CDMAF-CEST: Conditional Diffusion model for multi-acceleration factor CEST-MRI Reconstruction

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INTRODUCTION: Chemical Exchange Saturation Transfer (CEST) Magnetic Resonance Imaging (MRI) is a promising molecular imaging technique that provides molecular-level information about tissues[1]. However, the prolonged scan time required for acquiring high-resolution images at multiple saturation frequency offsets hinders its application in clinical settings[2]. To accelerate CEST-MRI acquisition, advanced deep learning techniques have been extensively explored for CEST MRI reconstruction[2-4]. Currently, diffusion-based generative models have demonstrated competitive abillity in image reconstruction (MR) tasks[5-8]. In this study, we leverage a diffusion model to reconstruct the high-resolution (HR) CEST images conditioned on its low-resolution (LR) counterparts undersampled in k-space, along with the M0 image. To the best of our knowledge, this is the first diffusion-based CEST-MRI reconstruction work.

METHODS: (1) CDMAF-CEST: As illustrated in Fig.1, the approach achieves multi-acceleration factor CEST-MRI reconstruction through forward and backward diffusion processes. Given a HR image $x_0 \sim q(x_0)$, the forward process gradually adds Gaussian noise to x_0 over T diffusion steps. On the other hand, the backward process p aims to denoise the image from x_T step by step, with the conditioning part of its associated LR image y and M0 image z. This process can be expressed as: $p_\theta(x_{0:T}) = \prod_{t=1}^{T} p_\theta(x_{t-1}|x_t)$, $p_\theta(x_{t-1}|x_t, y, z) = N(x_{t-1}; \mu_\theta(x_t, y, z, t), \sigma^2 \boldsymbol{I})$, where p_θ denotes a parameterized model with trainable parameters θ. To estimate the reverse distribution by learning latent representations of various inputs, we adopt a multi-stream U-Net model with disentanglement loss and charbonnier loss[8], as shown in (b). (2) Dataset: The dataset was fully sampled using a GE Signa 3T scanner on 25 healthy volunteers. Each subject was comprised of 12 slices and 39 offsets per slice. These images were normalized and center cropped to a size of 224×224. We split 25 healthy brain CEST-MRIs into 20 for training, 2 for validation, and 3 for testing. The LR images were undersampled by retaining varying numbers of central k-space lines. (3) Implementation Details: CDMAF-CEST was implemented using PyTorch with the following settings: diffusion steps T = 1000, batch size = 4. The model was trained for 100,000 iterations on four NVIDIA-SMI Tesla V100 16GB GPUs using the AdamW optimizer with a learning rate of 10^{-4}.

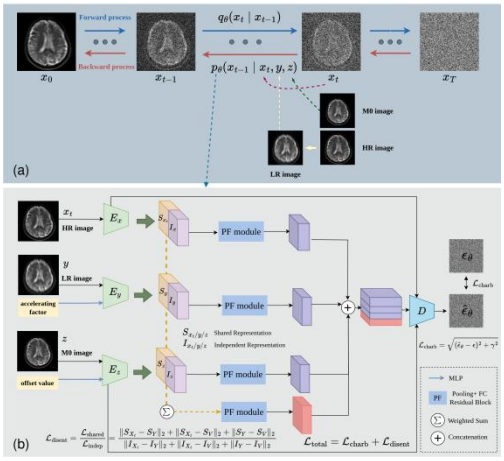

Fig.1. (a) The forward and backward process of the proposed conditional diffusion model (b) The network has three encoders to separately process HR, LR and M0 images, and is trained with disentanglement

RESULTS & DISCUSSION: Fig.2 shows example reconstruction results of CDMAF-CEST with AF ×20, ×16, ×14, ×12, ×8. Compared with the LR image, the proposed method can generate HR images consistent with the original images at different AFs with a relatively high PSNR and SSIM. Specifically, our method is able to restore spatial details even at a large AF (×20). This could be owing to diffusion models' ability to improve image clarity by sharpening and recover image details through learning distributions, which is not achievable with other generative models such as GAN and VAE. However, the inference of the CDMAF-CEST takes time, which could be mitigated through accelerating the diffusion sampling process. And in future work, we will focus on this problem and further improve the network performance by taking advantage of attention mechanism.

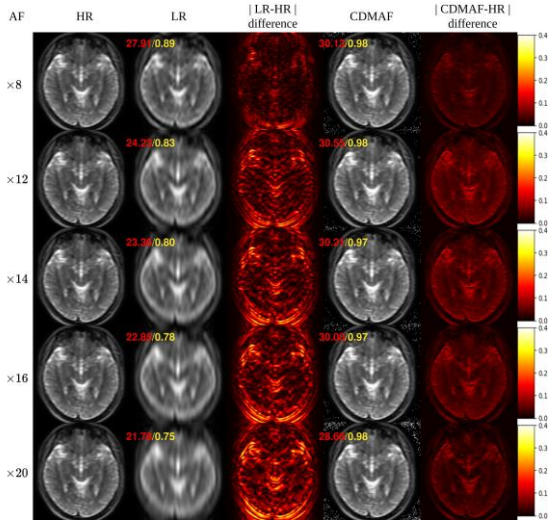

Fig.2. The reconstruction results of the CDMAF-CEST at various AFs. The red and yellow numbers are the PSNR and SSIM respectively.

CONCLUSION: This study demonstrates the feasibility of diffusion models for brain CEST-MRI reconstruction. The results have revealed great adaptability of CDMAF-CEST to a wide range of AFs, effectively restoring image details and consistently achieving high SSIM and PSNR values. We anticipate the implementation of the proposed method could promote the clinical application of CEST MRI by accelerating scan acquisition while preserving the image quality.

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