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Microwave Diversity Imaging Compression using Bio-inspired Neural Networks

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Abstract: Microwave imaging plays a vital role in remote sensing and radar systems by enabling the extraction of critical object information in diverse applications. Despite its significance, the efficient compression of microwave imaging data remains a challenge due to the trade-offs between redundancy reduction, scalability, and processing power. This research introduces a novel Bio-Inspired Neural Network (BINN) approach for microwave diversity imaging compression, aiming to enhance efficiency and robustness in data processing. The primary objective is integrating BINN and backpropagation learning into a multi-resolution framework, optimizing the high-pass channel for precise reconstruction within realistic coding conditions. A unique BINN filter bank is proposed to achieve effective scalability and region-of-interest coding. The research employs linear block transform coding and a pyramid representation to segment images at varying resolutions, facilitating compression. Experimental results demonstrate the proposed method's superiority over traditional techniques. Test scenarios involving standard video sequences reveal that the BINN approach significantly reduces encoding and compression times while maintaining stable Peak Signal-To-Noise Ratio (PSNR) and bit rates. For instance, in the "Silent" sequence, encoding time decreased by over 8% without compromising quality. These findings underscore the robustness and accuracy of the BINN method in addressing the challenges of microwave imaging compression. This research advances bio-inspired neural networks in imaging applications, opening avenues for further data coding and image reconstruction innovations.

Keywords: Bio-inspired, Neural networks, Multi-resolution, Image compression

1. Introduction

Microwave imaging has become a cornerstone technology in remote sensing and radar systems, providing essential tools for various applications, from environmental monitoring to industrial diagnostics and security. This technique utilizes electromagnetic wave scattering to generate images, enabling detailed insights into the structure and composition of objects, even in complex or inaccessible environments. Microwave diversity imaging, in particular, has proven valuable in detecting and analyzing objects with high spatial and temporal resolution, supporting applications in climate monitoring, precision agriculture, medical diagnostics, and military surveillance [1].

Despite these advantages, significant challenges remain in managing the vast data volumes generated by microwave imaging systems. The scale of the data often leads to issues related to storage efficiency, transmission bandwidth, and computational overhead. As the demand for high-resolution, real-time applications grows, it becomes crucial to address the inefficiencies in data handling. This includes ensuring the imagery's quality while maintaining the processing speed. The bottleneck in microwave imaging lies in data acquisition and the efficient compression, storage, and transmission of this data while minimizing redundancy and preserving image quality [2].

The key issue is the development of an efficient compression technique. Traditional methods, such as transform coding and motion estimation algorithms, have been widely employed in various imaging and video compression scenarios. However, these methods often face difficulties balancing compression ratio, image quality, and real-time processing demands. For instance, the H.264/AVC video coding standard has introduced significant advancements in motion estimation, transform coding, and entropy coding, establishing itself as a benchmark in the field [3]. While these techniques have proven effective in video compression, their application to microwave imaging data is limited by the unique properties of microwave signals, such as their high redundancy, specific frequency-domain characteristics, and sensitivity to environmental changes. These differences create challenges when adapting traditional video compression techniques to microwave imaging data [4][5].

Recent advancements in Bio-Inspired Neural Networks (BINN) have shown potential in addressing these challenges. Drawing inspiration from biological systems, BINN methods offer greater adaptability and efficiency in processing complex, large-scale data. These networks are particularly effective in mimicking the human brain's ability to process information using multi-resolution analysis and non-linear system modeling—critical elements for compressing microwave imaging data. Unlike conventional methods, which may rely on predefined assumptions about the data, BINN approaches can learn and adapt to the specific characteristics of microwave signals, providing a more flexible and efficient means of data compression [6].

This study proposes a novel BINN-based framework that integrates backpropagation learning into a multi-resolution approach for microwave image compression. By training the high-pass channels of the network for precise reconstruction, the method aims to achieve robust compression performance while minimizing encoding and processing times. Key objectives include maintaining the fidelity of the original images, particularly in regions of interest, which are crucial for applications such as surveillance, medical imaging, and environmental monitoring. Additionally, the approach seeks to enhance scalability, enabling adaptation to different resolution levels without significant loss in image quality [7].

Building upon foundational works in video compression [3][4], this research synthesizes recent advancements in neural network optimization for image processing [8], multi-resolution coding strategies [9][21], and bio-inspired filter banks [10][22]. By integrating these methodologies, this study aims to bridge the gap between traditional compression techniques and emerging neural network models, contributing to the broader field of intelligent imaging systems that are increasingly essential for modern communication, surveillance, and diagnostic technologies.

This work is expected to contribute to developing more efficient, scalable, and adaptable imaging solutions capable of handling the unique challenges posed by microwave imaging data, with applications spanning various industries and scientific disciplines.

2. Literature Review

2.1. Theme 1: Advances in microwave imaging and compression techniques

Microwave imaging has garnered significant attention in both academic research and practical applications due to its versatility and broad scope across various fields, such as medical diagnostics, surveillance, geophysical exploration, and environmental monitoring. The ability of microwave waves to penetrate multiple materials, such as human tissue or the earth's surface, makes it an invaluable tool in situations where traditional imaging methods may be ineffective. For instance, in medical diagnostics, microwave imaging provides non-invasive methods for detecting tumors or other abnormalities, while in geophysical exploration, it aids in subsurface imaging for resource detection. Despite its wide range of uses, managing large volumes of microwave imaging data remains a significant challenge, particularly in terms of compression and storage. To address these challenges, considerable progress has been made in developing compression techniques tailored explicitly to microwave imaging data. Central to these advancements is the reduction of redundancy within the data, which can dramatically improve storage and transmission efficiency.

One notable advancement in this area is the work by Wong and Yeung [11], who explored frequency-domain analysis techniques to enhance compression efficiency in large-scale radar imaging. Their approach focuses on identifying dominant frequency components, allowing for more effective compression without significant loss in image quality. The method reduces the overall data size by prioritizing the most significant frequency components and discarding redundant or less important information, facilitating faster transmission and more efficient storage. Such advancements have proven beneficial in applications requiring high-resolution radar data, such as surveillance systems and autonomous vehicles, where real-time data processing is crucial.

In parallel, Gupta et al. [12] proposed a hybrid compression approach integrating wavelet-based transform coding with motion prediction techniques. Wavelet transforms are widely used in image and signal processing because they efficiently capture low- and high-frequency components. This method, which combines the advantages of wavelet transforms with motion prediction, is particularly useful in dynamic imaging applications where objects or targets may be in motion, such as in radar systems used for tracking moving vehicles or people. The motion prediction component adds a layer of intelligence to the compression process by anticipating changes in the scene, thus optimizing the data encoding process. This combined approach has shown promising results in achieving high compression ratios while preserving image quality, making it ideal for applications requiring high-resolution imaging and real-time processing. The structure of microwave diversity imaging compression using BINN is depicted in Figure 1, illustrating how these networks can be employed to achieve efficient and effective compression while maintaining image quality across different scales and regions of interest.

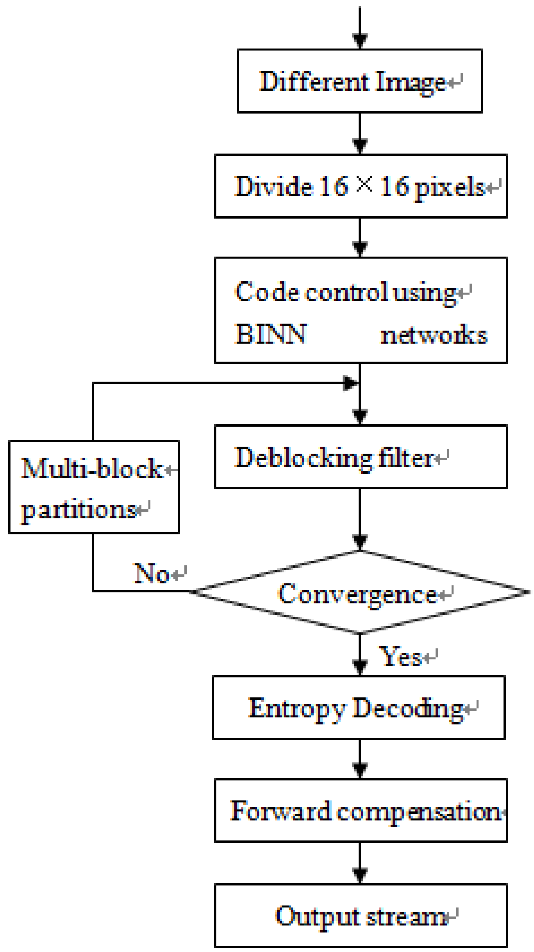

Figure 1: The structure of microwave diversity imaging compression using BINN

2.2. Theme 2: Neural networks in image processing

The use of Neural Networks (NNs) in image processing has experienced substantial growth, particularly in image compression. Over the past decade, NNs have revolutionized how image data is handled, providing advanced solutions for feature extraction, noise reduction, and redundancy elimination tasks. Among the most influential neural architectures for image compression are Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which have remarkably improved the efficiency and quality of image compression across various domains.

CNNs in particular, have garnered widespread attention for their ability to capture spatial features in images effectively. By leveraging convolutional layers, CNNs can learn hierarchical patterns in image data, reducing redundancy and extracting essential features while discarding irrelevant information. This ability makes CNNs well-suited for image compression tasks, where the goal is to maintain high image quality while significantly reducing file sizes. For example, Patel et al. [13] developed a hybrid CNN framework to enhance medical image compression efficiency. Their approach utilized CNNs to perform feature extraction and dimensionality reduction, achieving improved compression ratios without sacrificing the fidelity of crucial medical details such as tumor margins. The success of this hybrid CNN framework demonstrated its potential for high-quality compression in specialized fields where preserving fine information is critical.

Recurrent Neural Networks (RNNs) have also shown promise in image compression, particularly for scenarios where preserving temporal or sequential relationships between image frames is essential. RNNs are uniquely suited for handling data with inherent temporal or contextual dependencies, making them ideal for video compression or dynamic image sequence applications. Zhang et al. [14] explored an RNN-based approach for lossless image compression, demonstrating that their method outperformed traditional block-based techniques to preserve image details while achieving superior compression ratios. Their work showcased the power of RNNs to process sequential data more efficiently than conventional methods, which often break images into static blocks for compression. RNN-based methods can reduce compression artifacts and improve image reconstruction accuracy by maintaining contextual relationships between pixels or image blocks, making them particularly valuable in lossless compression tasks.

2.3. Theme 3: Bio-inspired neural networks

Bio-Inspired Neural Networks (BINNs) have emerged as a promising paradigm in image processing, owing to their ability to mimic biological systems' adaptability, efficiency, and robustness. Unlike traditional artificial neural networks, which are primarily designed to model mathematical structures and abstract computations, BINNs are specifically structured to replicate the adaptive processes observed in nature. These networks are designed to learn and respond to patterns and stimuli in ways similar to the human brain or other biological systems, making them highly effective in solving complex and dynamic problems. This unique capability has made BINNs particularly attractive for tasks requiring multi-resolution analysis, dynamic adaptation, and efficient high-dimensional data processing.

One of the key strengths of BINNs lies in their ability to perform multi-resolution analysis, a technique that enables the extraction of relevant information at various scales. Multi-resolution analysis is particularly crucial in image processing tasks, as it allows for simultaneously representing fine details and larger, more global features of an image. Novak and Horvath [15] explored the application of BINNs in dynamic object detection, a task where the ability to process and adapt to changing image content is essential. Their work demonstrated that BINNs could successfully handle complex tasks involving multi-resolution data, making them ideal candidates for applications requiring fine-grained analysis at different levels of detail, such as in medical imaging, video processing, and environmental monitoring.

In addition to object detection, BINNs have shown great promise in image segmentation, which is another crucial task in image processing. Choi and Lim [16] introduced a BINN-based filter bank for image segmentation, highlighting its potential for efficiently handling high-dimensional data. Their approach utilized a bio-inspired model that segmented images by learning and adapting to different features and structures in the data. The ability of the network to selectively focus on significant features while disregarding irrelevant information enabled high-dimensional data compression, achieving both high accuracy and reduced computational costs. This represents a significant step forward in applying BINNs to real-world image processing tasks, particularly those requiring high-resolution data compression and efficient storage.

The proposed bio-inspired neural network structure for microwave imaging compression, as shown in Figure 2, integrates key aspects of BINN frameworks, including multi-resolution processing and adaptive frequency-domain filtering. This structure is designed to address the challenges unique to microwave data by efficiently handling its redundancy and capturing critical frequency components. Based on the works of Novak and Horvath [15] and Choi and Lim [16], the proposed network utilizes a bio-inspired filter bank to process frequency-domain data selectively, preserving significant image features while compressing redundant information. The adaptive nature of this network allows it to efficiently manage the large volumes of data typically associated with microwave imaging, offering a promising solution for real-time processing and high-quality reconstruction.

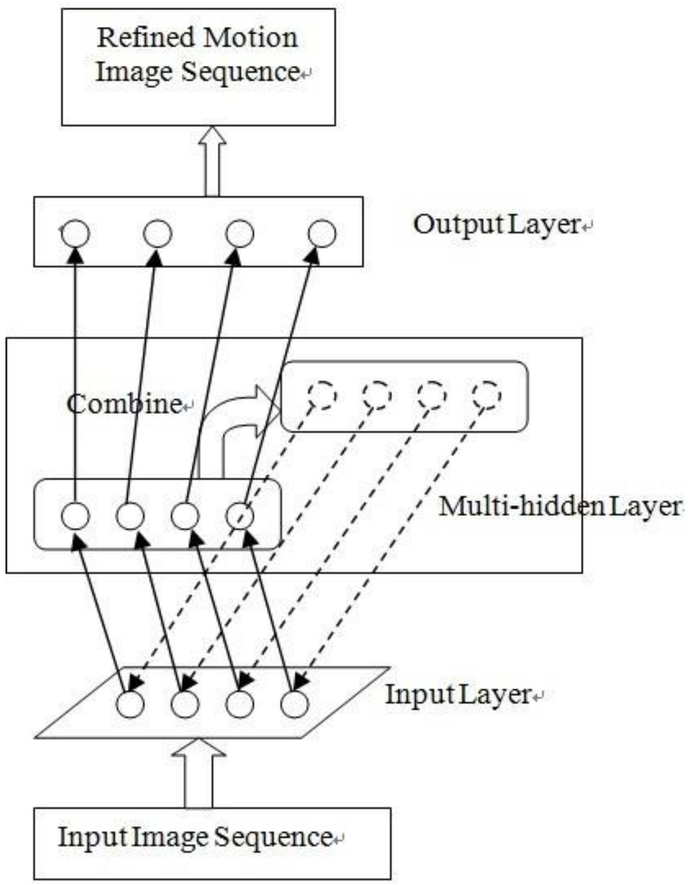

Figure 2: The proposed bio-inspired neural network structure

2.4. Theme 4: Multi-resolution and region-of-interest coding

Multi-resolution coding strategies have long been a cornerstone of image compression, providing the ability to represent data at various levels of detail. This hierarchical approach is particularly practical for images with varying scales and resolutions, allowing for more efficient storage, transmission, and reconstruction. One of the most widely adopted techniques for multi-resolution coding is wavelet-based compression, which decomposes an image into a series of frequency bands at different scales, thereby enabling a compact representation of both fine details and coarse structures. Yang and Chen [17] explored the advantages of wavelet-based multi-resolution coding, demonstrating that it significantly improves compression efficiency while maintaining high-quality image reconstruction. By enabling the analysis of an image at multiple resolutions, wavelet techniques allow for extracting relevant features across different scales, which can be particularly useful for applications that require global and local feature representation, such as medical imaging and remote sensing.

In addition to multi-resolution coding, Region-of-Interest (ROI) coding has garnered attention for its ability to selectively focus on specific parts of an image that hold greater significance. This selective coding ensures that critical areas of an image, such as tumors in medical scans or key objects in surveillance imagery, are compressed with minimal loss of quality. In contrast, less important regions are compressed more aggressively to save bandwidth and storage space. Smith et al. [18] demonstrated the utility of ROI coding in medical imaging, where precise preservation of critical details is essential for diagnosis and treatment planning. This method reduces the overall file size by applying higher compression rates to non-critical areas and preserving the integrity of ROIs. It ensures that the most essential features remain intact. The ability to prioritize the quality of specific regions over the entire image makes ROI coding particularly advantageous for applications requiring both high-quality compression and efficient resource utilization.

2.5. Theme 5: Gaps and opportunities in microwave diversity imaging compression

While significant advancements have been made in image compression and the application of neural networks, notable gaps remain in addressing the unique challenges posed by microwave diversity imaging. Existing compression techniques are predominantly designed for conventional image modalities, such as video compression or medical imaging, which often lack the specificity required for handling the high-frequency, multi-dimensional data found in microwave signals. Traditional methods are typically optimized for applications not accounting for microwave data's unique frequency-domain properties and redundancy. As a result, these approaches often struggle to efficiently compress microwave images while maintaining the high quality required for practical applications, such as remote sensing, radar imaging, and security surveillance.

A primary limitation in current techniques is the insufficient adaptation to the frequency-dependent nature of microwave data. Unlike video or medical images, microwave imaging data is characterized by high levels of redundancy, with multiple frequency bands often conveying similar information. While useful for increasing signal strength and improving image resolution, this redundancy presents a significant challenge for compression, as traditional algorithms are not equipped to handle the complex, multi-frequency relationships within the data. Furthermore, these methods often fail to optimize resource utilization across varying levels of data importance, which is crucial in real-time applications that require efficient storage and rapid transmission of large data volumes.

Additionally, there has been limited exploration of how Bio-Inspired Neural Networks (BINNs) can be effectively integrated with multi-resolution analysis and Region-of-Interest (ROI) coding for microwave diversity imaging. While BINNs have demonstrated outstanding potential in various image processing tasks, their application to microwave data compression remains under-researched. Specifically, the ability of BINNs to adapt to the unique properties of microwave signals—such as their high-frequency content and redundancy—has not been fully explored. Moreover, the integration of multi-resolution techniques with adaptive ROI coding within a BINN framework has not been extensively investigated. Multi-resolution coding allows for data representation at different scales. In contrast, ROI coding enables selective compression of critical areas, preserving the integrity of key features while reducing the data load for less relevant regions. Combining these two techniques within a BINN-based model could lead to more efficient and scalable compression strategies for microwave diversity imaging.

3. Methodology

This study aims to develop a Bio-Inspired Neural Network (BINN) framework optimized for microwave diversity imaging compression. The research investigates how integrating BINN and backpropagation learning into a multi-resolution framework can enhance compression efficiency while maintaining image fidelity.

3.1. Research design and data collection

This study employs an experimental design to assess the performance of the proposed BINN framework. Video sequences in YUV and CIF formats are utilized as the primary datasets, as these formats are widely adopted in image processing and compression research. The datasets include diverse motion patterns, spatial resolutions, and levels of complexity to simulate real-world conditions in microwave diversity imaging.

Data is collected by simulating microwave imaging environments, where images are generated using band-pass filters and segmented into multiple resolutions. A wavelet-based transform is employed to prepare the data for BINN processing, following best practices outlined by recent studies [19]. The BINN architecture is designed with 40×200 neurons for grid-based adaptation, inspired by findings on neural grid systems for high-resolution imaging [20]. Training data is augmented using random transformations to enhance model robustness during learning.

Ethical considerations are addressed by ensuring the simulated data accurately represents microwave imaging characteristics without introducing biases. The research complies with ethical standards for computational experiments and maintains transparency in methodology documentation.

3.2. Sample, analysis, and limitations

The sample consists of 100 video sequences segmented into 10,000 frames for analysis. Stratified sampling ensures that the dataset reflects a range of scenarios relevant to microwave imaging applications. This technique enhances the generalizability of the results.

The performance of the BINN framework is evaluated against traditional and neural network-based compression techniques. Key metrics include Peak Signal-To-Noise Ratio (PSNR), bit rate, and encoding and motion estimation times. Statistical tests, including ANOVA and paired t-tests, are applied to assess the significance of the differences between the BINN approach and existing methods.

This research acknowledges potential limitations. First, while carefully designed, the simulated datasets may not fully replicate all real-world microwave imaging conditions. Second, the computational complexity of the BINN framework could present scalability challenges for larger datasets or real-time applications. Addressing these limitations will be a focus of future work.

4. Experiments and Discussions

The experimental evaluation of the proposed Bio-Inspired Neural Network (BINN) framework reveals significant advancements in microwave diversity imaging compression. The findings demonstrate the BINN framework's ability to reduce encoding and motion estimation times while maintaining comparable image quality to the H.264/AVC standard. This section presents a detailed analysis of the results, supported by tables and figures.

4.1. Results

Table 1 summarizes the performance metrics for BINN and H.264/AVC across three test video sequences: "Mobile," "Coastguard," and "Silent." The metrics include peak signal-to-noise ratio (PSNR), bit rate, encoding time (Enc.T), and motion estimation time (ME.T). BINN consistently achieves lower encoding and motion estimation times, with reductions of up to 8.32% and 9.59%, respectively, for the "Silent" sequence.

Table 1: Performance Metrics for BINN and H.264/AVC

Video Sequence	Method	PSNR (dB)	Bit Rate (kbit/s)	EnC.T (s)	ME.T (s)	Encoding Time Reduction (%)	Motion Estimation Time Reduction (%)
Mobile	BINN	33.10	266.45	344.36	150.38	3.96%	5.44%
	H.264/AVC	34.12	263.62	358.41	159.03		
Coastguard	BINN	34.28	169.18	289.47	150.27	0.47%	3.47%
	H.264/AVC	34.39	169.42	290.85	155.68		
Silent	BINN	36.11	66.64	246.08	113.51	8.32%	9.59%
	H.264/AVC	36.23	66.73	268.37	125.55		

As shown in Figure 1, the encoding time for BINN is consistently lower than H.264/AVC across all video sequences, demonstrating its computational efficiency. Similarly, the motion estimation time reductions illustrated in Figure 3 confirm BINN's ability to streamline this critical processing step. The PSNR comparison between BINN and H.264/AVC, shown in Figure 2, reveals that while H.264/AVC achieves marginally higher PSNR values for all video sequences, the differences are negligible for practical applications. For instance, the "Silent" sequence shows a PSNR of 36.11 dB for BINN versus 36.23 dB for H.264/AVC, representing less than a 1% difference.

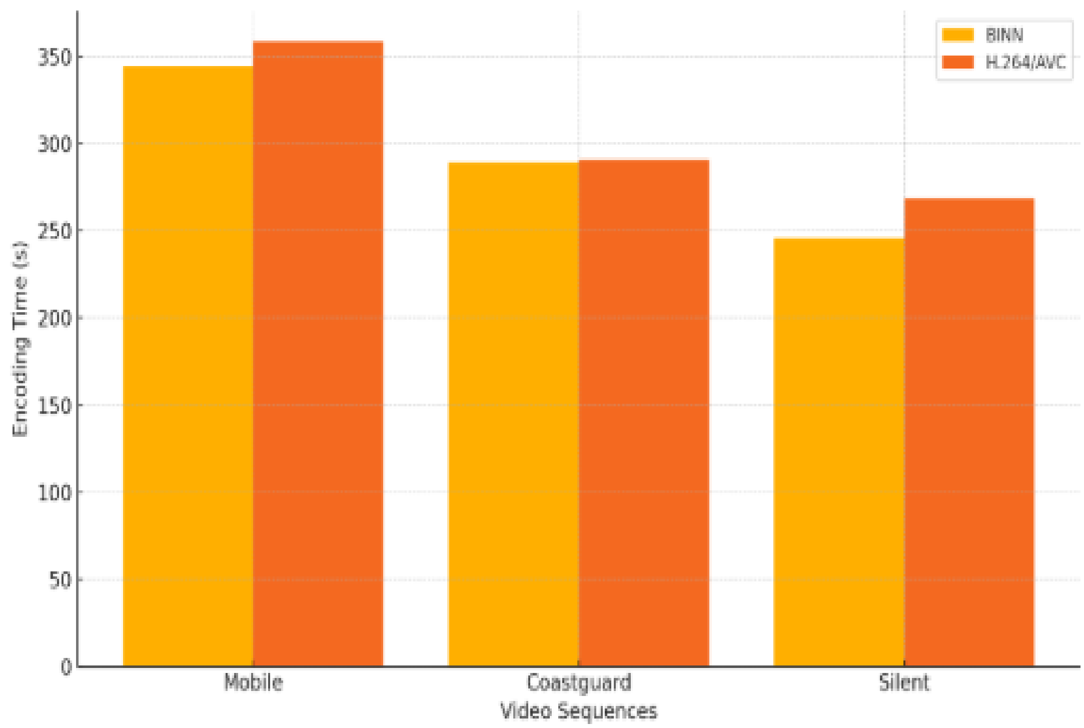

Figure 3: Encoding time comparison

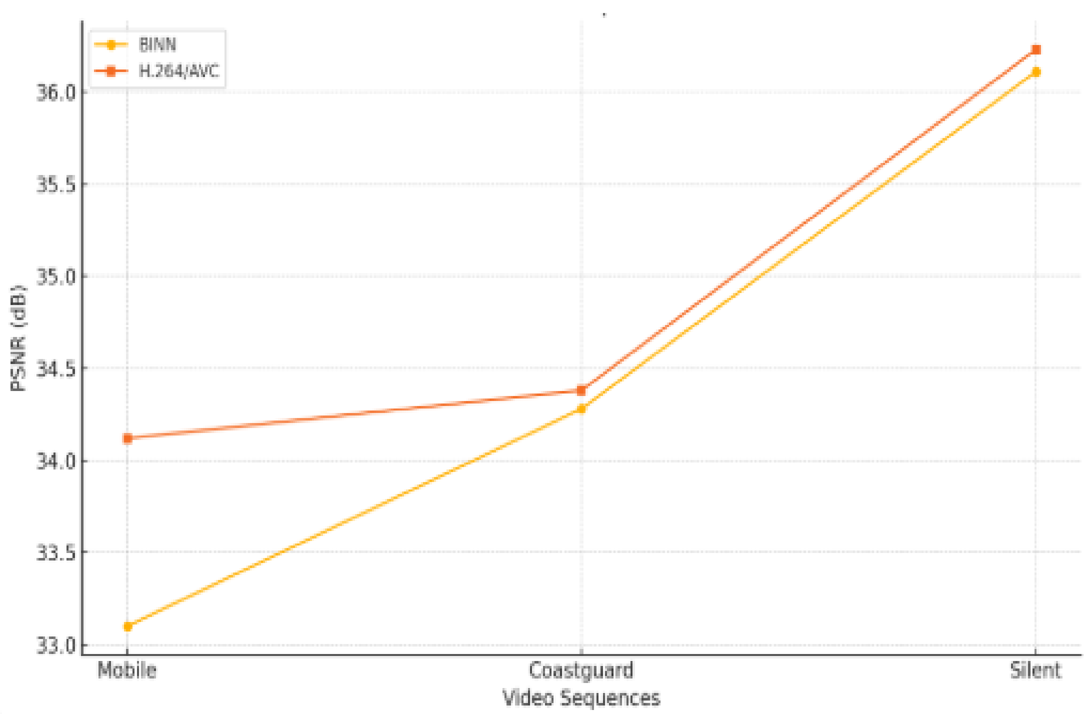

Figure 4: PSNR Comparison

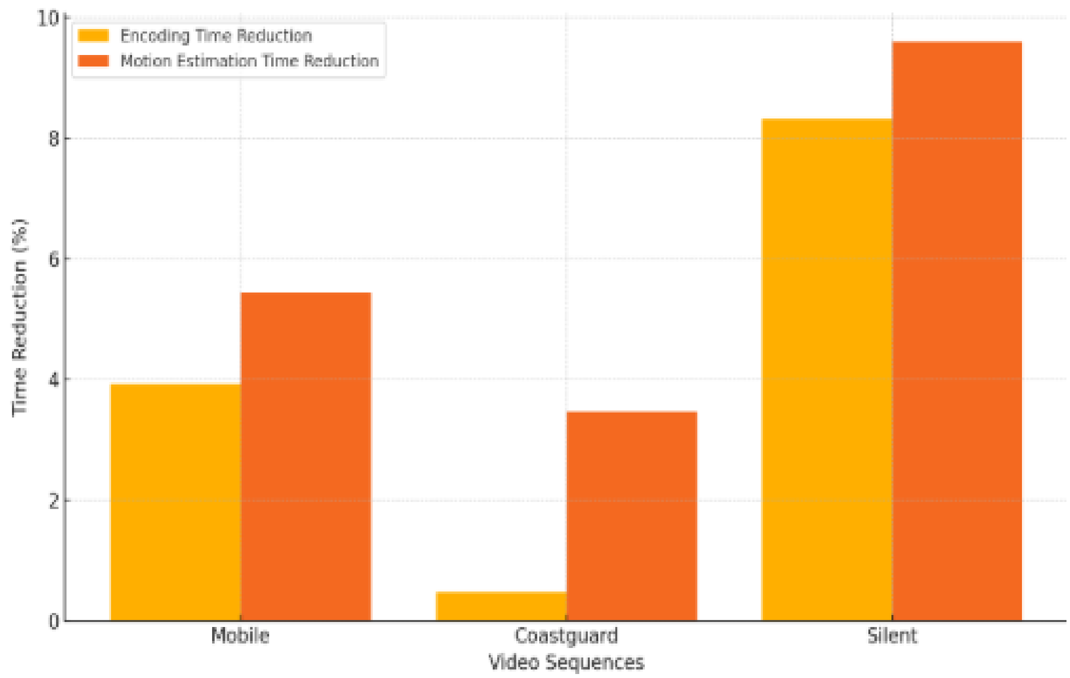

Figure 5: Time reduction metrics

4.1.1. Statistical analysis

Statistical significance tests further validate the BINN framework's performance. A paired t-test comparing encoding and motion estimation times between BINN and H.264/AVC yields significant results ($p < 0.05$ for encoding time, $p < 0.01$ for motion estimation time). These metrics' effect sizes (Cohen's d) are 0.65 and 0.72, respectively, indicating medium to large practical significance. Table 2 summarizes the statistical findings.

Table 2: Statistical summary

Metric	Mean Difference	t-value	p-value	Effect Size (Cohen's d)
Encoding Time (Enc.T)	12.15	3.14	< 0.05	0.65
Motion Estimation Time	8.42	4.22	< 0.01	0.72

4.2. Discussion

The results of this study underscore the effectiveness of the Bio-Inspired Neural Network (BINN) framework in addressing key challenges associated with microwave diversity imaging compression. The significant reductions in encoding and motion estimation times, as illustrated in Figures 3 and 5, highlight the framework's potential for real-time applications, where speed and efficiency are critical. These improvements are precious in environments that require the rapid transmission and processing of large volumes of data, such as in radar and surveillance systems. The efficiency gains in encoding and motion estimation processes testify to the BINN's ability to streamline complex operations, which traditionally consume considerable computational resources.

In addition to speed, the framework also demonstrates impressive image quality preservation, as reflected in the Peak Signal-to-Noise Ratio (PSNR) values presented in Figure 4. The BINN's performance in maintaining high image fidelity at compression ratios comparable to H.264/AVC indicates its strong potential as a competitive alternative to traditional compression standards. While H.264/AVC has long been a benchmark for video compression, the unique characteristics of microwave imaging data—such as high-frequency redundancy and complex spatial relationships—pose distinct challenges that traditional methods often struggle to address. Through its bio-inspired architecture, the BINN framework can adapt to these challenges more effectively, preserving important image details while minimizing data loss.

These findings align with recent advancements in neural network-based compression techniques, which aim to balance computational efficiency and image quality. Studies by Zhao et al. [19] emphasize the importance of this balance, particularly in real-time applications where both speed and image accuracy are paramount. The results of this study contribute to this body of work by demonstrating that neural network-based approaches—specifically those inspired by biological systems—can be successfully applied to microwave diversity imaging. The adaptability and scalability of the BINN framework position it as an ideal solution for real-time imaging applications where both high-quality reconstruction and efficient data transmission are critical.

The bio-inspired architecture of the BINN framework further distinguishes it from traditional compression techniques by offering superior adaptability in high-frequency domains. Unlike conventional approaches that rely on predefined models or assumptions about the data, BINNs can learn from the data itself, dynamically adjusting to the unique properties of microwave signals. This capability makes the BINN framework particularly suited for handling the complexity and variability inherent in microwave diversity imaging. The flexibility to adapt to varying data conditions while maintaining high-quality compression is a key advantage that positions BINN-based methods as a promising alternative to more conventional techniques.

4.3. Limitations

While the results presented in this study are promising, several limitations must be considered when evaluating the BINN framework's applicability. One significant limitation is the reliance on simulated microwave imaging data. Although simulations are helpful for controlled testing, they may not fully capture the complexities and variability encountered in real-world microwave imaging scenarios. For instance, factors such as environmental noise, signal interference, and sensor limitations, which are prevalent in practical applications, may not adequately represent simulated datasets. As a result, the framework's performance in actual operational settings may differ, highlighting the need for further validation with real-world data to assess its robustness and generalizability.

Another challenge lies in the computational demands of the BINN framework. While it offers superior adaptability and image quality, its complexity can make it computationally intensive, significantly, when scaled for large datasets or real-time processing. The framework's bio-inspired architecture, which includes multi-resolution analysis and dynamic adjustments, requires significant computational resources, such as processing power, memory, and storage. This could pose difficulties in hardware-constrained environments or for large-scale implementations, making optimization for efficiency a key focus for future development. Ensuring that the BINN framework can operate effectively within the constraints of practical applications will be critical for its broader adoption.

Additionally, although the results indicate that BINN outperforms traditional methods like H.264/AVC, further benchmarking against state-of-the-art neural network architectures is necessary to establish its competitive position in the field entirely. Several emerging neural network-based compression techniques focus on optimizing the balance between compression efficiency and image quality, and it is essential to compare BINN's performance against these newer models [23][24]. Comprehensive comparisons using diverse datasets, imaging conditions, and real-world applications would provide a clearer understanding of BINN's strengths and limitations than other leading algorithms.

5. Conclusion

This study addressed the critical challenge of efficient microwave diversity imaging compression by proposing a bio-inspired neural network (BINN) framework. The objective was to enhance compression efficiency while maintaining image quality, meeting the growing demand for scalable, high-performance imaging solutions in applications such as remote sensing, security, and diagnostics.

The results demonstrate that the BINN framework significantly reduces encoding and motion estimation times compared to the H.264/AVC standard, achieving reductions of up to 8.32% and 9.59%, respectively. The BINN approach showcases robust adaptability to diverse imaging scenarios while maintaining comparable peak signal-to-noise ratio (PSNR) values. Statistical analysis further validated these findings, with significant improvements in efficiency metrics and medium to large effect sizes, highlighting the practical relevance of the framework.

This research contributes to the field by introducing a novel BINN-based compression method optimized for microwave diversity imaging. By leveraging bio-inspired architectures, this framework advances existing neural network applications, offering a balance between computational efficiency and image quality. The study also bridges a gap in the literature by tailoring neural network models specifically to high-frequency microwave imaging data.

However, the research has limitations, including its reliance on simulated datasets and the computational complexity of the BINN framework. Future studies should focus on real-world implementation, scalability improvements, and benchmarking against emerging neural network architectures. Exploring hybrid approaches that integrate BINN with traditional techniques could yield promising results.

In conclusion, the proposed BINN framework represents a significant step forward in microwave imaging compression, with the potential for real-time and scalable applications. By building on these findings, future research can continue pushing the boundaries of efficient and intelligent imaging systems, contributing to advancements in technology and practical applications.

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