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Comparison of artificial neural network configurations to extract micro-architectural properties of cortical bone using ultrasonic attenuation: a 2-D numerical study

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***Abstract*— Osteoporosis is the most common metabolic bone disorder. It affects both cortical and trabecular bone and is characterized by low bone mass, tissue degradation, deteriorated macroscopic mechanical properties, and altered micro-architecture [1], [2], [3], [4]. Loss in bone mass leads to frequent fracturing, higher mortality rates and reduction in life expectancy [5], [6], [7]. The goal of this study is to move towards better diagnosis of osteoporosis through a data driven approach. Two different configurations of the same artificial neural network were used to take advantage of the relationship between frequency dependent attenuation and micro-structural properties such as porosity, pore density, pore diameter, and standard deviation of pore diameter. Finite difference simulation were conducted using in the 1-8MHz frequency range. The frequency-dependent attenuation data was used to create a 1x8 feature vector that was inputted into the neural network. Then a recursive feature elimination was used to optimize the network and identify the most relevant frequencies. Our results indicate that the most important frequencies are 1, 3, 4, and 8 MHz. A new 1x4 feature vector containing only data from these frequencies was used. Both configurations accurately predict pore diameter, porosity, and standard deviation but were less accurate on pore density. Overall the network using the 1x4 feature vector outperformed the one using the 1x8 when comparing results, computational efficiency, and accuracy.**

Keywords—Neural network, machine learning, inverse problem,

I. Introduction

Osteoporosis is the most common bone metabolic disorder. It is characterized by tissue degradation, low bone mass, and altered micro-architecture in cortical and trabecular bone. These changes lead to a greater occurrence of fractures, and a higher mortality. Thus early diagnosis and monitoring of osteoporosis is vital. Currently osteoporosis is diagnosed using a variety of methods. DXA(Dual X-Ray Absorption) is used to evaluate bone mineral density (BMD). High resolution peripheral quantitative computed tomography (HR-pQCT) and magnetic resonance imaging (MRI) can be used to characterize bone, but are associated with major issues, MRI lacks resolution, CT based methods cannot be used repeatedly due to radiation, DXA can assess BMD however BMD alone is only a partial reflection of the degree of osteoporosis and the likelihood of fracture. In addition to BMD, bone microstructure is now recognized as a marker of osteoporosis. Quantitative ultrasound has been used to evaluate bone microstructure. However, more work is needed to solve the inverse problem to extract micro-structural variables such as pore diameter, pore density, and porosity from ultrasound parameters.

Neural networks have been extremely useful in many different settings to date. Specifically, they can provide clinical level classification accuracies of skin and breast cancer. They achieve this through their ability to identify patterns and relationships in complex data sets.

This study aims to characterize micro-architectural properties of cortical bone such as pore diameter, pore density, standard deviation of pore diameter, and porosity, from ultrasound attenuation measurements using an artificial neural network (ANN). 2D finite-difference time-domain simulations were conducted to calculate the frequency-dependent attenuation in the range of 1-8 MHz in poly-disperse structures (non-uniform distribution of pore diameter) obtained from high resolution CT scans of human cortical bone. Using image processing, the distributions of pore diameter, porosity and pore density were calculated. The attenuation data combined with the porosity parameters were used to build the training data set. The dataset consisted of 960 polydisperse structures, extracted from 960 CT slices of human cortical bone.

This data set can be used to solve an inverse problem using machine learning. Since we have a large data set with known microstructural properties (obtained via high resolution CT), we can use supervised learning to map the input (the frequency dependent attenuation), to the output (the features of cortical porosity), and find relationships between the two.

II. Materials and Methods

All simulations of ultrasound propagation through structures mimicking cortical bone were carried out using SimSonic, an open source simulation software based on FDTD numerical methods. The simulated media were binary structures obtained from high resolution CT imaging of human femur [8]. The solid phase was given the properties of pure bone, density of 1.85 g/ml and speed of sound 4000 m/s, and the fluid filled pores were given properties of water, density of 1 g/ml and speed of sound of 1500 m/s. Absorption coefficients were attributed to both solid and fluid phases (10dB/cm/MHz for the solid phase and 0.1 dB/cm/MHz for the fluid phase). Both scattering and absorption (visco-elasticity) were therefore accounted for in the ultrasonic attenuation.

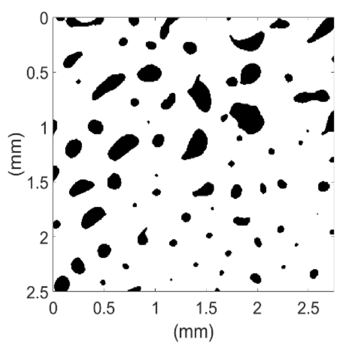

Figure 1 Poly-disperse bone schematic geometry

Simulations were carried out in the 1–8MHz range with 1MHz frequency intervals. The transmitted wave was a Gaussian ultrasonic pulse with a -6 dB, 20% bandwidth.

We used the resulting frequency dependent attenuation as our input feature vector into a neural network. We split our data, using 70% for training, 21% for testing, and 9% for validation and ran it for 6000 epochs. The neural network consists of 3 fully connected layers of 24, 12, and 6 neurons followed by an output layer that gives pore diameter, pore density, porosity, and the standard deviation of pore diameter.

After running this initial configuration, we sought to determine the driving parameters of our model by optimizing our feature selection. To do this we performed a recursive feature elimination (RFE) to reduce the size of the feature vector. This method uses model accuracy to identify which inputs contribute the most to each output.

Using this we were able to rank the features against each other on their abilities to predict each of the outputs. Finally, we reconfigured the neural network with this reduced feature vector by changing the input dimension and only running it for 4000 epochs. We then compared its results to the original configuration.

III. Results And Discussion

Fig2. shows the frequency dependent attenuation for two different structures (similar pore densities but different average pore diameter), resulting from the simulations. As expected, the behavior of attenuation as a function of frequency is a function of the porosity.

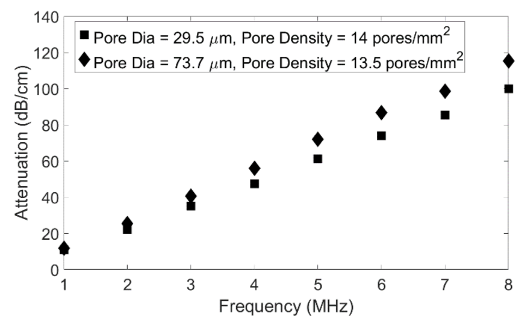

Figure 2: Frequency-dependent attenuation for two different porosities.

The comparison between true and estimated (by the ANN) parameters of the microstructure is shown in Fig.3.

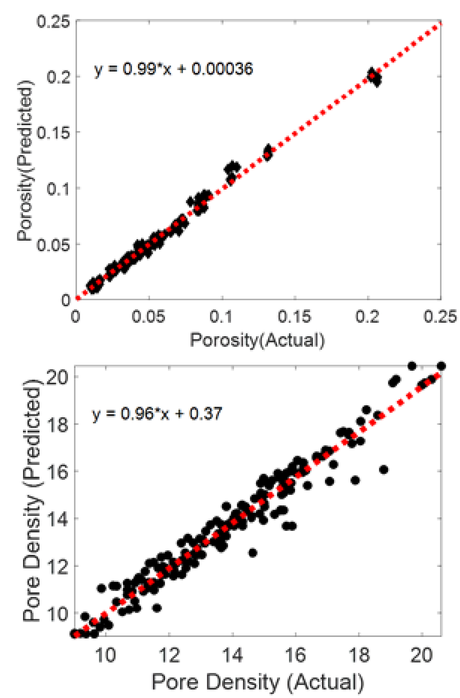

Figure 3: *Top*: true porosity vs porosity predicted by neural network with 1x8 feature vector. *Bottom*: true pore density vs pore density as predicted by neural network with 1x8 feature vector.

Overall the network was able to predict the parameters with very good accuracy. The mean squared and mean absolute error were 2.05% and 0.10% respectively.

Then, by performing the recursive feature elimination, we discovered that the accuracy stopped increasing significantly after the feature vector reached a size of 1x4, as shown in Fig 4.

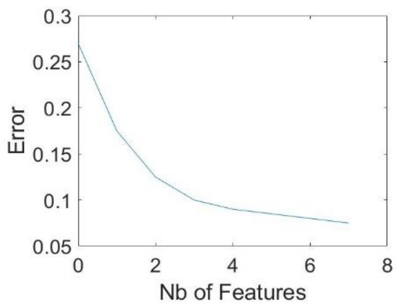

Figure 4 number of features vs error of the mode

Additionally, we used the recursive feature elimination to rank all the frequencies against each other for their ability to predict each parameter correctly. These scores were added up to identify the top 4 frequencies, shown in Table 1.

We then retrained the neural network using only these 4

Frequency (MHz)	1	2	3	4	5	6	7	8
Porosity (Ranks)	5	7	8	5	4	3	1	2
Pore Density (Ranks)	4	6	1	5	7	8	5	2
Pore Size (Ranks)	3	6	2	4	8	7	5	1
SD (Ranks)	4	1	2	5	8	6	7	3
Average Score	17	20	13	17	27	24	15	8

Table 1 Resulting rankings of the recursive feature elimination, with top 4 frequencies highlighted

frequencies (1,3,4 and 8 MHz) as the input feature vector. The results of this new network are shown in Fig 5. This new configuration had similar characteristics to the first one, they both have higher accuracy on porosity than on pore density. The 1x4 configuration had a higher mean squared error of 3.54% and higher mean absolute error of 0.13%.

Feature vector size	Pore Density (R^2)	Porosity (R^2)	Pore Diameter (R^2)	Standard Deviation (R^2)
1x8	.94	.99	.96	.97
1x4	.89	.99	.96	.98

Table 2 R^2 values of the true vs predicted values of the micro-structure for the 1x8 feature vector input.

The comparison of performance across all parameters, is shown in Table 2. The 1x8 configuration outperforms the 1x4 configuration in for the prediction of pore density, but both models don't predict pore density as well as the other microstructural features. For the prediction of all the other parameters the 1x4 performs as well or better than the 1x8, with the added benefits of faster run time and less risk of overfitting

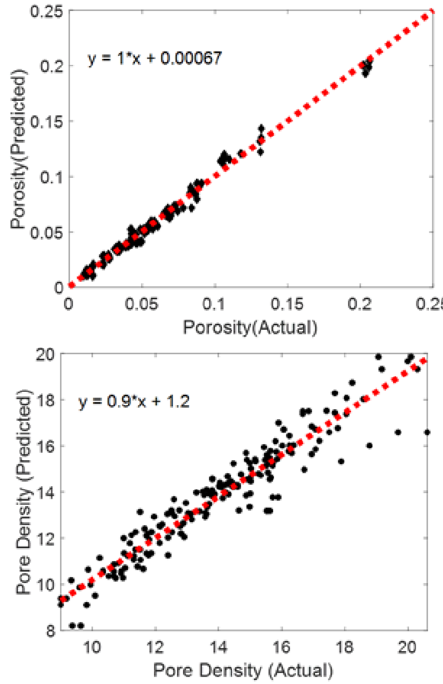

Figure 5 (Top) true porosity vs porosity predicted by neural network with 1x4 feature vector. (Bottom) true pore density vs pore density as predicted by neural network with 1x4 feature vector.

IV. Conclusions

An artificial neural network can be trained to match frequency-dependent attenuation values to features of cortical porosity. Two configurations were evaluated, using respectively 4 and 8 values of attenuation at frequencies ranging between 1 and 8 MHz. Comparing the results of the neural network for each configuration, we see that the neural network trained on frequencies 1 MHz, 3 MHz, 4 MHz, and 8 MHz matches or outperforms the neural network trained on frequencies 1-8 MHz. In both configurations the pore density predictor has a lower R^2 value relative to the other results, especially at lower pore densities (ranging from 3-10 pores/mm2). This could indicate that frequency dependent attenuation is not as influenced by pore density as it is by average pore diameter. The 1x4 network is less prone to overfitting, and less computationally intensive. Overall this algorithm could provide a tool to ultrasonically predict micro-structural parameters of bone and could be combined with other methods to help us better understand and more accurately diagnose osteoporosis in its early stages.

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References

[1] Chen, H., Zhou, X., Fujita, H., Onozuka, M. & Kubo, K. Y. Age-related changes in trabecular and cortical bone microstructure. International Journal of Endocrinology (2013). doi:10.1155/2013/213234

[2] Yerramshetty, J. & Akkus, O. in Skeletal Aging and Osteoporosis 115–131 (2013).

[3] McCalden, R. W., McGlough, J. A., Barker, M. B. & Court-Brown, C. M. Age-related changes in the tensile properties of cortical bone. The relative importance of changes in porosity, mineralization and microstructure. J. Bone Jt. Surg. - Ser. A 75,1193–1205 (1993).

[4] Schaffler, M. B. & Burr, D. B. STIFFNESS OF COMPACT BONE : EFFECTS OF POROSITY AND DENSITY. 21, 13–16 (1988).

[5] Sornay-Rendu, E., Munoz, F., Duboeuf, F. & Delmas, P. D. Rate of forearm bone loss is associated with an increased risk of fracture independently of bone mass in postmenopausal women: The OFELY study. J. Bone Miner. Res. (2005). doi:10.1359/JBMR.050704

[6] Braithwaite, R. S., Col, N. F. & Wong, J. B. Estimating Hip Fracture Morbidity, Mortality and Costs. 364–370 (2003).

[7] Schuit, S. C. E. et al. Fracture incidence and association with bone mineral density in elderly men and women: The Rotterdam Study. Bone (2004). doi:10.1016/j.bone.2003.10.001

[8] Mohanty, K., Yousefian, O., Karbalaeisadegh, Y.. and Muller, M. (2019). Predicting Structural Properties of Cortical Bone by Combining Ultrasonic Attenuation and an Artificial Neural Network (ANN): 2-D FDTD Study. In: International Conference on Image Analysis and Recognition. Waterloo: Springer.