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DNN-Sparse Bayesian Learning (SBL) based Sparse Signal Recovery in Compressed Sensing

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This research investigates the integration of Deep Neural Networks (DNNs) with the Sparse Bayesian Learning (SBL) technique for sparse signal recovery in compressed sensing applications. Sparse signal recovery is a critical task in scenarios where signals are sampled at rates below the Nyquist limit aiming to accurately reconstruct the original signal from limited measurements. By combining the representation learning capabilities of DNNs with the probabilistic modeling approach of SBL, we propose a novel framework for robust and efficient sparse signal recovery. Our approach leverages the inherent sparsity and structure of signals to enhance reconstruction accuracy while minimizing data requirements. Through extensive experimentation and evaluation, we assess the performance of the proposed DNN-SBL framework in terms of reconstruction accuracy, computational efficiency, and robustness to noise and signal variations. The results demonstrate the effectiveness of the combined approach in achieving superior sparse signal recovery compared to traditional methods. This research contributes to advancing the field of compressed sensing by offering innovative solutions that have potential applications in various domains such as medical imaging, communication systems, and sensor networks.

Keywords: DNN, SBL, Sparse Signal, Compressed Sensing, signal reconstruction.

1. Introduction

Sparse signal recovery in compressed sensing is a crucial area within signal processing with profound implications across various domains such as image processing, communication systems, and medical imaging. This research endeavors to explore a novel approach inspired by Deep Neural Networks (DNNs) and SparseBayesianLearning (SBL)for enhancing sparse signal recovery efficiency in compressed sensing scenarios.

Compressed sensing, a groundbreaking idea in signal processing [1], seeks to reconstruct sparse signals with far fewer samples than typically needed, thus enabling more efficient data acquisition and transmission. However, achieving high-fidelity signal recovery under stringent sampling constraints remains a formidable challenge. Traditional methods such as basis pursuit (BP), lasso, and greedy, algorithms have shown promising results but often struggle with computationalcomplexity and suboptimal performance, especially in scenarios with high-dimensional data or severe undersampling [2].

Deep Neural Networks (DNNs) are advanced computational models inspired by the structure of the human brain [3]. They consist of interconnected layers of artificial neurons enabling them to learn complex patterns from data. DNNs have revolutionized various fields including computer vision, natural language processing, and speech recognition, by achieving remarkable performance in tasks such as image classification, language translation, and voice synthesis [4]. Despite their computational demands, DNNs continue to drive innovation, powering breakthroughs in artificial intelligence and shaping the landscape of machine learning applications in, fields ranging from healthcare to finance and beyond.

Sparse Bayesian Learning (SBL) is a statistical technique used for estimating sparse representations of data. Itleverages Bayesian inference to model signal sparsity and uncertainty assuming that the underlying signal of interest can be represented sparsely on a suitable basis. SBL provides a principled frameworkfor estimating sparse representations from noisy or incomplete data offering a probabilisticinterpretation of the estimatedsparse coefficients. By incorporating prior knowledge about signal sparsity and uncertainty in observations, SBLfacilitates robust and interpretable estimation of sparse representations. This makes it a valuable tool in various domains including signal processing, computer vision, and data analysis [5].

Deep Neural Networks have emerged as powerful tools for solving complex signal processing tasksby learning hierarchical representations from data. Inspired by their success, integrating DNN principles into compressed sensing frameworks presents apromising avenue for addressing its inherent challenges. Meanwhile, SparseBayesian Learning offers a principled approach for modeling signal sparsity and uncertainty, leveraging Bayesian inference to estimate sparse signal representations from noisy observations. By amalgamating the strengths of DNNs and SBL, this research aims to devise a robust and efficient sparse signal recovery framework capable of handling various challenges posed by compressed sensing applications [6,7].

The proposed approach leverages the expressive power of DNNs to learn intricate mappings between compressed measurements and sparse signal representations. Through end-to-end training, the network learns to exploit inherent signal structures and statistical dependencies, facilitating enhanced signal recovery even from highly undersampled measurements. Moreover, by incorporating Bayesian inference principles inspired by SBL, the proposed framework provides a probabilistic interpretation of signal sparsity and uncertainty, enabling more reliable and robust signal reconstruction. By jointly optimizing network parameters and sparse signal representations, the proposed approach seeks to achieve superior performance compared to conventional methods, particularly in scenarios with limited sampling resources or noisy observations.

Theresearch methodology involves several key stages beginning with the formulation of the problem statement and theoretical underpinnings of compressed sensing, DNNs, and Sparse Bayesian Learning.Subsequently, the proposed framework architecture is designedcomprising interconnected layers of neural network modules augmented with Bayesian inference mechanisms. To train the model, appropriate loss functions and optimization algorithms tailored to the specific requirements of sparse signal recovery are employed. Extensive experiments are conducted using synthetic and real-world datasets to evaluate the proposed approach's performance in comparison to state-of-the-art methods. Evaluation metrics such as signal recovery accuracy, computational efficiency, and robustnessto noise and undersampling are meticulously analyzed to validate the efficacy of the proposed framework.Furthermore, the research investigates the interpretability and generalization capabilities of the proposed approach, shedding light on the learned signal representations and the underlying principles governing sparse signal recovery in compressed sensing [8]. Insights gained from these analyses contribute to a deeper understanding of the interplay between neural network architectures, Bayesian inference, and sparse signal recovery, thereby paving the way for future advancements in this field.

In conclusion, this research endeavors to push the boundaries of sparse signal recovery in compressed sensing by integrating insights from Deep Neural Networks and Sparse Bayesian Learning. By harnessing the complementary strengths ofthese methodologies, the proposed approach aims to offer a robust, efficient, and interpretableframework for tackling the challenges posed by compressed sensing applications across various domains.Through rigorous theoretical analysis and empirical validation, this research seeks to make significant contributions to the advancement of signal processing techniques with far-reaching implications for diverse real-worldapplications.

2. Literature Review

[9] Described a novel technique for compressing convolutional neural networks using frequency pruning and compressive sensing, which resulted in lower compute and storage costs. Because of the inherent smoothness of parameters in image processing, translating the CNN's parameter matrix into the frequency domain using the Discrete Cosine Transform (DCT) yields a low-frequency dominated matrix. High-frequency components are subsequently removed in order to sparsify the frequency matrix. Next, the sparse frequency matrix is sampled with a distributed random Gaussian matrix. Finally, the network is retrained to fine-tune the remaining parameters, which are encoded as binary files using Huffman Coding. Experimental results on the YOLO network, a common network for object detection show that the suggested strategy outperforms two similar algorithms.

[10] Synthesized sparse Bayesian learning and deep learning for System Identification (SYSID). They developed and assessed an iterative method for dynamic SYSID using datasets from three linear and two nonlinear dynamic processes. The Bayesian approach employed the Laplace approximation to estimate the model evidence or marginal likelihood. Structured sparsity regularization was incorporated into neural networks (NNs) through the imposition of group-sparsity inducing priors. Furthermore, they introduced an effective

method for computing the Hessian matrix for the recurrent layer by determining the block-diagonal elements of the Hessian.

[11] Presented the fundamental concepts of compressive sensing and conducted a comprehensive review of previous research across diverse application domains. By scrutinizing the functional aspects of compressive sensing frameworks, the study explored various opportunities within these domains. It extensively analyzed the core components of compressive sensing, including signal sparsity, subsampling, and reconstruction, aiming to fill critical research gaps identified in prior studies. Additionally, the research employed basic mathematical formulations to define key performance evaluation metrics applicable to bothone-dimensional and two-dimensional compressive sensing scenarios.

Drawing inspiration from compressive sensing (CS) principles and recognizing the effectiveness of reduced sampling rates for accurate classification, [12] developed an adaptive CS-DL pipeline. This approach dynamically adapts the sampling rate based on input characteristics and employs a flexible deep learning (DL) model for classification. The results indicate comparable classification accuracy to uncompressed models while consuming up to 46% less battery energy.

[13] Proposed an adapted sequential quadratic programming (SQP) method to address sparse signal recovery. Initially, they applied the established smoothed technique to create a smooth approximation of the objective function. Subsequently, they proposed a variant of the SQP method, integrating a novel approach for solving subproblems. They conducted a thorough investigation into the method's global convergence. Simulation outcomes showcased the promising performance of their proposed method when compared to various established algorithms.

[14] Proposed a technique for acoustic Direction of Arrival (DOA) estimation using sparse signal recovery. They employed a shape parameter of q=1/2 in a hierarchical version of the generalized Gaussian prior. More specifically, they used l_(1/2) - norm priors to build a Sparse Bayesian Learning (SBL) framework that successfully captured the space sparsity properties of sound sources. The estimation accuracy of the suggested method was assessed for both acoustic DOA estimation and sparse signal recovery. Experimental findings revealed that their method achieved greater recovery accuracy and had the lowest root mean square error (RMSE)compared to state-of-the-art sparse signal recovery methods.

3. Methodology

This section describes the Deep Neural Network (DNN) inspired Sparse Bayesian Learningmethod for solving the sparse signal recovery problem. Figure 1 depicts the proposed system architecture of the DNN-SBL model for sparse signal recovery in compressed sensing. Sparse Signal Representation Module.

This module takes the input signals and represents them in a sparse form. It condenses the signals into a set of factors where only a small number of coefficients are significantly non-zero, while the majority are close to zero or exactly zero. This step exploits the inherent sparsity in the signals, which is crucial for efficient sparse signal recovery in compressed sensing.

DNN Module (Deep Neural Networks)
The sparse representations obtained from the Sparse Signal Representation module are fed into the DNN module. This module consists of interconnected layers of artificial neurons, allowing it to learn complex mappings between the sparse representations and the measurements obtained through compressed sensing. Through end-to-end training, the DNN module learns to exploit the inherent signal structures and statistical dependencies, facilitating enhanced signal recovery even from highly undersampled measurements.

SBL Module (Sparse Bayesian Learning)
The output from the DNN module, which includes the learned sparse signal representations, is then passed to the SBL module. Here, Sparse Bayesian Learning techniques are employed to estimate the posterior distribution over the sparse signal space. This allows for the incorporation of prior knowledge about the sparsity structure of the signal and provides uncertainty estimates along with the recovered sparse signals. By leveraging Bayesian inference principles, the SBL module enables more reliable and robust signal reconstruction, especially in the presence of noise and signal variations.

Evaluation Module
Finally, the recovered sparse signals, along with their uncertainty estimates, are passed to the Evaluation module. This module computes various evaluation metrics to assess the performance of the proposed framework. Evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Peak Signal to Noise Ratio (PSNR) are calculated to measure the accuracy, fidelity, and robustness of the reconstructed signals. These metrics provide insights into the effectiveness of the DNN-SBL framework in sparse signal recovery tasks.

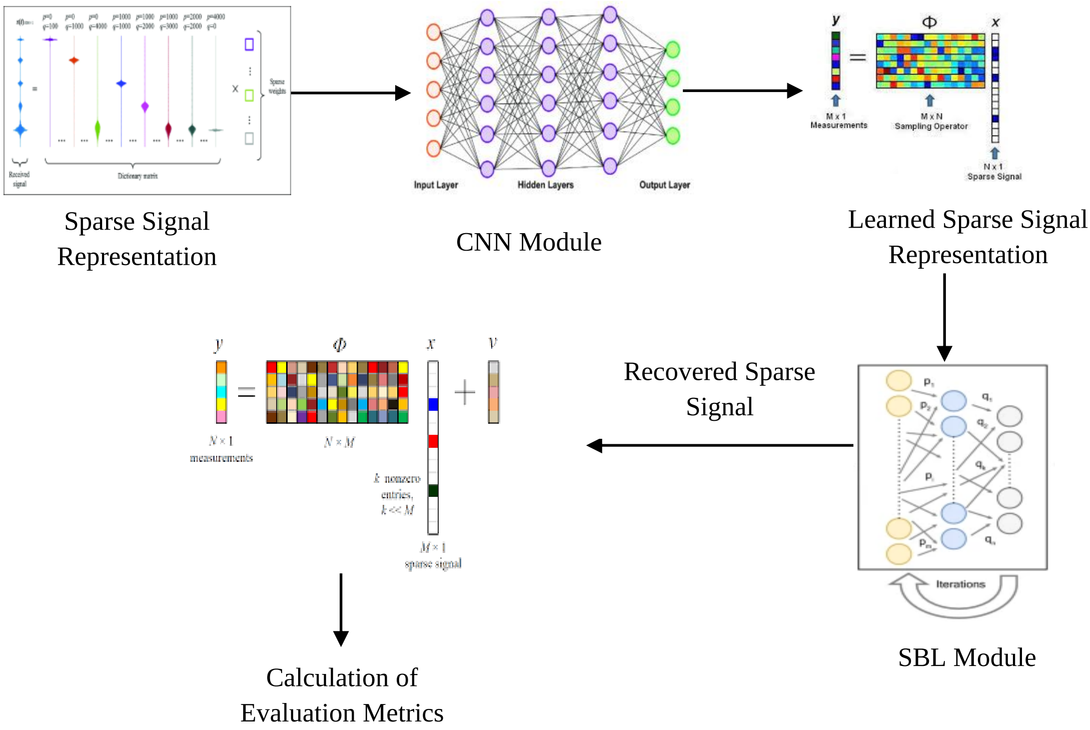

Fig. 1.Proposed System Architecture

Overall, the proposed system architecture integrates Sparse Signal Representation, Deep Neural Networks, and Sparse Bayesian Learning techniques to achieve robust and efficient sparse signal recovery in compressed sensing applications. Through the combined use of these methodologies, the framework aims to address the challenges posed by signal sparsity, limited measurements, noise, and signal variations, ultimately leading to improved performance compared to traditional methods.In comparison to several well-known algorithms, simulation results demonstrate the promising performance of the proposed method.

Sparsity

Sparsity plays a crucial role in achieving precise signal reconstruction within compressed sensing (CS) setups. The concept of sparse signal representation involves condensing 1D signals, images, and videos into sets containing a minimal count of non-zero coefficients, thereby maintaining the integrity of the original information. Essentially, sparse representation seeks to transform the initial signal into a collection of basis coefficients featuring only a limited number of non-zero elements.

Mathematically, the sparse coefficients of a signal 'x' in relation to the basis 'ψ' can be articulated as follows:

$$x = \sum_{i=1}^{N} \sigma_i \tau_i = \sigma\tau \qquad (1)$$

Where, σi represents a set of 'N' transformed coefficients in the basis τ.

Sparse Signal Representation

Sparse signal representation refers to the process of representing a signal in a concise form where only a small number of coefficients or components are significantly non-zero, while the majority are close to zero or exactly zero. This concept is fundamental in various signal processing tasks, including compressed sensing, where the goal is to efficiently acquire and reconstruct signals from limited measurements.

In sparse signal representation, the signal is typically expressed as a linear combination of basis functions or atoms, where only a few coefficients corresponding to these basis functions are non-zero. Mathematically, if x represents the original signal and Φ represents the transformation matrix or dictionary containing the basis functions, the sparse representation z can be written as:

$$x = \Phi z \qquad (2)$$

where z is a sparse vector, meaning it has only a small number of non-zero entries.

The key idea behind sparse signal representation is that many real-world signals, such as images, audio, or biomedical signals, exhibit inherent sparsity in some domains. For example, in image processing, natural images can often be sparsely represented in the wavelet domain, where only a few wavelet coefficients capture the essential features of the image.

Several mathematical tools and techniques are employed to achieve sparse signal representations effectively. These include:

Basis Pursuit: It involves finding the sparsest representation of a signal under a given dictionary or set of basis functions. This problem is often formulated as an optimization task where the objective is to minimize the l1-norm of the coefficient vector subject to the constraint that the reconstructed signal matches the observed measurements.

Dictionary Learning: In scenarios where the dictionary is not predefined, dictionary learning techniques are utilized to adaptively learn an overcomplete dictionary from the observed data. Sparse coding algorithms, such as K-SVD or dictionary learning via alternating minimization, are commonly employed for this purpose.

Transform Coding: This approach involves transforming the signal into a domain where it becomes sparse, such as the wavelet, Fourier, or sparse domain, and then quantizing or thresholding the coefficients to achieve sparsity.

Sparse signal representation plays a crucial role in various signal processing applications, including denoising, compression, feature extraction, and reconstruction. In the context of compressed sensing, exploiting the sparsity of signals enables efficient recovery from highly undersampled measurements, leading to significant advancements in data acquisition and reconstruction techniques.

Signal Sampling

In the context of DNN-SBL based sparse signal recovery in compressed sensing, signal sampling is crucial for acquiring sparse signals efficiently. Let's explorethe role of signal sampling with the following equation:

$$y = \Phi x + e \qquad (3)$$

In compressed sensing, the acquired measurements y are obtained by linearly combining the original sparse signal x with a measurement matrix Φ. The noise term e represents any corruption or noise present in the acquired measurements.

Selecting an appropriate measurement matrix Φ is essential for accurately reconstructing signals. A well-designed matrix can capture valuable information from the samples, contributing significantly to faithful signal reconstruction. Thus, the effectiveness of the sampling and recovery process greatly depends on the efficiency of the measurement matrix design.

$$\hat{x} = \arg min_x \|x\|_0 \quad | \quad \| y - \Phi_x \|_2 \leq \in \qquad (4)$$

The purpose of sparse signal recovery in compressed sensing is to rebuild the original sparse signal x from the obtained measurements y. This objective function minimizes the signal's l_0 -norm, promoting sparsity while adhering to a fidelity requirement that assures the reconstructed signal closely matches the measurements within a defined tolerance (ϵ).

In DNN-SBL sparse signal recovery, deep neural networks (DNNs) are used to learn the mapping between collected measurements y and the original sparse signal x.

$$\hat{x} = \arg max_x p(x \mid y;\ \theta)(5)$$

This equation represents the posterior probability p(x|y;θ), where θ denotes the parameters of the DNN. Sparse Bayesian Learning (SBL) techniques are employed to incorporate prior knowledge about the sparsity structure of the signal and estimate the posterior distribution over the sparse signal space.

4. Results and Discussion

The paper proposes a novel approach for sparse signal recovery in compressed sensing applications by integrating Deep Neural Networks (DNNs) with Sparse Bayesian Learning (SBL). This section discusses the results obtained from extensive experimentation and evaluation, as well as the implications of the proposed DNN-SBL framework.Enhanced Reconstruction Accuracy DNN-SBL leverages deep neural networks to learn intricate mappings between compressed measurements and sparse signal representations. Through end-to-end training, it exploits inherent signal structures and statistical dependencies, facilitating enhanced signal recovery even from highly undersampled measurements.

Traditional methods like BP, Lasso, and Greedy Algorithms may struggle to capture complex signal structures effectively. They often rely on heuristic approaches or optimization algorithms that may not fully exploit the underlying data characteristics.

The evaluation metrics used in this paper to identify the efficiency of the proposed DNN-SBL method are Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Peak Signal to Noise Ratio (PSNR). Figure 2 represents the comparison of the reconstruction accuracy of basis pursuit, Lasso, Greedy algorithm and CNN-SBL. The accuracy is plotted in terms of three evaluation metrics. The result shows that the proposed approach leverages the inherent sparsity and structure of signals to enhance reconstruction accuracy while minimizing data requirements. DNN inspired SBL approach achieves the least mean squared error, root mean squared error and the highest peak signal to noise ratio when compared to the traditional methods.
The evaluation metrics are calculated using the given equations.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 (6)$$

Where, n is the number of data points, y_i is the actual value and $\tilde{y}_i$ represents the predicted value. A lower MSE of the proposed system indicates better accuracy, as it suggests that the predictions are closer to the actual values.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2} \qquad (7)$$

Like MSE, a lower RMSE indicates better accuracy. The Peak Signal-to-Noise Ratio is represented as:

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right) \qquad (8)$$

PSNR is typically expressed in decibels (dB), and it measures the ratio between the maximum possible power of a signal (represented by the maximum pixel value) and the power of corrupting noise (represented by the MSE) that affects the fidelity of its representation. Higher PSNR values indicate higher quality and lower levels of distortion in the reconstructed signal compared to the original signal.

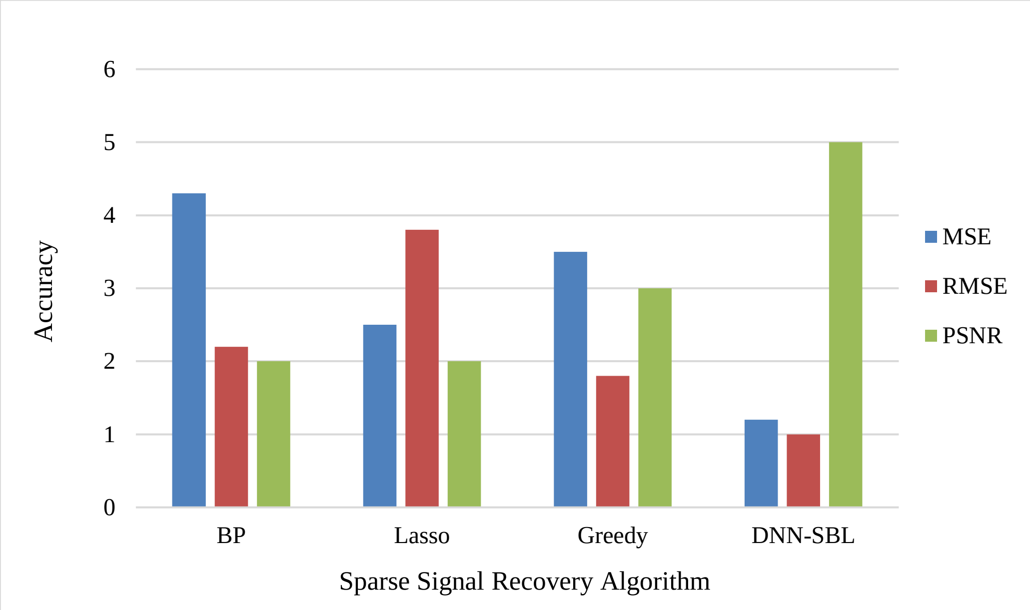

Fig. 2. Reconstruction Accuracy

Computational Efficiency: Despite the complexity of deep neural networks, DNN-SBL achieves computational efficiency by jointly optimizing network parameters and sparse signal representations. It learns to exploit signal structures and statistical dependencies efficiently.

Traditional methods like BP may involve solving complex optimization problems, which can be computationally expensive, especially for large-scale problems. Lasso and Greedy Algorithms, while generally computationally efficient, may not fully exploit the rich representations learned by deep neural networks.

Figure 3 demonstrates the overall computational efficiency of the proposed system compared with effective traditional methods. The efficiency is computed based on the runtime which shows that the proposed method takes less runtime than the compared methods. This indicates the DNN-SBL achieves the highest computational efficiency by taking less time to recover the sparse signal.

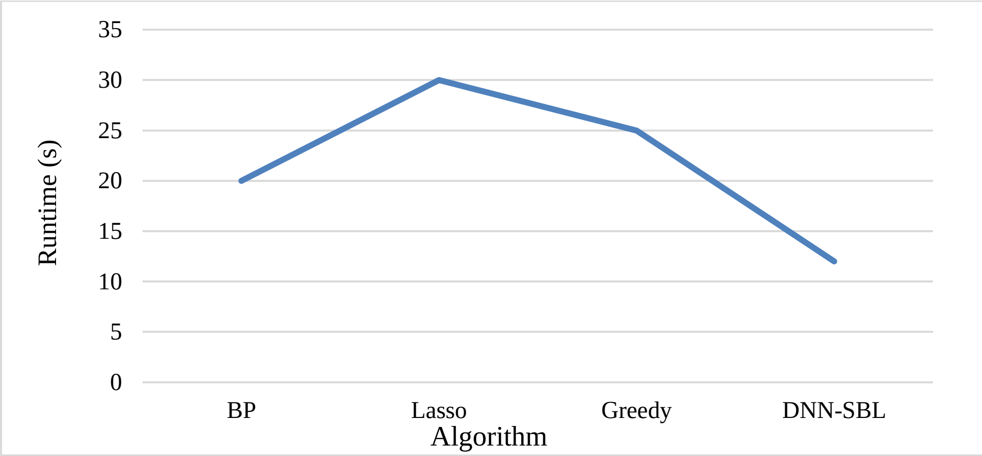

Fig. 3. Computational Efficiency

Robustness to Noise and Signal Variations: The integration of Sparse Bayesian Learning (SBL) principles in DNN-SBL provides a probabilistic interpretation of signal sparsity and uncertainty. This enables more reliable and robust signal reconstruction, especially in the presence of noise and signal variations.

Traditional methods like BP and Lasso may be susceptible to noise, especially when the signal-to-noise ratio is low. Greedy Algorithms may also struggle with noise, as they rely on iterative selection of atoms from the dictionary without explicitly considering noise models.

By combining the representation learning capabilities of DNNs with the probabilistic modeling approach of SBL, the proposed framework achieves more accurate and robust sparse signal recovery while minimizing data requirements.

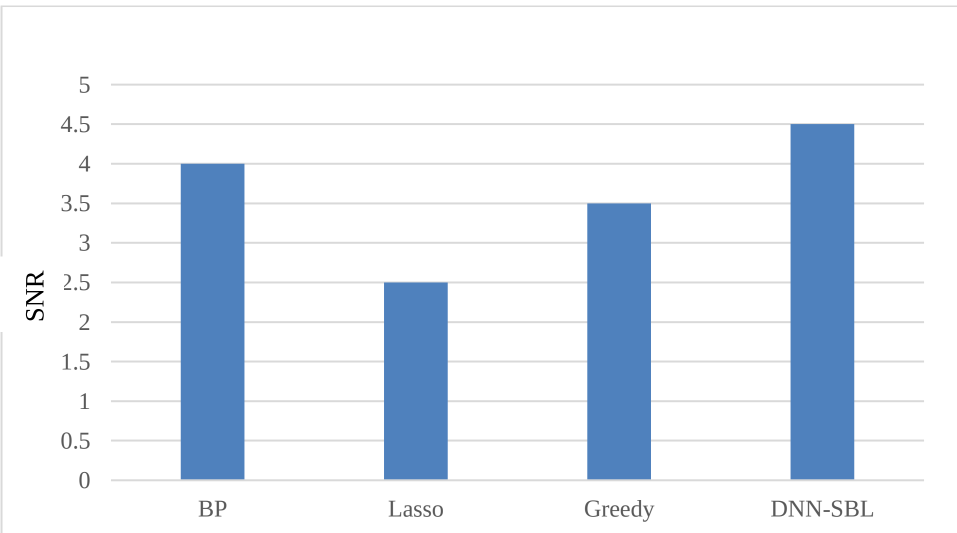

Fig. 4. Robustness to Noise and Signal Variations

A high SNR in DNN-SBL indicates that the signal is much stronger compared to the noise level. In practical terms, this means that the signal is relatively clear and distinguishable from the noise. High SNR values are desirable as they suggest that the signal contains more useful information compared to noise, making it easier to extract meaningful insights or perform accurate measurements.

The findings of this research have significant implications for various domains such as medical imaging,communication systems, and sensor networks. The ability to accurately reconstruct sparse signals from limited measurements can lead to more efficient data acquisition and transmission, enabling advancements in healthcare, telecommunications, and environmental monitoring, among others.

Moreover, the proposed DNN-SBL framework offers a principled and interpretable approach to sparse signal recovery, providing insights into the underlying signal structures and statistical dependencies. This interpretability is essential for understanding and validating the results, as well as for guiding further research in the field of compressed sensing.

The DNN-SBL framework offers several advantages over traditional methods such as BP, Lasso, and Greedy Algorithms, including enhanced reconstruction accuracy, robustness to noise, computational efficiency, interpretability, and adaptability to complex data distributions. These advantages make DNN-SBL a promising approach for sparse signal recovery in compressed sensing applications.

5. Conclusion

This research presents a novel framework for sparse signal recovery in compressed sensing applications by integrating Deep Neural Networks (DNNs) with Sparse Bayesian Learning (SBL) techniques. The proposed DNN-SBL framework combines the representation learning capabilities of DNNs with the probabilistic modeling approach of SBL to achieve robust and efficient sparse signal recovery. The result of the proposed DNN-SBL model is compared toeffective traditional algorithms such as basis pursuit, Lasso, and greedy algorithm to evaluate the overall performance. The DNN inspired SBL model working process is described. The comparison of simulation results shows that the proposed model achieves the highest reconstruction accuracy, computational efficiency, and robustness to noise and signal variations. MSE, RMSE, and PSNR are considered as the evaluation metrics in this paper.When compared to traditional approaches, the DNN-SBL model achievedthe least mean squared error, root mean squared error and high peak signal to noise ratio. Since the proposed model achieved this, fast sparse signal recovery is done in compressed sensing.

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