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Multichannel Crossed Convolutional Neural Network for Combined Estimation of Cortical Thickness and Bulk Velocities Using Ultrasonic Guided Waves: A Simulation Study

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***Abstract*—Ultrasonic guided waves (UGW) propagated in the long cortical bone can be measured via axial transmission method. However, ultrasonic identification of long cortical bone is a multi-parameter inverse problem and the optimal solution of the inverse problem often involves complex solving process. Deep neural network is essentially a multi-parameter powerful predictor based on universal approximation theorem. In the study, we investigate the feasibility of applying the multichannel crossed convolutional neural network (MCC-CNN) for simultaneous estimation of cortical thickness and bulk velocities. Finite-difference time-domain method (FDTD) is used to obtain the simulated UGW signals. The results illustrated that the proposed method confirms the feasibility and accuracy, which could be helpful to the UGW based evaluation of long cortical bone.**

Keywords—Ultrasonic guided waves, Cortical bone, Convolutional Neural Network, Cortical Thickness, Bulk Velocities

I. INTRODUCTION

Ultrasonic guided waves (UGW) theory has been applied to evaluate the quality of long cortical bone via so-called axial transmission method [1-9]. In most of the previous studies, the recorded temporal-spatial matrix signals were transformed to wavenumber-frequency (k-f) domain to quantify the UGW dispersive modal energy. To enhance the SNR and improve extraction of dispersion curves for low amplitude modes, some array signal processing algorithms, such as the Radon transform [1, 10] and SVD-based method [11, 12] were proposed. The SVD-based method has been combined with a sparse penalty, which successfully achieves a high resolution extraction for dispersion curves [13]. Recently, Xu *et al.* [14] proposed a dispersive Radon transform (DRT) which projects the temporal signals of dispersive waves on the space of parameters of interest for waveguide or media property estimation.

After solving a model based inverse problem by minimizing the cost function defined as the difference between the extracted dispersion curves and theoretical dispersion trajectories, the physical parameters of long cortical bone, such as thickness [15-20], porosity [15-17], bulk velocities [17], phase velocity [21], modulus [22], can be predicted. However, it is challenging to develop a robust and global optimized approach for such an intractable multi-parameter optimization problem [23].

Machine learning, especially deep learning, has recently shown significant performance improvement in diverse fields compared to traditional methods, such as natural image classification [24], speech recognition [25], computer gaming [26]. There has been an explosion of interest in the ultrasound community using classical machine learning methods or deep neural networks (DNNs) to replace traditional methods or procedures, especially in the field of ultrasound imaging but not limited to that. A support vector machine (SVM) was utilized to classify the demineralized bones [27]. The Generative Adversarial Network (GAN) was trained to form an end-to-end transformation that has been applied to reconstruct B-mode images from raw RF data and concurrently segment cyst from surrounding tissue [28]. The convolutional neural network (CNN) learned the compounding operation to produce high-quality images [29]. The CNN was proposed for estimation of porous material parameters from synthetic ultrasound tomography data [30].

Theoretically, DNN can approximate and fit any continuous functions, which could be used for parameters prediction. Due to the spatial correlation calculations of convolutional kernels with different sizes, the CNN based neural networks would have strong feature extraction abilities, which are very suitable for end-to-end self-learning processes. Unlike traditional machine learning methods that the input is features extracted from the original data rather than raw data, such as SVM, end-to-end means the input of CNN is the original data and the output is the final prediction, in which features of input can be self-learned. This study is aiming to introduce the CNN method to solve the inverse problem arisen from UGW based long cortical bone evaluation. Considering cortical thickness and bulk velocities are three key parameters for long cortical bone assessment, a combined determination is designed. Whereas, few studies in

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UGW by means of deep learning have been reported. Such a challenge motivates the development of a deep learning method for combined estimation of the cortical thickness and bulk velocities.

II. Data Collection and Methodoloy

A. Simulation

The long cortical bone was modeled as a 2-D isotropic free plate with homogenized elastic properties. Regarding the forward problem, the finite-difference time-domain method (FDTD) [7, 31, 32] was applied to simulate UGW datasets. As show in Fig.1, a single 1 MHz emitter and 20 receivers are aligned in axial direction for array signal acquisition. Perfectly matched layers (PML) are added to both sides of the model plate for absorbing the reflection. Theoretically, the simulation results are more accurate and more stable with smaller time and space steps when Courant–Friedrichs–Lewy (CFL) conditions are satisfied [31, 32].

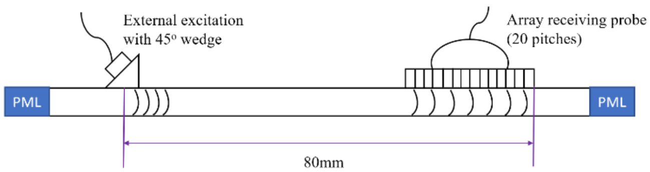


Fig. 1. Simulation model setup

B. Training, validation and test dataset

The model parameters are listed in TABLE I. The training, validation and test datasets consist of 19840, 6262, 6262 samples, respectively. In practice, the cortical physical parameters with some kind of correlation, such as the longitudinal and transverse bulk velocities, cannot be synchronously and uniformly linear distribution within the parameters ranges. For a fixed longitudinal bulk velocity, there may be a local range of transverse bulk velocities corresponding to it. Hence, the bulk velocities in training dataset are composed of two parts of samples to ensure that the trained network have a reasonable and practical prediction ability. In one part, the overall distributions of bulk velocities are uniform. In the other part, the distributions of bulk velocities are locally random. The local parameters ranges are shown in the four right-most columns of TABLE I. Meanwhile, the parameters of thickness are only uniformly distributed in the global range of interest.

To mitigate the inverse crime and test the robustness of the network, the training and test dataset should not be produced with the same time and space steps, so the UGW signals in training dataset were simulated with relatively smaller FDTD temporal step and spatial scale than the settings of the validation and test dataset, further corrupted by additional Gaussian noises (SNR=10dB).

C. Neural network architecture

Fig.2 shows the architecture of the multichannel crossed convolutional neural network (MCC-CNN), which is composed of three crossed channels with a depth of 42 layers. Each channel contains 7 convolutional layers with varied kernel sizes for features extraction. The sizes of the convolutional kernels range from 1×1 to 12×20. The UGW time domain signals were sampled and combined into 20 channels pseudo images as input signals. The input image size of each channel is 34×56. The network was trained to minimize the mean-squared-error (MSE) losses between the true parameters and the neural network predictions utilizing the Adam optimization algorithm [33], with the initial learning rate of 0.001 over 6 epochs using mini-batch learning (mini-batch size = 32).

TABLE I. Model Parameters

Variable Name	Symbol	Global Range		Increment	Local Range1[a]	Local Range2[a]	Local Range3[a]	Local Range4[a]
		Minimum	Maximum					
Bone Thickness	Th	1.0 mm	4.0 mm	0.1 mm	—	—	—	—
Longitudinal bulk velocity	VL	3.37 mm/μs	4.20 mm/μs	0.01 mm/μs	3.37 mm/μs - 3.57 mm/μs	3.58 mm/μs -3.78 mm/μs	3.79 mm/μs - 3.99 mm/μs	4.00 mm/μs -4.20 mm/μs
Transverse bulk velocity	VT	1.34 mm/μs	2.17 mm/μs	0.01 mm/μs	1.34 mm/μs - 1.54 mm/μs	1.55 mm/μs -1.75 mm/μs	1.76 mm/μs - 1.96 mm/μs	1.97 mm/μs -2.17 mm/μs

——There is no random distribution of thickness in local range.
[a] In the other part, the distributions of bulk velocities are locally random.

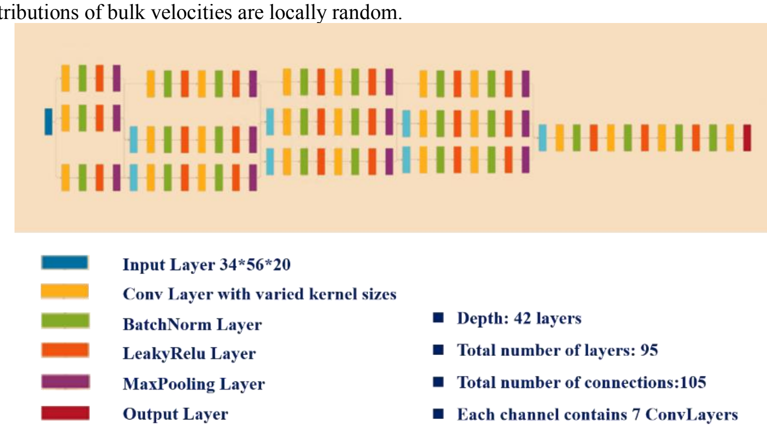


Fig. 2. Architecture of the multi-channel crossed convolutional neural network (MCC-CNN)

III. RESULTS

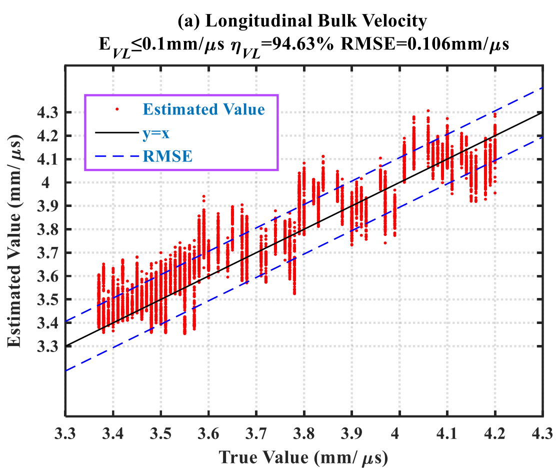
As shown in Fig. 3, the joint prediction accuracy rates of three parameters within absolute error thresholds (E_{VL}≤0.1 mm/μs, E_{VT}≤0.1 mm/μs, E_{Th}≤0.1mm) are all above 90%. The accuracy rate of longitudinal bulk velocities, transverse bulk velocities, cortical thickness is 94.63%, 99.85%, 98.74%, respectively. The accuracy rate for longitudinal bulk velocities is relatively lower compared with the other two parameters on this occasion. The prediction accuracy rates is defined as:

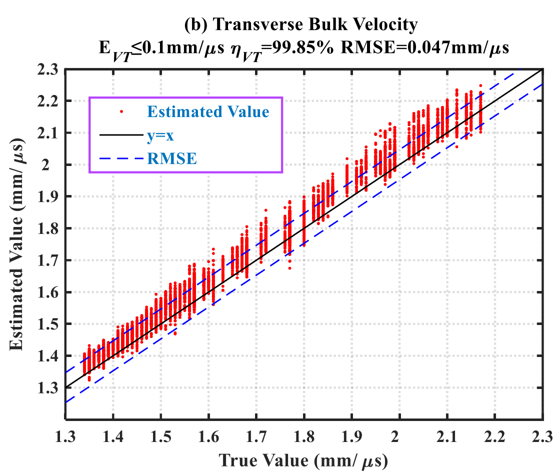
$$\eta = \frac{\sum_i S^i_{E_{\{\cdot\}}}}{N_{all\_test}} \times 100\% \quad S^i_{E_{\{\cdot\}}} = \begin{cases} 1 & E_{\{\cdot\}} \le 0.1 \\ 0 & others \end{cases}$$

where i is the serial number of samples in test dataset. $E_{\{\cdot\}}$ denotes absolute prediction error (E_{VL}, E_{VT}, E_{Th}). N_{all_test} is the number of samples in test dataset.

The mean percentage estimated error of longitudinal bulk velocities, transverse bulk velocities, cortical thickness is 2.35%, 2.36% and 2.56%, respectively. The estimation root-mean-square error (RMSE) of three parameters is 0.139. The estimated RMSE for each of them is 0.106 mm/μs, 0.047 mm/μs and 0.077 mm, respectively.

From the prediction results, it can be found that the MCC-CNN has a good performance in terms of the prediction accuracy rates and mean relative errors. The designed MCC-CNN is robust for the test dataset.





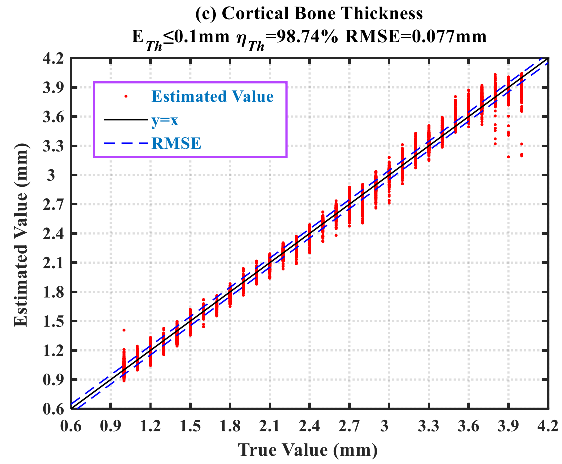


Fig.3. Estimated results. (a) Longitudinal bulk velocity. (b) Transverse bulk velocity. (c) Cortical bone thickness. Blue dashed lines are associated with RMSE.

IV. DISCUSSION

Cortical thickness and bulk velocities (longitudinal and transverse) are important parameters to characterize the quality of long cortical bone. Single parameter estimation cannot fully evaluate the cortical situation. A simultaneous estimation of three parameters for cortical samples in the study would be a relatively comprehensive evaluation of long cortical bone.

Inspired by previous studies[17, 30], an MCC-CNN network was designed to solve the complicated optimization problem for estimating the long cortical bone material parameters using the UGW signals domain. Once trained, the mapping is constructed between the UGW signals domain and the long cortical bone material parameters domain in virtue of features extracted via multiscale convolutional kernels in different channels. Different from the multi-parameter estimation in most of previous studies, the proposed technique avoids to directly solve the tough multi-parameter optimization problem. The results indicate that the parameters of long cortical bone can be estimated simultaneously with faithful accuracy at the SNR of 10dB.

It should be mentioned that other networks including famous pretrained network, for instance, LSTM, AlexNet, GoogleNet, can also be applied to solve the optimization problem involved in present study. The trade-off is that the more complicated network is chosen, the higher the training computation time is consumed. Meanwhile, the complicate design of the loss-function between true values and predictions will also bring other challenges, such as network convergence efficiency and more hyperparametric adjustments. As a perspective for the future work, robustness and generalization of the proposed technique should be verified by *in vitro* and *in vivo* experiments.

V. CONCLUSION

In this study, a parameters estimation method based on deep learning was proposed to solve intractable optimization problem for long cortical bone identification. The analysis of the results suggested that the MCC-CNN method using the UGW has potential to improve the long cortical bone evaluation, which may become a significant advantage when trying to characterize long cortical bone by solving model-based inverse problems. In future work, the proposed method should be further verified by *in vitro* and *in vivo* datasets.

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