Toward photothermal damage detection during laser osteotomy using optical coherence tomography

Aikaterina Grava1,∗, Arsham Hamidi1, Alvaro Gonzalez-Jimenez2, Yakub A. Bayhaqi1, Alexander A. Navarini2,3, Philippe C. Cattin4, and Ferda Canbaz1,∗∗

1University of Basel, Department of Biomedical Engineering, Biomedical Laser and Optics Group (BLOG), Allschwil, Switzerland
2University of Basel, Department of Biomedical Engineering, Digital Dermatology, Allschwil, Switzerland
3University Hospital of Basel, Department of Dermatology, Basel, Switzerland
4University of Basel, Department of Biomedical Engineering, Center of medical Imaging Analysis & Navigation (CIAN), Allschwil, Switzerland

Abstract. Feedback systems have been utilized to reduce the possible thermal side effects of lasers for surgery by means of temperature monitoring to control irrigation systems. In this study, we investigated the potential application of optical coherence tomography as a means of detecting bone dehydration status. We investigated the penetration depth of the OCT laser and its respective relation to the hydration status of bone. A deep-learning method was utilized to differentiate between different levels of water content in bone tissue (fresh/hydrated, dehydrated, and carbonized) based on the OCT images. The proposed model achieved an accuracy of 0.912 on an independent test set, demonstrating its ability to accurately predict the state of the bone considering these three conditions. We believe this method can potentially accelerate the detection of dehydration during laser surgery, improving the safety of using lasers with real-time feedback.

1 Introduction

The conventional method for bone surgery (osteotomy) involves the use of mechanical tools such as bone saws and drills [1]. However, recent studies have highlighted the advantages of laser osteotomy over conventional methods, including higher accuracy, reduced bacterial contamination, and faster patient healing [2]. Nevertheless, achieving safe laser osteotomy requires consideration of several parameters, such as the desired depth of cut, tissue type, and temperature feedback during laser-tissue interaction.

Over time, various feedback systems based on optics and acoustics have been developed to provide the necessary information and achieve smart laser osteotomy. Among these systems, optical coherence tomography (OCT) offers superior advantages compared to other methods for monitoring and controlling laser surgery [3]. It is a non-invasive interferometric imaging system that provides high-resolution and high-speed tomographic images of biological tissues. Despite that OCT’s wavelength is selected based on minimum absorption in the water to increase the penetration depth in tissues, water content is still a primary parameter to reduce the imaging range in biological tissues.

It is worth noting that Er:YAG laser operating at 2.9 μm is a promising tool for achieving deep laser cuts with minimal thermal damage through photothermal ablation. However, dehydration due to temperature rise can lead to thermal damage. Therefore, the water content of bone tissue is an important parameter to measure.

Since the water content has a direct influence on the imaging range of the OCT system in biological tissue, this study investigates the potential of using deep-learning-assisted OCT to differentiate the water content of pig femur bone in three conditions: fresh, dehydrated, and carbonized. This differentiation is based on the imaging range of the OCT images obtained from different bone samples at the corresponding three conditions. The proposed method has the potential to determine the condition of bone tissue from the OCT image, without requiring an attenuation map [4]. This method can be used as feedback for the irrigation system during laser osteotomy.

2 Methods

2.1 Sample preparation and Experiments

We utilized thirteen pig bone femurs obtained from local vendors. Soft tissues, including bone marrow and muscle, were meticulously removed, and the bone tissue was cleaned with tap water. We took special care not to employ any fixation material, as we aimed to preserve the integrity of the bone structure.

Different states of bone were classified as fresh (hydrated), dehydrated, and carbonized. All the samples were imaged using a custom-made swept-source OCT system (λ0 = 1060 nm, Δλ = 100 nm, sweep rate 100 kHz) with axial and lateral resolutions of 12 μm utilized to capture

*Corresponding author. E-mail: aikaterina.grava@unibas.ch
**Corresponding author. E-mail: ferda.canbaz@unibas.ch
cross-sectional images of the bone [5]. The OCT images of the samples were acquired using volume images, including 400 B-scans and seven individual parts of each bone image (with a field of view of 5.2 mm).

After cleaning the bones, the first set of images was collected, in which the bone tissue was classified as fresh bone. Subsequently, we let the samples naturally dehydrate at room temperature to maintain the bone tissue structure. Images were captured in one, seven, and nineteen days during the dehydration process. Eventually, we carbonized the dehydrated bone tissue utilizing an Er:YAG laser at a 50 Hz repetition frequency and an energy per pulse of 5.2 mJ. The bone tissue was placed out of focus at a 4 cm distance from the focusing lens (f=7.5 cm) to avoid ablation. The dehydrated bones (left) and carbonized bones (right) are shown in Figure 1.

2.2 Implementation and Dataset

We used a pre-trained ResNet50 model [6] on ImageNet. The models were trained for 20 epochs with $10^{-5}$ learning rate, cross-entropy loss, and Adam optimizer. We augmented the data with random rotations, flips, and crops to increase the training set and resized the input images to $512 \times 512$ pixels. Validation accuracy was monitored to stop the training with early stopping after ten epochs without improvement to prevent overfitting. Models were evaluated with Accuracy (ACC), Precision (PR), Recall (RC), and F1 scores. PyTorch library and an NVIDIA Tesla V100 32 GB accelerated the training process.

We ensured the model’s robustness through rigorous data split into three sets: 174,400 images for training, 72,400 for validation, and 62,400 remaining images for testing. Each set used OCT images of fresh, dehydrated, and carbonized conditions from different bone samples. The final set was kept separate to report unbiased results, ensuring the model was well-trained, validated, and thoroughly tested with unused data.

3 Results

Our proposed model achieved results with an ACC of 0.912, PR of 0.923, RC of 0.833, and F1 score of 0.912, on the independent test set. In addition, we generated ROC curves for each of the three bone conditions: fresh, dehydrated, and carbonized, as shown in Figure 2. The ROC curves demonstrate the ability of our model to distinguish between different bone conditions. These results further validate the efficacy of our proposed model for bone characterization.

4 Discussion and Conclusions

Our proposed deep-learning assisted OCT system has the potential to be used as real-time feedback for the irrigation system during laser osteotomy. The results demonstrated that our simple processing method could achieve a 0.912 accuracy to differentiate the type of tissue by using an intensity-based OCT image. Further improvement of the data processing and optical setup can lead to adding extra features to the OCT-guided laser surgery to prevent thermal damage in addition to the visual feedback and tissue type detection.

References