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Consistency Analysis of Generative Priors and Sparse Optimization for Signal Reconstruction

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Abstract:

Signal reconstruction from incomplete or noisy measurements is still challenging when signals contain complex structures and small details. Traditional sparse methods, including LASSO and total variation, are easy to explain, but they often rely on fixed sparse assumptions. This study presents a generative-sparse reconstruction method that combines a variational autoencoder prior, an L1 sparse term, and a data-consistency term. The VAE learns a compact latent representation of high-dimensional signals. The L1 term helps control unstable latent activation during reconstruction. Experiments were conducted on FastMRI for MRI reconstruction and BSD500 for compressed sensing image recovery. The sampling rates were set to 10% and 20%. Compared with LASSO and total variation, the proposed method increased PSNR by 2.8–4.3 dB, improved SSIM by 0.05–0.09, and reduced NMSE by about 18.7%. Under Gaussian noise with σ = 25, the model remained stable and preserved useful image details. These results show that the learned prior improves structural recovery, while the sparse term improves stability and noise resistance. The method provides a useful approach for MRI reconstruction and compressed sensing image recovery with limited measurements.

Keywords: *generative prior, sparse optimization, signal reconstruction, compressed sensing, variational autoencoder, MRI reconstruction, data consistency*

INTRODUCTION

Signal reconstruction from incomplete or noisy measurements is a fundamental inverse problem in medical imaging, computational imaging, and wireless communications. In these applications, the observed data are usually obtained through undersampled, corrupted, or indirect measurement processes, which makes the recovery of the original signal highly ill-posed. Classical sparse optimization methods, including LASSO, total variation regularization, wavelet sparsity, and dictionary learning, address this problem by assuming that the target signal has only a small number of active coefficients in a suitable transform domain [1,2]. These methods are mathematically clear and computationally tractable, and they have been widely used in compressed sensing and magnetic resonance imaging reconstruction. Recent comparative studies on fast MRI

reconstruction also show that traditional greedy or sparse recovery strategies remain useful baselines, especially when the sampling rate is low and the reconstruction model needs to maintain explicit measurement consistency [3]. However, such methods often depend on predefined sparse bases or handcrafted regularization terms. As a result, they may have limited ability to represent complex textures, fine anatomical boundaries, and nonlinear signal structures [4,5]. Recent research has improved sparse reconstruction by introducing structured sparsity, adaptive dictionaries, and more efficient iterative optimization algorithms [6,7]. These approaches allow the sparse representation to better match signal characteristics and can reduce artifacts caused by simple fixed-basis assumptions. At the same time, deep learning has been increasingly incorporated into inverse reconstruction models. Learned priors, unrolled optimization networks, and data-driven regularization models have shown strong performance in MRI and image recovery tasks [8,9]. These methods can learn reconstruction patterns directly from training data and often produce higher visual quality than conventional compressed sensing methods. However, their effectiveness usually depends on large paired datasets, careful training, and stable acquisition settings. When the sampling mask, noise level, or image distribution changes, the reconstruction quality may degrade. This limits their robustness in practical imaging scenarios where acquisition conditions are not always fixed [10,11]. Generative priors provide another promising direction for signal reconstruction. Variational autoencoders, generative adversarial networks, normalizing flows, and diffusion models can learn compact latent representations from high-dimensional training data and use the learned latent space to guide reconstruction [12,13]. Compared with fixed sparse transforms, generative priors can describe edges, textures, and anatomical continuity in a more flexible manner [14,15]. They are especially attractive for highly undersampled reconstruction tasks because they can constrain the solution space to a learned signal manifold. Nevertheless, many existing generative-prior-based methods mainly rely on the learned prior and the data-consistency term. Explicit sparsity constraints are often weak or absent. This may reduce the model's ability to suppress noise, preserve small details, and control unstable latent activations, particularly when the test images differ from the training distribution [16,17]. This issue is highly relevant to MRI reconstruction and compressed sensing image recovery. Traditional compressed sensing MRI relies on transform-domain sparsity and total variation to recover images from undersampled k-space measurements, while recent learning-based methods use data-driven priors to reduce aliasing artifacts and improve structural fidelity [18,19]. However, each approach has clear limitations when used alone. A purely sparse model may oversmooth image structures and lose subtle anatomical details. A purely generative model may introduce unrealistic patterns when the learned prior does not fully match the test data [20,21]. Therefore, combining sparse optimization with generative modeling is a meaningful way to balance interpretability, stability, and structural representation. To address this problem, this study proposes a unified reconstruction framework that integrates a VAE-based generative prior with an explicit L1 sparse constraint. The VAE is used to learn a compact latent representation of high-dimensional signals, allowing the reconstruction process to benefit from learned structural information. The L1 regularization term encourages sparse and stable latent activation, which helps control noise and reduce unstable reconstruction behavior. The data-consistency term ensures that the reconstructed signal remains faithful to the observed measurements. In this way, the proposed framework combines the structural modeling capacity of generative priors with the robustness and interpretability of sparse optimization. The main purpose of this study is to examine whether a generative prior can improve the structural representation ability of sparse reconstruction models and whether an explicit sparse constraint can improve the stability of generative reconstruction under noisy or incomplete measurements. Experiments are conducted on FastMRI and BSD500 datasets under 10% and 20% sampling rates. PSNR, SSIM, and NMSE are used to evaluate reconstruction accuracy, structural

similarity, and error stability. The expected contribution of this study is to provide a reconstruction strategy that is more robust than purely data-driven generative models and more flexible than conventional sparse optimization methods. This is important for medical imaging and compressed sensing applications where high-quality reconstruction must be achieved under limited sampling conditions, noise interference, and possible distribution shifts.

2.Materials and Methods

2.1 Samples and Study Description

This study used two public datasets to evaluate the proposed reconstruction framework. The first dataset was FastMRI, which was used for accelerated MRI reconstruction. A total of 1,200 knee MRI slices were selected after removing slices with severe motion artifacts or incomplete anatomical coverage. The data were acquired from multi-coil MRI scans and converted into single-image magnitude data for model training and testing. The second dataset was BSD500, which was used for compressed sensing image recovery. A total of 500 natural images were included, covering indoor scenes, outdoor scenes, objects, animals, and complex texture regions. All images were resized to a fixed resolution of 256 × 256 pixels. For both datasets, 70% of the samples were used for training, 15% for validation, and 15% for testing. The sampling rates were set to 10% and 20% to examine reconstruction performance under different levels of measurement loss.

2.2 Experimental Design and Control Groups

The experiment was designed to compare the proposed generative-sparse reconstruction method with commonly used sparse reconstruction methods. The proposed group used a VAE-based generative prior, an L1 sparse constraint, and a data-consistency term in the same optimization process. Three control groups were included. The first control group used LASSO reconstruction to represent classical sparse recovery. The second control group used total variation regularization to evaluate edge-preserving reconstruction. The third control group used a VAE prior without the L1 sparse constraint to test the effect of explicit sparsity. These control groups were selected because they represent traditional sparse optimization, image-smoothing regularization, and generative-prior reconstruction, respectively. All methods were tested under the same sampling masks, noise levels, and test samples to ensure fair comparison.

2.3 Measurement Methods and Quality Control

MRI reconstruction was performed from undersampled k-space data, while BSD500 reconstruction was performed from randomly projected compressed measurements. For MRI data, Cartesian undersampling masks were generated at 10% and 20% sampling rates. For BSD500 images, Gaussian random sensing matrices were used to simulate compressed sensing measurements. Gaussian noise with $\sigma = 25$ was added in the robustness experiment. Before model training, all images were normalized to the range of [0, 1]. The same normalization rule was used during testing. To reduce random bias, each experiment was repeated three times with different random seeds, and the average result was reported. Quality control included checking image size, removing corrupted samples, fixing sampling masks across methods, and using the same stopping criteria for all optimization-based models. Validation loss was monitored to avoid overfitting.

2.4 Data Processing and Model Formulation

Let yyy denote the observed measurement, A denote the sampling operator, and x denote the original signal. The VAE decoder G(z) maps the latent variable z to the reconstructed signal. The proposed method estimates z by minimizing the difference between the measured data and the generated reconstruction, while adding an L1 sparse constraint to the latent variable. The objective function is written as:

$$\hat{z} = \arg\min_{z} \| y - AG(z) \|_2^2 + \lambda \| z \|_1$$

where λ controls the strength of sparse regularization. After optimization, the reconstructed signal is obtained as $\hat{x}=G(\hat{z})$. Reconstruction quality was evaluated by peak signal-to-noise ratio, structural similarity, and normalized mean square error. NMSE was calculated as:

$$NMSE=\frac{\|x-\hat{x}\|_2^2}{\|x\|_2^2}$$

where *x* is the ground-truth image and x^\hat{x}x^ is the reconstructed image.

2.5 Statistical Analysis and Evaluation Criteria

The final results were reported as mean values over the test set. PSNR, SSIM, and NMSE were used as the main evaluation indicators. Higher PSNR and SSIM values indicate better reconstruction quality, while lower NMSE indicates smaller reconstruction error. The proposed method was compared with all control methods under the same sampling rates and noise settings. Paired comparisons were used because each method was tested on the same image samples. A significance level of $p<0.05$ was used to judge whether the performance difference was statistically meaningful. In addition, convergence curves were recorded to compare optimization stability across methods. This analysis was used to examine whether the L1 sparse constraint improved reconstruction accuracy and reduced instability in latent-space search.

3.Results and Discussion

3.1 Reconstruction Performance at Different Sampling Rates

The proposed method obtained better reconstruction results than LASSO and total variation at both 10% and 20% sampling rates. At the 10% sampling rate, LASSO lost many fine image details because it relied on a fixed sparse assumption. Total variation kept the main edges but caused smooth regions near anatomical boundaries and texture areas. The proposed method gave clearer MRI structures and more complete natural image textures. This result shows that the VAE prior helped recover global image structure, while the L1 term reduced unstable latent responses. The higher PSNR and SSIM values also indicate lower pixel error and better structural similarity. This trend is consistent with recent MRI reconstruction studies, which showed that learned priors can improve reconstruction quality when measured data are limited [22,23].

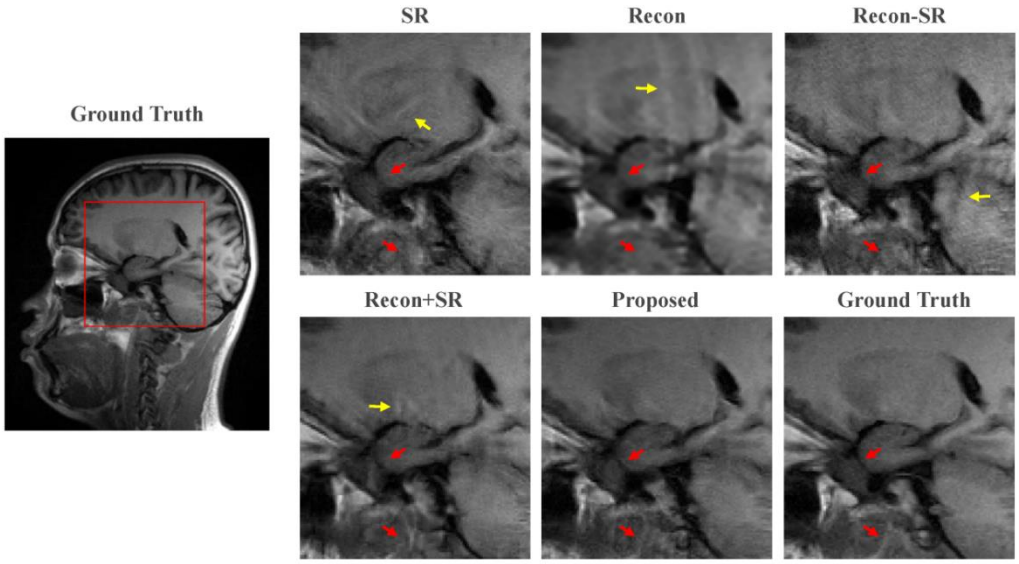


Fig. 1. Reconstruction performance of different methods at 10% and 20% sampling rates.

3.2 Role of the Generative Prior and L1 Constraint

The ablation results showed that the VAE-only model performed better than traditional sparse methods, but it was less stable under strong undersampling. Some images contained local artifacts or blurred edges because the latent search had weak control. After adding the L1 sparse constraint,

the reconstruction became more stable, and NMSE was further reduced. This means that the sparse term helped limit unnecessary latent activation and improved the match between the reconstructed image and the measured data. Previous studies on generative compressed sensing also reported that generative priors can improve recovery from limited measurements, but model mismatch may still cause errors [24,25]. The present results show that explicit sparse control can reduce this problem in latent-space reconstruction.

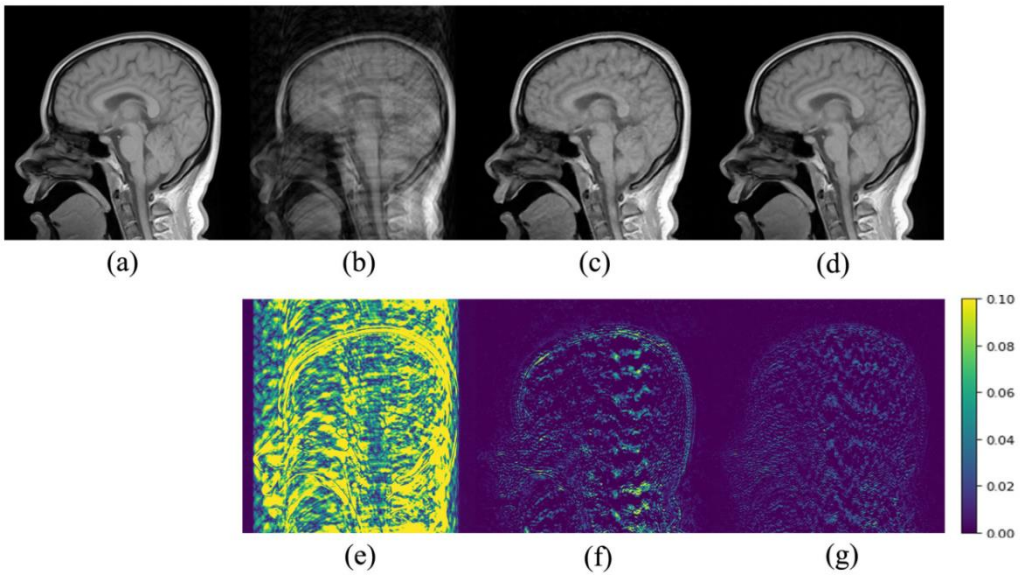


Fig. 2. Reconstructed images from LASSO, total variation, VAE-only, and the proposed method.

3.3 Noise Robustness and Comparison with Existing Studies

Under Gaussian noise with $\sigma = 25$, the proposed method still showed stable convergence and lower reconstruction error. LASSO controlled noise to some extent, but it removed useful details. Total variation reduced noise but over-smoothed edges and texture regions. The proposed method achieved a better balance between noise reduction and detail preservation. This finding is close to recent MRI reconstruction studies, which reported that learned priors should be combined with data consistency to avoid false image structures [26,27,28]. For example, Malagi et al. used a reference-driven compressed sensing MRI method and added k-space correction to keep data consistency. Xu et al. also showed that deep compressed sensing generation improved reconstruction accuracy and SSIM in limited-observation tasks. These studies support the view that a generator alone is not enough for stable reconstruction.

3.4 Overall Discussion and Limitations

The results show that the proposed framework improves reconstruction through three parts: data consistency, VAE-based structure learning, and L1 sparse control. The VAE prior helps describe complex image patterns, while the L1 term improves stability under undersampling and noise. Compared with GAN- or diffusion-based reconstruction methods, this method has a simpler optimization form and lower training difficulty. However, several limits remain. First, FastMRI and BSD500 cannot cover all clinical images or all natural image types. Second, the VAE latent space may still miss very small details when the sampling rate is very low. Third, iterative latent optimization may increase reconstruction time. Future work should test larger MRI datasets, compare different generative models, and design faster update strategies.

4.Conclusion

This study developed a generative-sparse reconstruction method for signal recovery from incomplete and noisy measurements. The method combines a VAE-based prior, an L1 sparse term, and a data-consistency term in one reconstruction model. Tests on FastMRI and BSD500 showed

higher PSNR and SSIM and lower NMSE than LASSO and total variation at 10% and 20% sampling rates. The method also remained stable under Gaussian noise, which shows that sparse control in the latent space can reduce unstable reconstruction and keep useful image details. The main value of this study is that it links learned image structure with clear sparse regularization. This provides a useful approach for MRI reconstruction and compressed sensing image recovery when measured data are limited. Some limits remain. The datasets do not cover all clinical images or natural image types, and iterative latent optimization may increase reconstruction time. Future work should use larger multi-center datasets, compare different generative models, and improve the update process for practical imaging tasks.

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