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Fat-saturated image generation from multi-contrast MRIs using generative adversarial networks with Bloch equation-based autoencoder regularization

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ABSTRACT

Obtaining multiple series of magnetic resonance (MR) images with different contrasts is useful for accurate diagnosis of human spinal conditions. However, this can be time consuming and a burden on both the patient and the hospital. We propose a Bloch equation-based autoencoder regularization generative adversarial network (BlochGAN) to generate a fat saturation T2-weighted (T2 FS) image from T1-weighted (T1-w) and T2-weighted (T2-w) images of human spine. To achieve this, our approach was to utilize the relationship between the contrasts using Bloch equation since it is a fundamental principle of MR physics and serves as a physical basis of each contrasts. BlochGAN properly generated the target-contrast images using the autoencoder regularization based on the Bloch equation to identify the physical basis of the contrasts. BlochGAN consists of four sub-networks: an encoder, a decoder, a generator, and a discriminator. The encoder extracts features from the multi-contrast input images, and the generator creates target T2 FS images using the features extracted from the encoder. The discriminator assists network learning by providing adversarial loss, and the decoder reconstructs the input multi-contrast images and regularizes the learning process by providing reconstruction loss. The discriminator and the decoder are only used

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Background & Goal

Background

- Because MRI has a relatively long scanning time per pulse sequence, acquiring FS images in addition to T1-w and T2-w images is burdensome for both patients and hospitals
- Existing deep learning-based models do not consider physical information (Bloch equation)

Goal

- Aimed to acquire T2 FS images from T1-w and T2-w images
- BlochGAN applies Autoencoder Regularization based on the Bloch Equation to produce more physically consistent synthetic results

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Bloch Equation

- An equation that describes the process (time evolution) in which the magnetization of hydrogen nuclei (proton s) returns to its original state when RF pulses are turned on and off.

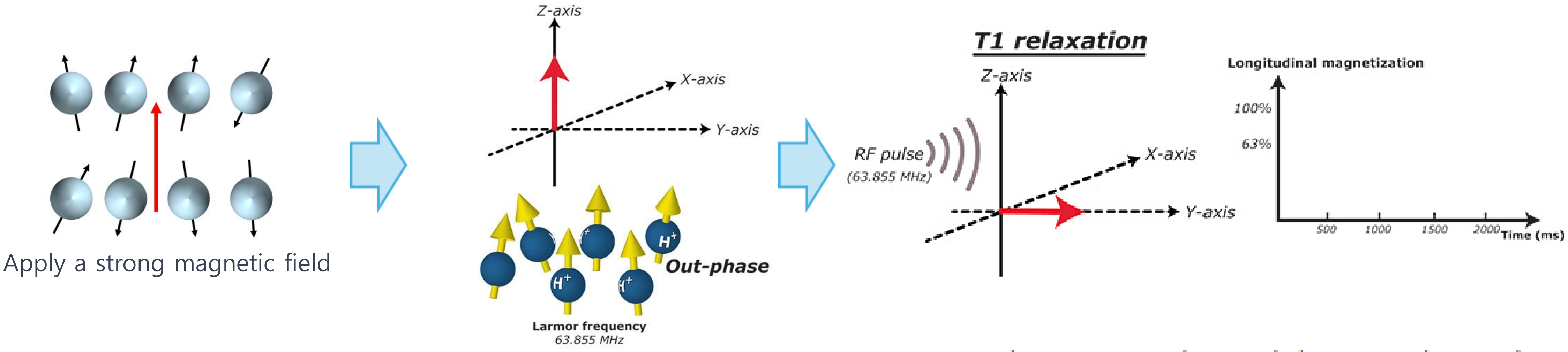

Fig 1. Polarization & Excitation & Relaxatio n

$$S = S_0\left(1 - \exp\left(-\frac{TR}{T_1}\right)\right)\exp\left(-\frac{TE}{T_2}\right)$$

Eq 1. Bloch equation representing the signal obtained by the spin echo pulse sequence

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Network Architecture

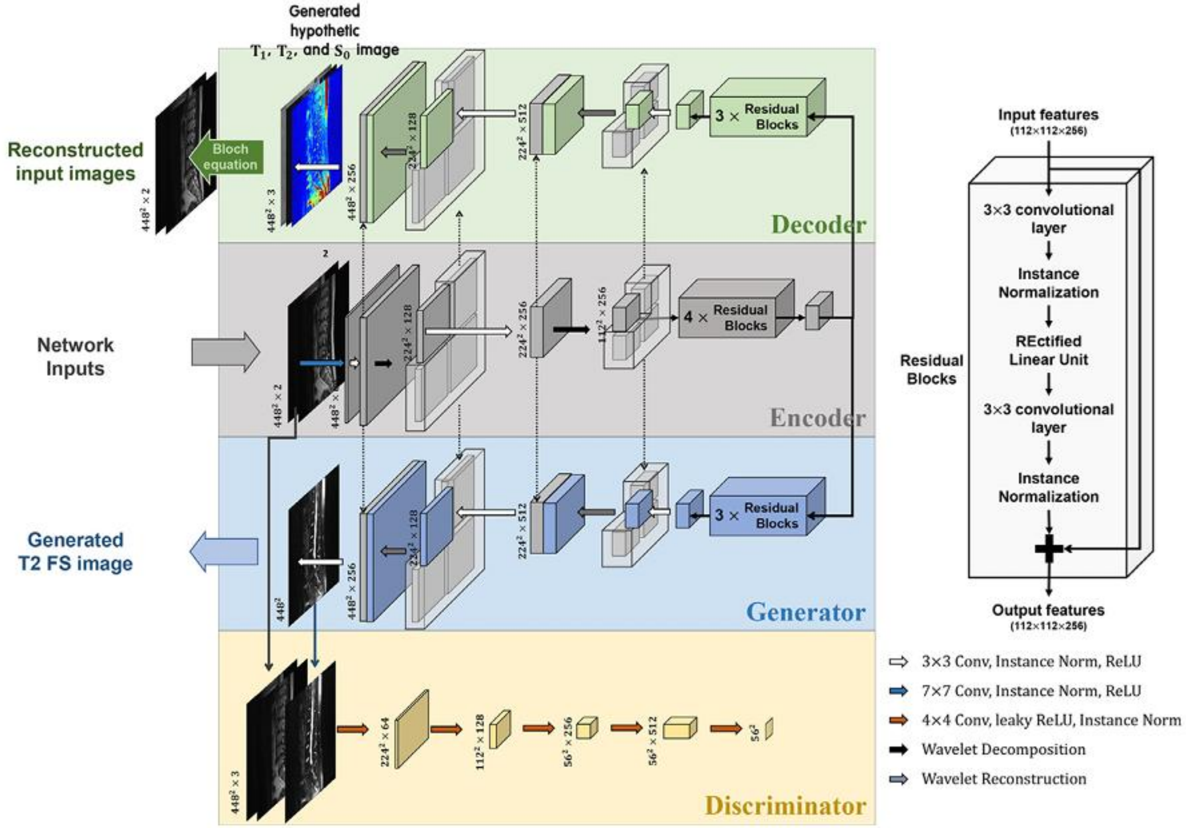

Fig 2. Overall of BlochGAN

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Network Architecture

Encoder

- Receives multi-contrast images as network inputs and extracts the features

Decoder

- Generates MR parameter maps from the features of the encoder
- Restores synthetic input multi-contrast images with the Bloch equation functions

Generator

- Receives features from the encoder and generates synthetic T2 FS images

Discriminator

- Distinguishes images generated by the generator from the acquired T2 FS image

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Network Architecture

Haar Wavelet Decomposition & Reconstruction

- Used as a down- and up-sampling layer, to preserve detail information
- Low frequency data generated from wavelet decomposition: delivered to the next layer as layer input
- High frequency: delivered to the decoder and the generator at the same resolution for wavelet reconstruction

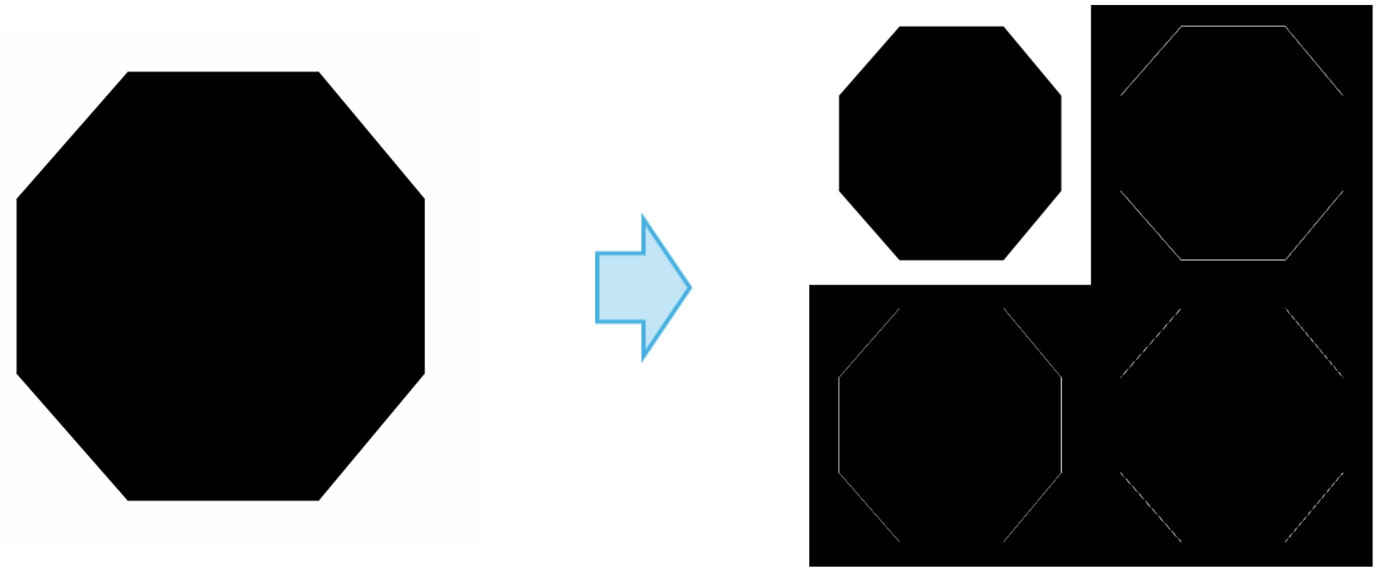

Fig 3. Example of Haar Wavelet Decomposition

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Loss Functions

Bloch equation-based generative adversarial network

- Receives multi-contrast images as network inputs and extracts the features
- Regularization help the encoder avoid overfitting and learn efficient feature extraction during training

$$\hat{y} = Ge(En(\mathbf{x}))$$

Eq 2. Synthetic T2 FS images

$$\mathcal{L}_{l1} = \frac{1}{w \times h} \sum_{i}^{w} \sum_{j}^{h} |y_{i,j} - Ge(En(\mathbf{x}))_{i,j}|,$$

$$\mathcal{L}_{vgg} = \frac{1}{n_k \times w_k \times h_k} \times \sum_{c}^{n_k} \sum_{i}^{w_k} \sum_{j}^{h_k} |VGG_k(y)_{c,i,j} - VGG_k(Ge(En(\mathbf{x})))_{c,i,j}|$$

Eq 3. Pixel-wise loss & Perceptual loss

$$\mathcal{L}_{adv} = \frac{1}{2} \mathbb{E}_{\mathbf{x}}[(D(\mathbf{x}, Ge(En(\mathbf{x}))) - 1)^2]$$

Eq 4. Adversarial loss of the BlochGAN

$$\mathcal{L}_R = \frac{1}{w \times h \times 2} \sum_{i}^{w} \sum_{j}^{h} \sum_{k}^{2} |\mathbf{x}_{i,j,k} - B(De(En(\mathbf{x})))_{i,j,k}|$$

$$B(\mathbf{t}; \mathbf{TR}, \mathbf{TE}) = t_3 (1 - \exp^{-\frac{\mathbf{TR}}{t_1}}) \exp^{-\frac{\mathbf{TE}}{t_2}},$$

Eq 5. Regularization function used in BlochGAN

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Results

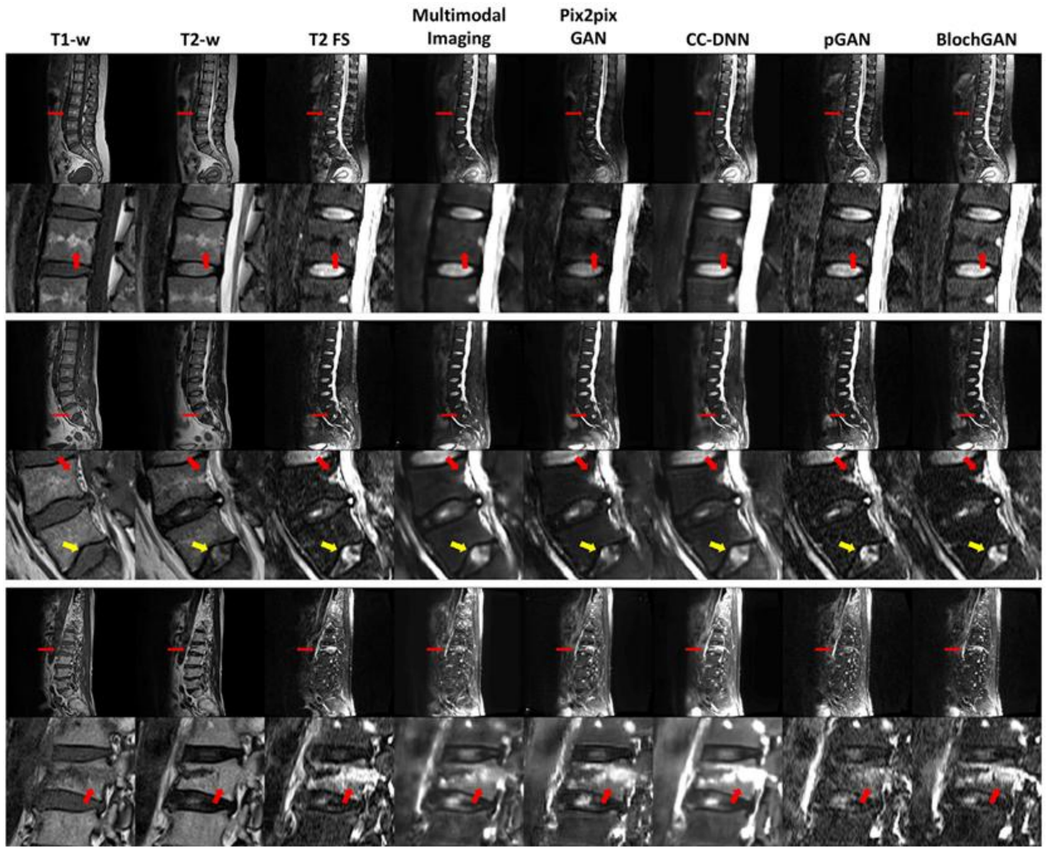

Fig 4. Compared the synthetic T2 FS images generated by various methods

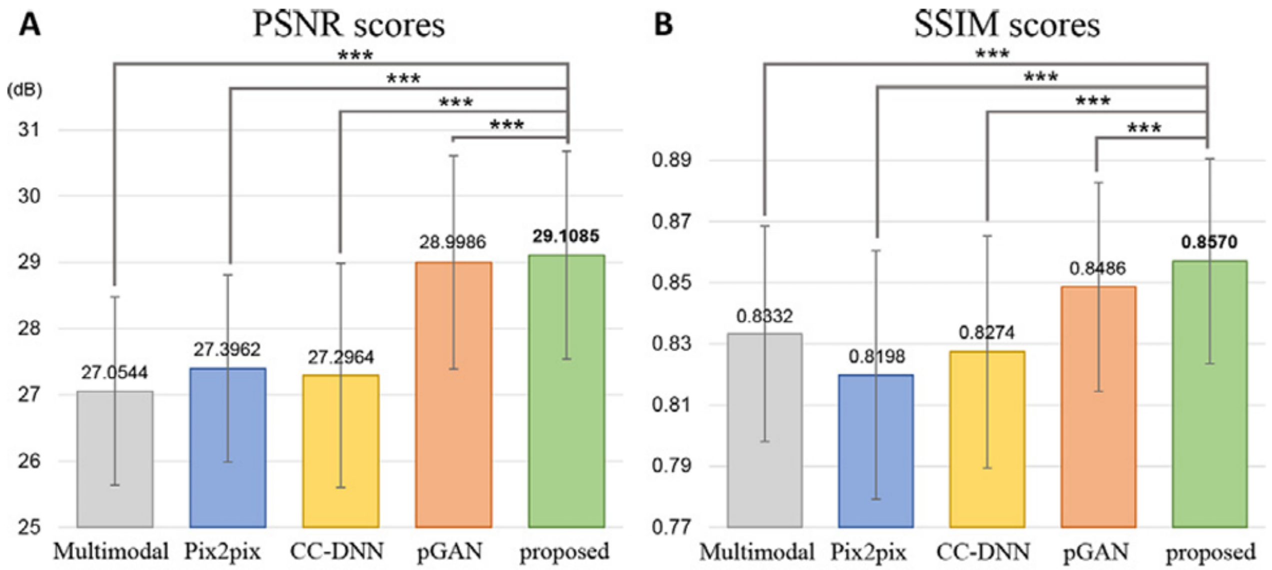

Fig 5. Quantitative Evaluation results of the proposed method and other met hods

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Ablation Study

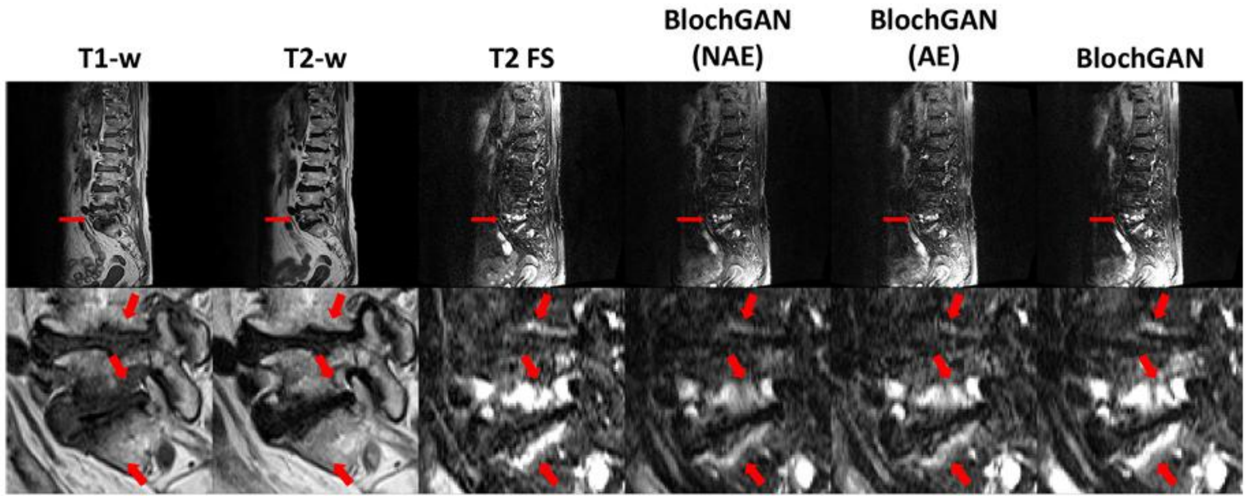

Fig 6. Comparison between the generated T2 FS images by BlochGAN(NAE), BlochGAN(AE), BlochGAN

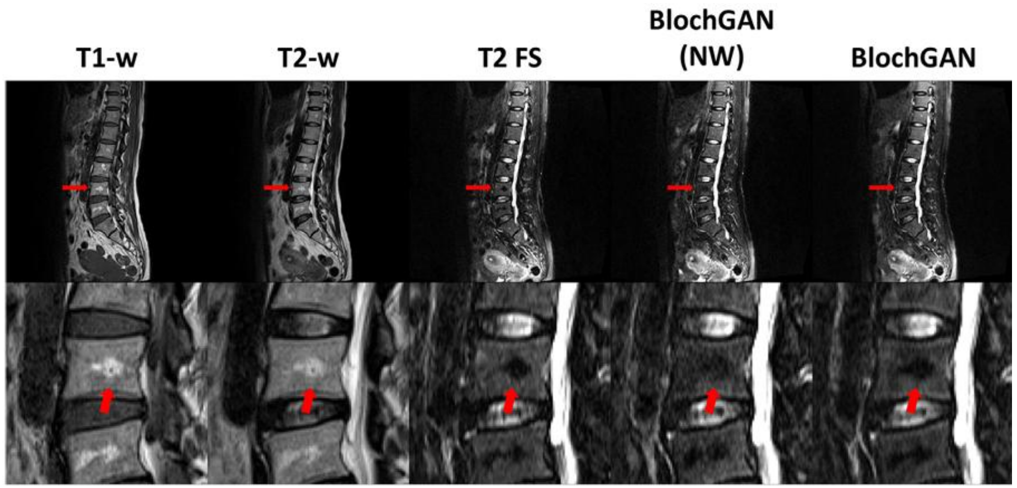

Fig 7. Images generated by BlochGAN(NW), BlochGAN

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Implications & Limitations

Implications

- First attempt to train the network in medical image synthesis using a Bloch Equation

Limitations

- Because of a hardware limitation, BlochGAN were carried out for 2D data, rather than 3D data
- BlochGAN still needs further validation to apply to more complex pulse sequences and diverse anatomies

Dar, S. U., Yurt, M., Karacan, L., Erdem, A., Erdem, E., & Cukur, T. (2019). Image synthesis in multi-contrast MRI with conditional generative adversarial networks. *IEEE transactions on medical imaging*, *38*(10), 2375-2388.