Enhanced Image Processing of Implanted Hydrogel Scaffold Images Using Propagation-Based Imaging Computed Tomography

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Abstract— **This study showed how effective masking of dense components (i.e., bone) in propagation-based imaging computed tomography (PBI-CT) scans of biological samples can enhance the outcomes of deep learning denoising techniques. This was performed on ex vivo scans of hydrogel scaffolds implanted into animal hind limb and suppressing the overwhelming signal from the bone allowed for clearer and more distinct visualization of hydrogel scaffolds. This proved essential for observing the interactions of hydrogel within the physiological environment. The detailed image processing steps offer to improve the practical application of PBI-CT in tissue engineering and regenerative medicine research.**

Keywords— **Synchrotron Imaging, Image Processing, Deep Learning, Hydrogel Scaffolds, Ex Vivo**

INTRODUCTION

Synchrotron radiation-based propagation based computed tomography (PBI-CT) is a phase contrast imaging method that has been shown to be an excellent method for studying low-density hydrogel scaffolds *in vitro* [1]. However, in complex biological images, it becomes difficult to make accurate observations [2].

Firstly, there is an assumption of homogeneity in the sample in PBI-µCT which biological samples are not. The phase contrast of dense components (i.e., bone) becomes the dominant signal and obscures the surrounding tissues. Secondly, the overwhelming signal from the bone also skews the histogram of the images, which poses a challenge when attempting to use deep learning algorithms tasks such as blind denoising such as Noise2Noise [5] and Noise2Inverse [6]. These algorithms rely on a balanced histogram to function optimally, and distortions prevent accurately deep learning of spatial features.

Thus, this study aimed to develop the image processing steps to mitigate the limitations posed by strong signal from bone in PBI-CT of low-density hydrogel scaffolds *ex vivo*.

MATERIALS AND METHODS

The image processing steps taken to suppress signal from the bone are shown in Figure 1. First, a raw PBI-CT dataset was reconstructed using filtered back projection (FBP) to two separate datasets: (1) with phase contrast to improve the image contrast of the bone to create a bone mask because the bone contrast is overwhelming greater than the surrounding tissues, and (2) without phase contrast to have a measure of the grey value and noise of the surrounding tissues. Second, this bone mask created from data (1) was used to replace the bone in data (2) with value and noise from the measured tissue. The bone-masked result images are then enhanced through deep-learning based blind denoising using Noise2Noise or Noise2Inverse.
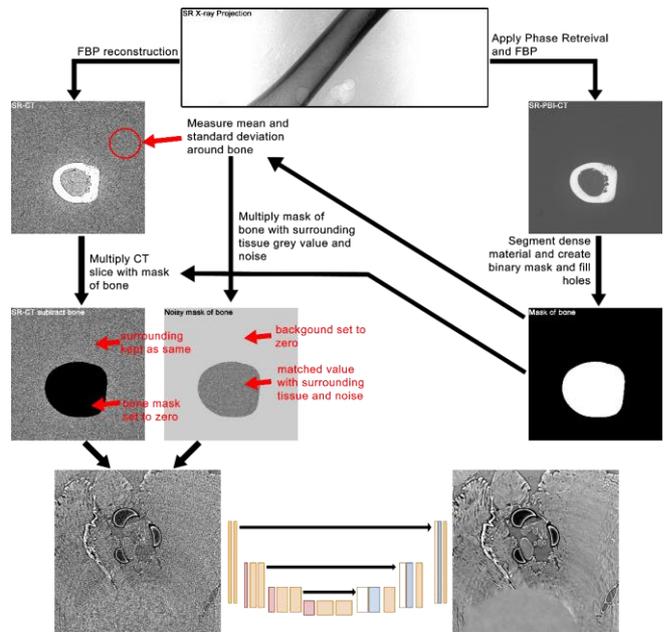
Figure 1: Image processing steps taken to mask the overwhelming signal from the bone starting from raw PBI-CT dataset. The bone-masked results are then enhanced by deep-learning based blind denoising.

The signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR) were used to assess the image results with and without bone masking. In addition, the perception-based image quality evaluator (PIQE), a no-reference image quality score used for image quality assessment part of MATLAB Image Processing Toolbox was used. PIQE is useful for image assessment when there are no *a priori* references such as the denoising results.

Image acquisition took used synchrotron radiation-based propagation-based imaging microcomputed tomography (SR-PBI-μCT) performed at the 05ID-2 beamline of Canadian Light Source (CLS) using a 30 keV monochromatic beam, a 1.5 m sample-to-detector distance, a Hamamatsu AA-60 beam monitor, a 500 µm LuAG scintillator, and a Hamamatsu Orca Flash 4 camera with an effective pixel size of 13 µm. CT reconstruction used the UFO toolkit [3] with the transport of intensity equation phase retrieval algorithm [4].

RESULTS AND DISCUSSION

Figure 2 shows the results from different image processing approaches as well as a grey value profile across the hydrogel material. The bone masking greatly enhanced the denoising capability of Noise2Noise, which was shown to be greater than Noise2Inverse. This was shown not only in the images but also in the profile, which only the bone masking plus Noise2Noise could reveal the characteristic edge enhancement of PBI-CT.
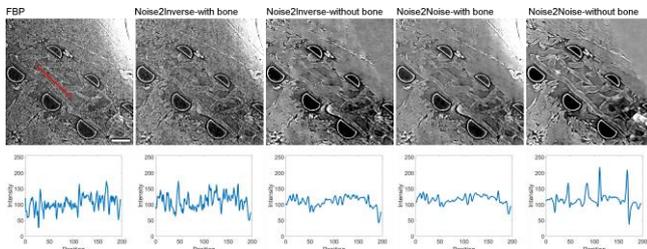

Figure 2: Comparison of different image processing methods for visualizing hydrogel scaffold implanted into rat hind limb. The scale bar represents 1 mm.

Quantitative image measures are shown in Table 1. Deep learning denoising methods, Noise2Inverse and Noise2Noise, are capable of greatly improving both the SNR and CNR compared to FBP as a baseline. Especially with Noise2Noise when the signal from the bone is suppressed.

The SNR increases dramatically, indicating the method effectively reduces noise and enhances the clarity of the image features. Higher CNR values suggest improved visibility of meaningful structures against the background. Noise2Noise without bone produced the lowest PIQE score which shows that this result is perceived as having better highest quality.

Table 1: Quantitative measures of image quality image processing methods.

	FBP	Noise2Inverse with bone	Noise2Invese without bone	Noise2Noise with bone	Noise2Noise without bone
SNR	29.21 ± 1.97	42.61 ± 0.25	71.33± 0.58	110.32 ± 31.22	173.06 ± 40.61
CNR	0.54 ± 0.16	0.85 ± 0.19	1.25± 0.29	1.13 ± 0.25	2.19 ± 0.60
PIQE	7.61 ± 0.69	7.96 ± 1.06	7.85 ± 0.78	6.47 ± 0.96	5.44 ± 0.41

Figure 3 shows the progression of a hydrogel scaffold implantation for nerve regeneration in rat hind limb samples, as observed nondestructively through PBI-CT and processed through bone masking and Noise2Noise. These results show changes in scaffold structure and density within a protective spiral shaped PCL stent over two days inside the animal body. This longitudinal imaging provides insights into the interactions between the implant and surrounding physiological environment.
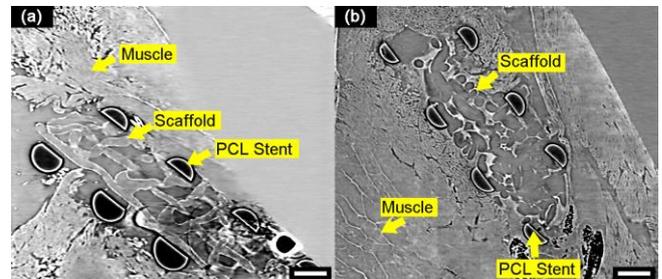

Figure 3: PBI-μCT scans of rat hindlimb samples containing hydrogel scaffold implant at longitudinal time points. (a) Immediately after implantation to set a baseline. (b) 2 days after implantation. Scale bars represent 1 mm.

At baseline shown in Figure 3 (a), the scaffold remained within the PCL stent with distinct strands visible. However, after 2 days, the scaffold has become swollen, squeezed between the PCL stent, and less dense as indicated by a lower grey value shown in Figure 3 (b). The decrease in grey value over the 2 days reflect the evolving interaction between the scaffolds within the physiological environment which could not previously be observed due to the strong signal from the bone and noise.

CONCLUSION

This study showed that suppressing the signal from bone in PBI-CT can enhance the results of deep learning denoising techniques. Using SNR, CNR, and PIQE, denoising results without the bone consistently showed improved results compared to denoising results with the bone. This allowed clearer visualization of hydrogel scaffolds *ex vivo* and crucial for observing the dynamic interactions of hydrogel scaffolds within the physiological environment. The refined imaging approach promises to improve the practical application of PBI-CT in tissue engineering and regenerative medicine research

ACKNOWLEDGEMENTS

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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