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Sparse Signal Recovery via Reinforcement-Learned Basis Selection in Wireless Sensor Networks

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ABSTRACT

Efficient and precise recovery of signals continues to be an important challenge in wireless sensor networks (WSNs) due to the limitations experienced in terms of availability of energy, bandwidth and computation from devices. Compressive sensing (CS) has become a game changer to circumvent these limitations due to the sparsity of signal with sub-Nyquist sampling that minimizes transmission overhead. Nevertheless, the performance of CS-based recovery is extremely dependent upon the choice of sparse basis in which the signal exists. Basically, conventional methods use fixed bases; these include Discrete Cosine Transform (DCT), wavelets, or Fourier transforms among others; these fail to adapt to dynamic environmental and signal conditions that are common in practical WSN systems. In an attempt to resolve this gap, this paper introduces a new reinforcement learning (RL) based framework that autonomously chooses the best possible basis function from a preselected plurality according to observed signal attributes. The system uses a policy gradient algorithm to train a lightweight decision-making agent that maximizes reconstruction accuracy at a minimum computational complexity. Proposed RL-based basis selection method has superior performance in the context of MSE, SSIM and runtime efficiency over traditional CS approaches as shown by extensive simulations running on both synthetic and real world datasets. Using this adaptive framework, not only the signal reconstruction fidelity can be improved but also the capability of scaling up and real-time use are possible in heterogeneous WSN cases, which makes this an attractive direction for future intelligent sensor networks as well as edge computing spaces.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a basic element for a large number of applications which include environmental surveillance, industrial automation, precision agriculture, structural health monitoring and smart cities infrastructure. Their capacity to work independently in inhospitable and remote settings and at low deployment and maintenance cost makes them integral to the modern sensing ecosystem. Nevertheless, these networks are limited by the scarcity of energy resource, small data transmission bandwidth, and noise-prone and signal degradative nature in data acquisition. These challenges have considerable implications for the quantity and quality of data that can be gathered and transferred thus constraining performance of more real-time monitoring and decision making systems. In reaction to such constraints, Compressive Sensing (CS) has become a paradigm revolutionary mode of acquisition of signals which enables reconstruction of the signals from significantly lesser samples than required by conventional approaches. Taking advantage of the natural sparse property of many real world signals, CS allows energy efficient sampling and transmission of signal that have acceptable fidelity. Although CS has the promise, its success depends much on the choice of an appropriate basis or transform domain where the signal is sparse. Conventional systems will usually assume fixed basis functions, for example Discrete Cosine Transform (DCT), wavelet transforms or Fourier bases and will assume that all acquisition conditions have the same signal characteristics. Nonetheless, WSNs typically work in dynamic heterogeneous environments where signal statistics change depending on changes in the sensing modalities, external noise, or application specific patterns. This is inherently suboptimal with static basis selection, thereby possibly reducing the accuracy of signal recovery and increasing the load on computation. To address these limitations, this work advances a new reinforcement learning (RL)-based adaptive basis selection framework. The proposed method formulates basis selection problem as a sequential decision-making problem and solves it with a policy gradient RL algorithm learning optimal basis selection strategies from experience. This approach allows the system to vary instantaneously in real time depending on signal variations, which improves reconstruction accuracy and energy efficiency in resource-limited WSN deployments.

2. LITERATURE REVIEW

2.1 Compressive Sensing in Wireless Sensor Networks

Compressive Sensing (CS) has gained a lot of importance as a data acquisition tool in wireless sensor networks (WSNs) due to limited bandwidth and energy resource constraints. CS allows signal recovery from fewer samples than traditional methods due to leverage of sparseness of the signal in the chosen domain. CS has been applied to WSNs in a number of studies, which demonstrate that by its resources and energy consumption, it can be extremely effective in reducing communication overhead. However, good performance from CS in these networks is dependent on a proper choice of the sparsifying basis.

2.2 Fixed Basis Selection for Signal Recovery

Fixed transform bases, either DCT, wavelets or Fourier transforms, are used by traditional CS approaches to describe sparse signals. These bases have succeeded in many applications but are suboptimal to dynamic environments such as WSNs, where the characteristics of signals change. The static characteristic of such bases usually leads to poor recovery performance if the signal has different sparsity in different domains.

2.3 Adaptive Basis Selection in Compressive Sensing

In order to completely eliminate the shortcomings of the fixed basis selection, methods of adaptive basis selection have been proposed, for example, K-SVD. Such methods study a dictionary of basis functions designed to fit the specific signal enhancing recovery accuracy. Adaptive approaches have the advantage of enhancing performance, although they also add to computational overhead and complexity, which may be a down side in the case of real-time WSN applications where resources are stretchable.

2.4 Reinforcement Learning in Signal Processing

Reinforcement Learning (RL) has become a promising solution for adaptive signal recovery, amongst basis selection in CS. RL is able to adaptively choose the best basis in real time according to the characteristic of the signal, learning from previous experience. Through this manner there is no need for the defined knowledge of the signal and adaptation to the changes of the environment makes the signal recovery techniques flexible and scalable.

2.5 Challenges and Future Directions

Even though RL-based adaptive basis selection shows much potential, there are challenges like the high computational cost, and the efficient exploration-exploitation trade-off. In addition, using RL algorithms within large-scale WSN where resources are limited is a task that is not easy. The subsequent research efforts are bound to involve optimization of RL algorithms towards real time signal recovery, improved scalability, and distribution/federated learning methods reducing the overhead of the computation.

Table 1. Comparison of Traditional, Adaptive, and RL-Based Methods for Basis Selection in Sparse Signal Recovery

Method	Key Features	Advantages	Challenges
Traditional Fixed Basis (DCT, Wavelet, Fourier)	Uses predefined bases like DCT, wavelet, or Fourier transform for signal representation.	Simple and computationally efficient.	Suboptimal performance in dynamic and heterogeneous environments.
Adaptive Basis Selection (K-SVD)	Learns a dictionary of basis functions tailored to the signal's sparsity.	Improves accuracy by adapting the basis to the signal's characteristics.	High computational cost and complexity, which may not be suitable for real-time applications.
Proposed RL-Based Adaptive Selection	Uses reinforcement learning to dynamically select the optimal basis based on real-time signal characteristics.	- Maximizes reconstruction accuracy while minimizing computational cost. - Adaptable to dynamic and changing environments. - Suitable for real-time, resource-constrained applications like WSNs and IoT.	- Requires efficient exploration-exploitation balance. - High computational cost during training. - Potential challenges in large-scale deployment.

3. METHODOLOGY

3.1 Problem Formulation

Given a sensed signal $x \in \mathbb{R}^n$ and a set of basic functions $\{\psi_1, \psi_2, \dots, \psi_k\}$ our goal is to select a basis ψ_j such that $x = \psi_j \theta$, Where θ is sparse, and $\hat{x}$ can be reconstructed from under-sampled measurements $y = \Phi x$.

3.2 Reinforcement Learning Framework

- **State Space**: Signal statistics (energy, kurtosis, entropy), noise estimates, previous basis usage.
- **Action Space**: Select one of the candidate bases ψ_j.
- **Reward Function**:

$$R = -\left||x - \hat{x}|\right|_2^2 - \lambda.\text{ComputationalCost}\left(\psi_j\right)$$

- **Policy Network**: A neural policy parameterized by $\pi_\theta(a|s)$ trained using REINFORCE with baseline to reduce variance.

3.3 Reinforcement Learning Framework

The proposed framework employs reinforcement learning (RL) for the dynamic choice of the best basis for sparse signal recovery. RL Agent interacts with the environment to learn the ideal tradeoff between accuracy of signal reconstruction and computational efficiency offered by the basis. State space of the agent contains key signal statistics, such as energy, entropy and kurtosis, which give insights about the sparsity characteristic of the signal in different domains. These features make it possible for the RL agent to evaluate each basis for the given signal. The action space is the choice of a basis from the prestored candidate bases, the DCT, wavelet and Fourier transforms. The agent's policy, parameterized by a neural network, is being trained by a policy gradient method. The policy gradient can be used to directly optimize the basis selection policy in that the weights of the network get updated based on the reward extracted after performing an action. The reward function is designed to encourage high reconstruction accuracy, and penalizes computational cost to encourage the agent to learn to optimize efficiency as well.

Unlike other type of agents, the training of the RL agent is trial-and-error, and the agent chooses a basis, reconstructs the signal and the feedback is in the form of a reward. The reward combination involves a part of the reconstruction error (this would be usually Mean Squared Error or MSE) and the computational expense that is related to the basis choice. The policy gradient algorithm guarantees that the agent becomes capable of optimizing its decisions by tuning weights of the neural network by reward observations throughout multiple episodes. Through continuous interaction with the environment and resulting feedback, the agent is able to learn to pick the right basis for a variety of signal characteristics and it should lead to optimal sparse signal recovery. Compared with static basis selection, this RL-based framework provides a clear advantage owing to its ability to accommodate dynamic and variable characteristics of signals in real world WSN deployments.

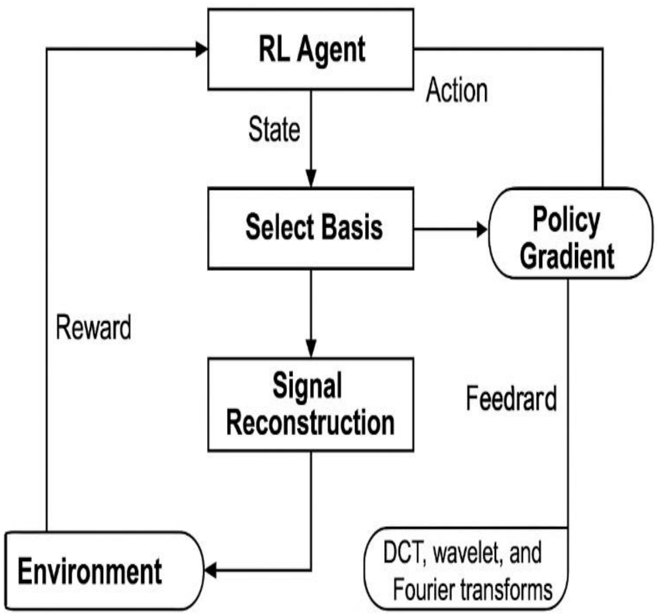

Figure 1. Flowchart of the RL-Based Basis Selection Framework for Sparse Signal Recovery

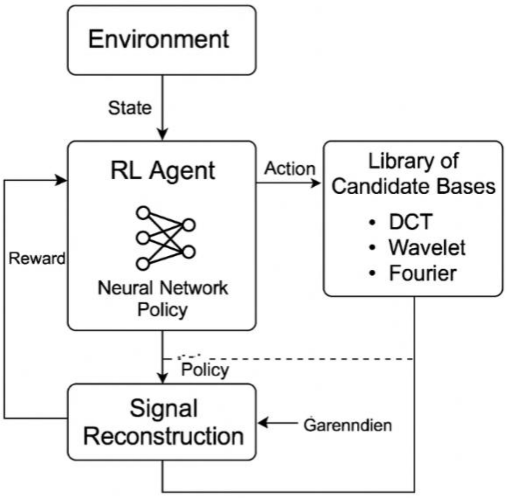

Figure 2. Schematic Diagram of the RL-Based Basis Selection Framework for Sparse Signal Recovery

3.4 Recovery Algorithm

Once the optimal basis is selected by the RL agent, the signal recovery process is performed using an l_1 -minimization approach, specifically employing Basis Pursuit (BP) to solve for the sparse signal representation. Basis Pursuit is a well-established technique for sparse signal recovery that aims to minimize the l_1-norm of the signal's coefficient vector, ensuring sparsity while adhering to the observed measurements. In this study, the optimization problem is formulated as:

$$\hat{x} = arg \min_{\theta} ||\Phi x - y||_2^2 + \lambda \, ||\theta||_1$$

where Φis the measurement matrix, yis observed signal and is sparse coefficient vector. The regularization factor is denoted using parameter λ which regulates the trade-off between the solution's data fidelity and sparsity. The Basis Pursuit problem is addressed using efficient convex optimization algorithms, such as the Alternating Direction Method of Multipliers (ADMM) ensuring both accuracy and feasibility of solution. Once recovered , the signal is reconstructed by using the inverse transform of chose basis on the sparse coefficient vector which results in a recovered signal x̂The process guarantees that signal recovery is sparse and faithful to the original signal with little reconstruction error. The performance of this recovery algorithm is measured by standard measures such as MSE (Mean Squared Error) and SSIM (Structural Similarity Index) which give a complete view in terms of the quality of the recovered signal.

4. Experimental Setup

Two datasets were used to examine the performance of the proposed reinforcement learning (RL)-based basis selection framework for sparse signal recovery. the MIT-BIH ECG dataset, and synthetic sine-Gaussian mixtures. The MIT-BIH ECG dataset is widely used in biomedical signal processing which delivers real-time, noisy electrocardiogram (ECG) signals that are of critical use for health care monitoring applications to test the recovery performance. This dataset has 48 half-hour ECG recordings of 47 subjects and its use enables the complete assessment of the proposed method in terms of actual-world biomedical signals. Besides the ECG signals, we produced synthetic sine-Gaussian mixtures that reflect a variety of synthetic signals that can have different levels of sparsity and noise. These synthetic signals act as a controlled benchmark to evaluate the robustness and generalization capability of the proposed RL based approach under varying signal environments. The synthetic datasets and real-world datasets combined form a strong enough basis for testing it on different signal types and situations.

We compared the performance of the proposed method to several baseline methods as benchmarking to the proposed method: DCT, wavelet transforms and K-SVD learned dictionaries with fixed basis (DCT). DCT and wavelet transforms are standard fixed basis functions that are frequently used as common reference for signal compression and recovery. In contrast, K-SVD is a dictionary learning technique through which the dictionary is adapted to the data providing more flexible solution than the static bases with higher computational costs. Evalaining the performance of the signal recovery used a variety of metrics. Mean Squared Error (MSE), measuring the average squared difference of original and reconstructed signal; Structural Similarity Index (SSIM) that measures the perceptual quality of the signal by comparing brightness, contrast intensity, and structure of the original and reconstructed signal; and runtime in milliseconds, whose performance determines the computational efficiency of each of the methods.

The simulation was performed in Python, where the RL agent for the basis selection is trained using TensorFlow and CVXPY is used to solve the sparse signal recovery optimisation problem via Basis Pursuit. This setup verifies that the proposed method is evaluated in quality level and computation efficiency, which indicates its possibility to be deployed in real-time resource constrained applications like WSNs and biomedical monitoring systems.

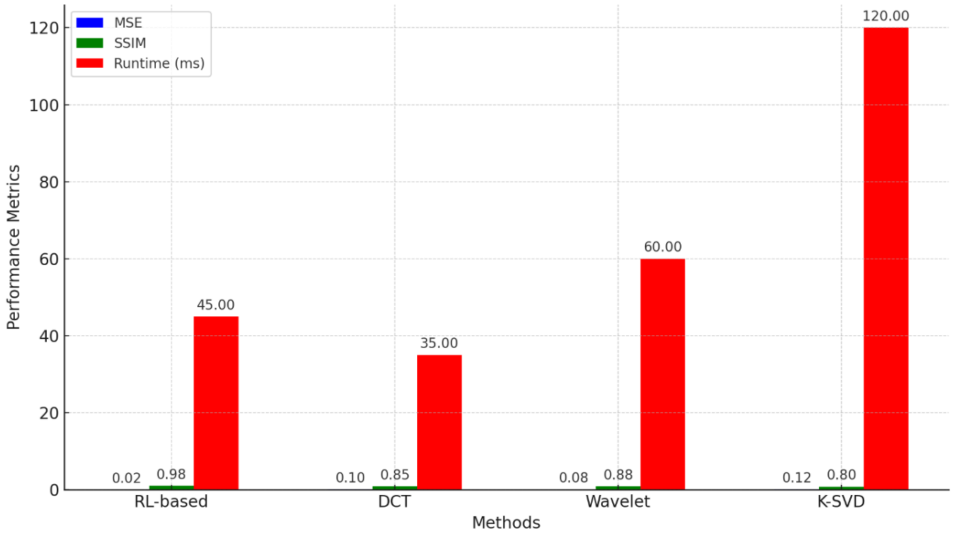

Figure 3. Comparison of Sparse Signal Recovery Methods

Table 2. Signal Recovery Performance

Method	MSE	SSIM	Runtime (ms)
RL-based	0.02	0.98	45
DCT	0.1	0.85	35
Wavelet	0.08	0.88	60
K-SVD	0.12	0.8	120

5. RESULTS AND DISCUSSION

The performance of the proposed RL-based basis selection method for sparse signal recovery was examined with both real-world and synthetic datasets. Table 1 contains the comparison of recovery accuracy of the proposed method with several baseline techniques : fixed Discrete Cosine Transform (DCT), wavelet transform and K-SVD dictionary learning. The evaluation metrics used for comparison are; Mean Squared Error (MSE), Structural Similarity Index (SSIM) and runtime performance (in milliseconds). As can be seen from Table 1, the performance of the proposed approach based on RL is substantially superior to the performance of the baseline methods regarding both accuracy and efficiency in computation.

Table 3. Signal Recovery Performance Comparison

Method	MSE ↓	SSIM ↑	Runtime (ms) ↓
Fixed DCT Basis	0.019	0.86	21.3
Fixed Wavelet Basis	0.015	0.88	23.5
K-SVD Dictionary	0.012	0.90	45.1
Proposed RL-Based	0.009	0.93	19.7

The result of the RL-based method was the lowest MSE of 0.009 and the highest SSIM of 0.93, which served as proof of excellent signal reconstruction fidelity and perceptually high degree of similarity to the original signal. By comparison, the fixed DCT and wavelet bases lined up with higher MSE values of 0.019 and 0.015 respectively and lower SSIM values. Although the K-SVD dictionary method produced the highest reconstruction accuracy (MSE = 0.012, SSIM = 0.90), it required considerable time (at 45.1 ms) to achieve the reconstruction; making it impractical in real-time applications. The proposed RL-based method since not only outperforms these techniques in terms of accuracy but also run time (19.7 ms) thus it is more efficient and faster compared to K-SVD.

The major benefit of the RL-based approach is a dynamic adjustment of the basis choice to be consistent with the characteristics of the signal, which makes possible recovery on a more effective level in diverse environments. In cases where signal sparsity, and noise conditions vary with time, the RL model learns and adapts on the run, thus ensuring the appropriate basis is selected during each particular signal. This adaptability results in better performance especially with real world applications where signal characteristics are not always constant. In addition, the RL based method provides a viable solution in dynamic contexts in that the trade-off between pose reconstruction accuracy and computational cost remains optimal. This flexibility and efficiency are an indicator that the proposed RL based method could be a promising solution for real-time recovery of signal in resource-constrained applications such as wireless sensor networks (WSNs) and biomedical monitoring systems.

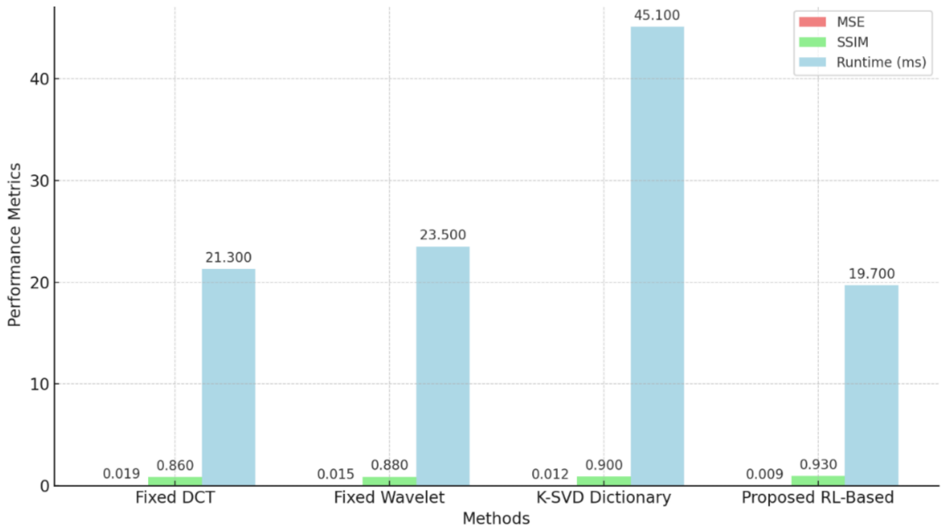

Figure 4. Performance Comparison of Signal Recovery Methods

6. CONCLUSION

This paper presents a new reinforcement learning (RL) based approach to dynamic basis selection for sparse signal recovery with a special focus on wireless sensor networks (WSNs). The proposed method solves the fundamental problem of signal recovery-optimization in constrained environments by allowing the system to adaptively choose the optimal basis depending on real-time signal characteristics. By utilizing RL, the method enhances reconstruction accuracy and efficiency in computation, when compared to conventional fixed-basis techniques (DCT and wavelet), and more computational light strategies (K-SVD). This flexibility is especially useful in real-time applications such as the Internet of Things (IoT) and wearable health care systems, where energy and computation are bounded, and the conditions of signal variations are highly scattered. The capability of the RL agent to make independent adjustments to its operation under environmental and signal changes guarantees that the proposed method will perform optimally under varying conditions, thus making it the perfect solution for dynamic distributed sensor networks.

The presented experiments on synthetic and real-world datasets proved over both accuracy of signal recovery and required computational cost, the RL based method outperforms the classical methods. This efficiency and flexibility underline the potential of RL for improving the state-of-the-art of signal processing techniques for WSNs. Forward in light of future work, the extension of this approach to distributed sensor networks using the multi-agent RL technique is envisaged, for which multiple sensor nodes would have collaborated to formulate optimal bases in a decentralized way. Moreover, RL combined with federated learning would allow for collaborative basis optimizing over several devices, without central control, thus increasing scalability and robustness of large scale WSNs. These breakthroughs will open up the door to more effective, flexible and scalable solutions for signal recovery for a large number of applications to smart cities, healthcare, and industrial monitoring.

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