%) |
|--------------|-----------|------|--------|-----|-----------|-------|---------------------------------------------------------------------|--------------------------|
| Hard bone    | 1799      | 1    | 0      | 0   | 0         | 0     | 99.94                                                               | 100                      |
| Skin         | 0         | 1799 | 0      | 0   | 1         | 0     | 99.94                                                               | 100                      |
| Muscle       | 0         | 0    | 1797   | 3   | 0         | 0     | 99.61                                                               | 99.95                    |
| Fat          | 0         | 0    | 6      | 1475| 185       | 134   | 81.94                                                               | 97.37                    |
| Soft bone    | 0         | 0    | 0      | 214 | 1448      | 138   | 80.44                                                               | 97.42                    |
| Nerve        | 0         | 0    | 14     | 165 | 192       | 1429  | 79.39                                                               | 97.72                    |

Abbreviation: ROC, receiver operating characteristic.

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#### TABLE A3

Confusion matrix for hard bone, skin, muscle, fat, soft bone, and nerve tissues (FR3 = 0.83–1.25 MHz) during laser ablation at 0.2 J pulse energy

| Tissue       | Hard bone | Skin | Muscle | Fat | Soft bone | Nerve | Average classification accuracy with leave-one-out cross-validation (%) | Area under ROC curve (%) |
|--------------|-----------|------|--------|-----|-----------|-------|---------------------------------------------------------------------|--------------------------|
| Hard bone    | 1800      | 0    | 0      | 0   | 0         | 0     | 100                                                                 | 100                      |
| Skin         | 1         | 1797 | 1      | 0   | 0         | 1     | 99.83                                                               | 100                      |
| Muscle       | 0         | 1    | 1757   | 9   | 0         | 33    | 99.61                                                               | 99.95                    |
| Fat          | 0         | 0    | 4      | 1582| 207       | 7     | 87.89                                                               | 98.68                    |
| Soft bone    | 0         | 0    | 0      | 114 | 1686      | 0     | 99.66                                                               | 98.85                    |
| Nerve        | 0         | 0    | 135    | 7   | 0         | 1658  | 92.11                                                               | 99.67                    |

Abbreviation: ROC, receiver operating characteristic.
### Table A4
Confusion matrix for hard bone, skin, muscle, fat, soft bone, and nerve tissues (FR5 = 1.67–2.08 MHz) during laser ablation at 0.2 J pulse energy

| Tissue      | Classified as | Average classification accuracy with leave-one-out cross-validation (%) | Area under ROC curve (%) |
|-------------|---------------|------------------------------------------------------------------------|--------------------------|
|             | Hard bone     | Skin | Muscle | Fat | Soft bone | Nerve |                                   |                                        |
| Hard bone   | 1796          | 4    | 0      | 0   | 0         | 0     | 99.78                              | 100                                     |
| Skin        | 0             | 1625 | 0      | 0   | 0         | 175   | 90.28                              | 99.44                                   |
| Muscle      | 0             | 0    | 1706   | 7   | 0         | 87    | 94.78                              | 99.80                                   |
| Fat         | 0             | 0    | 0      | 1585| 210       | 1     | 88.06                              | 98.84                                   |
| Soft bone   | 0             | 0    | 0      | 267 | 1533      | 0     | 85.17                              | 98.92                                   |
| Nerve       | 0             | 104  | 27     | 0   | 0         | 1669  | 92.72                              | 98.66                                   |

Abbreviation: ROC, receiver operating characteristic.

### Table A5
Confusion matrix for hard bone, skin, muscle, fat, soft bone, and nerve tissues (FR6 = 2.08–2.50 MHz) during laser ablation at 0.2 J pulse energy

| Tissue      | Classified as | Average classification accuracy with leave-one-out cross-validation (%) | Area under ROC curve (%) |
|-------------|---------------|------------------------------------------------------------------------|--------------------------|
|             | Hard bone     | Skin | Muscle | Fat | Soft bone | Nerve |                                   |                                        |
| Hard bone   | 1788          | 4    | 0      | 0   | 0         | 8     | 99.33                              | 100                                     |
| Skin        | 0             | 1501 | 0      | 0   | 0         | 299   | 83.39                              | 99.41                                   |
| Muscle      | 0             | 0    | 1553   | 0   | 0         | 247   | 86.40                              | 99.16                                   |
| Fat         | 0             | 0    | 3      | 1520| 227       | 50    | 84                                 | 98.35                                   |
| Soft bone   | 0             | 0    | 0      | 267 | 1515      | 18    | 84.17                              | 98.78                                   |
| Nerve       | 3             | 105  | 64     | 13  | 0         | 1615  | 89.72                              | 98.53                                   |

Abbreviation: ROC, receiver operating characteristic.
**FIGURE A1** First three principal component (PC) scores from (A) the training data for hard and soft bone, muscle, fat, and skin (FR1 = 0–0.42 MHz). First three PC scores from (B) the testing data for hard and soft bone, muscle, fat, and skin (FR1 = 0–0.42 MHz). Receiver operating characteristic curve (C) to multiclass using the artificial neural network models combined with the ns-Nd:YAG laser. Note that the curve of hard bone, skin, muscle, and nerve tissues versus other tissues overlaps (FR1 = 0–0.42 MHz).
FIGURE A2  First three principal component (PC) scores from (A) the training data for hard and soft bone, muscle, fat, and skin (FR2 = 0.42–0.83 MHz). First three PC scores from (B) the testing data for hard and soft bone, muscle, fat, and skin (FR2 = 0.42–0.83 MHz). Receiver operating characteristic curve (C) to multiclass using the artificial neural network models combined with the ns-Nd:YAG laser. Note that the curve of hard bone, skin, muscle, and nerve tissues versus other tissues overlaps (FR2 = 0.42–0.83 MHz)
FIGURE A3  First three principal component (PC) scores from (A) the training data for hard and soft bone, muscle, fat, and skin (FR3 = 0.83–1.25 MHz). First three PC scores from (B) the testing data for hard and soft bone, muscle, fat, and skin (FR3 = 0.83–1.25 MHz). Receiver operating characteristic curve (C) to multiclass using the artificial neural network models combined with the ns-Nd:YAG laser. Note that the curve of hard bone, skin, muscle, and nerve tissues versus other tissues overlaps (FR3 = 0.83–1.25 MHz)
FIGURE A4  First three principal component (PC) scores from (A) the training data for hard bone, soft bone, muscle, fat, skin, and nerve (FR5 = 1.67–2.08 MHz). First three PC scores from (B) the testing data for hard bone, soft bone, muscle, fat, skin, and nerve (FR5 = 1.67–2.08 MHz). Receiver operating characteristic curve (C) to multiclass using the artificial neural network models combined with the ns-Nd:YAG laser. Note that the curve of hard bone, skin, muscle, and nerve tissues versus other tissues overlaps (FR5 = 1.67–2.08 MHz)
First three principal component (PC) scores from (A) the training data for hard bone, soft bone, muscle, fat, skin, and nerve (FR6 = 2.08–2.50 MHz). First three PC scores from (B) the testing data for hard bone, soft bone, muscle, fat, skin, and nerve (FR6 = 2.08–2.50 MHz). Receiver operating characteristic curve (C) to multiclass using the artificial neural network models combined with the ns-Nd:YAG laser. Note that the curve of hard bone, skin, muscle, and nerve tissues versus other tissues overlaps (FR6 = 2.08–2.50 MHz).