Motivation

• Brain MRI often repeated sequentially over patient lifetime
• Challenges: Long scans, motion susceptibility prompt undesirable patient outcomes
• Prior scan contain considerable shared information with current scan
• Idea: Use prior scan to accelerate the MRI imaging process

Background

• Fundamental MRI reconstruction problem
  \[ f = \frac{1}{2} \max_{x} \left[ \| \Phi \Omega(\mathbf{y}) - \mathbf{y} \|_{2}^{2} + \lambda \| L f \|_{2} \right] \]
• Prediction: prior-based norm regularization [4]
• Sensitive to noise amplification and hyper-parameters
  \[ \mathbf{E} f = \frac{1}{2} \frac{1}{2} \| L f \|_{2}^{2} + \lambda \| L f \|_{2} \]
• Diffusion models can serve as a strong prior by modelling \( p_{\text{diff}}(x) \) [1]
• Latent Diffusion Models (LDM) [2]: Diffusion in learned low-dimensional space \( \mathbf{y} \)
• MRI images can be effectively represented in a lower-dimensional space
• Advantage: Robust to scan noise regularization and other task differences
• Reconstruction by posterior sampling [3]:
  \[ \mathbf{E} f = \frac{1}{2} \frac{1}{2} \| L f \|_{2}^{2} + \lambda \| L f \|_{2} \]
• Latent data consistency:
  \[ \mathbf{E} f = \frac{1}{2} \frac{1}{2} \| L f \|_{2}^{2} + \lambda \| L f \|_{2} \]
• Stable Diffusion: Pre-trained Foundation LDM
• Training a high quality diffusion model from scratch is expensive
• Fine-tuning: SC fast, efficient transfer of pre-existing knowledge base to MRI

Method

• Fine-tune SD LDM over all prior and new scans in latent space to learn \( \mathbf{E} f = \frac{1}{2} \frac{1}{2} \| L f \|_{2}^{2} + \lambda \| L f \|_{2} \)
• Calibrate the reverse sampling process using the prior scan \( f_{p} \)
• Projected transform \( f_{p} \) based on SHI, roughly matched to MSE between scans
• Better condition and reduce sample time compared to previous methods (LCP)
• himetabolally alternate between denoising diffusion and data consistency (DC)
• DC: stochastic optimization over latent-to-expose forward model

References


Figure 1: Visual Explanation of PIPS Algorithm. Left: input to LDM is the encoded prior at noise levels \( p_{\text{n}} \). Denoising sampling process updated with DC steps based on the MRI forward model. Right: reconstruction is done with latent projected into image space. 80 Visual comparison of simple intermediates in UCPs (our algorithm without the prior vs. PIPS (ours). Conditioning is visibly improved by prior information.

Figure 2: Comparison between BOSS and PIPS. BOSS water leakage in ROI due to prior bias, learning based (BOSS, PIPS) collapse due to high SNR wedge shaped effect.

Figure 3: Reconstruction for unencoded data in DCPs for all 85. Boisson collapse due to prior do-similarity. PIPS maintains high quality both locally and overall.

| Acceleration | BOSS | PIPS | DCP | LAC | DC | SC
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Table 1: Joint UCBM and SNR of all different acceleration rates evaluated on our test set in = 125. The upper (down) row of each dans is the joint UCBM and the split is (similar-total patches) (first result per category is undefined).