Received 26 April 2024, accepted 26 April 2024, date of current version 22 May 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3395071

COMMENTS AND CORRECTIONS

Corrections to "Deep-Learning Approach for Tissue Classification Using Acoustic Waves During Ablation With an Er:YAG Laser"

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In the above article [1], we found major issues with the data we used. Specifically, we received data from [2] for five distinct tissues, with ten specimens per tissue. However, upon closer examination, we realized that the data for these specimens were not unique; rather, they were scaled variations derived from a single specimen. As a result, our training, testing, and validation datasets were not independent, leading to an artificially high accuracy rate of 100%.

Consequently, we re-conducted the experiments and updated the neural networks for data analysis, which we describe in more detail in [3].

We replicated the experiment detailed in [2], using identical transducers and an Er:YAG laser (model: Syneron Candela litetouch LI-FG0001A). This laser features a wavelength of 2940 nm and operates with a pulse duration of 300 μs. We aimed to closely match the experimental conditions of the original study for consistency and accuracy in our results.

Data Acquisition: In the revised experiments, we altered the sample preparation slightly. Instead of uniform tissue sizes of $10\times50\times5$ mm^3, we used varying sizes, as depicted in Figure 2 of the updated manuscript. In addition to replicating the original experimental setup, we made specific adjustments to the data acquisition parameters. The data acquisition time was extended to 2.3 ms (instead of the previous 0.82 ms). Moreover, we expanded the time window from 100 μs to 384 μs, which we used as an input for our neural networks. These changes are illustrated in Figure 1. We initially trained the networks described in [1], using time windows of 100 μs and 384 μs (refer to Table 1). Our findings indicate that the larger time window notably enhanced the results. However, the accuracy remained limited, prompting us to conduct a comprehensive analysis. This analysis included examining raw data, time data, their combination, and Principal Component Analysis (PCA). We also implemented a hyperparameter search to optimize the network performance. The most effective network, utilizing a single measurement as input, achieved an accuracy of 65.6%, a significant improvement over the previous method's accuracy of below 43% (see Table 1).

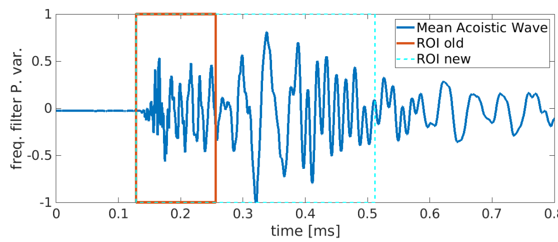

FIGURE 1. In red the old region of interest (ROI) is shown at 100μs, and in cyan the new ROI of the size 384μs.

TABLE 1. Comparison of the Frequency- and Time-dependent data with our new data and the best-performing model using a combination of both using our newly fined tuned neural network (CNN+FcNN).

	Freq. (100µs)	Freq. (384µs)	Time (100µs)	Time (384µs)	Freq.+Time (384µs)
FcNN	34.86%	33.36%	38.31%	41.72%	-
CNN	35.72%	36.51%	40.42%	38.73%	-
RNN	33.96%	33.28%	38.73%	33.28%	-
^{1}CNN+FcNN	-	-	-	-	65.6%
^{10}CNN+FcNN	-	-	-	-	75.5%

Further, we observed that expanding the frequency range to 0–1 MHz increased the accuracy of the Convolutional Neural Network (CNN) analyzing frequency-dependent data to 44.57%, particularly with a time window of 384 μs. In our comparison, we evaluated the network's performance using inputs of 1, 5, and 10 consecutive acoustic waves. The highest level of accuracy, reaching a peak of 75.5%, was attained with inputs of 10 consecutive acoustic waves. In addition, we show that our neural networks outperform the Artificial Neural Network (ANN) method from [2]. Lastly, it is noteworthy that our analysis, along with the findings in [1] and [2], consistently highlights the substantial impact of low frequencies on the classification task.

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