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A Survey of Methods and Architectures for Deep Learning-based Area Efficient 1024-Point Pipelined Radix-4 FFT Processor for Biomedical Application

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Abstract

The Fast Fourier Transform (FFT) is a fundamental algorithm widely used in biomedical signal processing, including electroencephalogram (EEG), electrocardiogram (ECG), and medical imaging systems. The demand for real-time, low-power, and high-throughput processing has led to the development of area-efficient FFT architectures, particularly the 1024-point pipelined Radix-4 FFT processor. This survey presents a comprehensive analysis of recent methods and architectures integrating deep learning with FFT processors to enhance biomedical applications. FFT reduces computational complexity from $O(N^2)$to $O(N\log N)$, making it highly efficient for large-scale signal processing. Recent studies have focused on optimizing hardware architectures using pipelining, parallel processing, and memory-efficient techniques such as single-path delay feedback (SDF) and mixed-radix approaches. Additionally, deep learning models such as convolutional neural networks (CNNs) leverage FFT-based feature extraction to improve classification accuracy in biomedical systems. Furthermore, emerging technologies such as processing-in-memory (PIM) and FFT-based neural network acceleration have demonstrated significant improvements in energy efficiency and computational speed. This survey highlights key advancements, comparative analysis, and research challenges, providing insights into future directions for efficient biomedical FFT processor design.

Introduction

The increasing demand for efficient biomedical signal processing systems has significantly accelerated the development of advanced digital signal processing (DSP) architectures. Among these, the Fast Fourier Transform (FFT) plays a crucial role in converting time-domain signals into frequency-domain representations, enabling accurate analysis of physiological signals such as EEG, ECG, and MRI data. FFT is widely adopted because it reduces computational complexity from $O(N^2)$to $O(N\log N)$, making it suitable for large-scale real-time processing. In biomedical applications, signal accuracy and processing speed are critical. For example, EEG signal classification requires precise frequency analysis to detect neurological disorders, while ECG signal processing is essential for identifying cardiac abnormalities. Traditional FFT architectures often face challenges such as high-power consumption, large chip area, and increased latency. To address these issues, advanced architectures such as pipelined and parallel FFT processors have been developed.

Among various FFT algorithms, the Radix-4 FFT is widely preferred due to its reduced arithmetic operations compared to Radix-2. By grouping computations in sets of four, Radix-4 reduces the number of stages required, leading to improved computational efficiency. Pipelined architectures further enhance performance by allowing continuous data flow through multiple processing stages, making them suitable for real-time biomedical systems. Recent advancements have also introduced deep learning techniques into FFT-based systems. FFT is increasingly used as a preprocessing step for deep learning models, enabling efficient feature extraction in the frequency domain. For instance, FFT-based feature learning methods have demonstrated improved performance in EEG classification tasks. Additionally, FFT-based convolution techniques are used to accelerate neural network computations, reducing overall processing time.

Moreover, emerging hardware architectures such as Processing-in-Memory (PIM) and hybrid pipeline-memory FFT designs have further enhanced performance by reducing memory bottlenecks and improving throughput. These innovations are particularly beneficial for wearable and implantable biomedical devices, where energy efficiency is critical. This survey focuses on recent advancements in deep learning-based area-efficient 1024-point pipelined Radix-4 FFT processors for biomedical applications. It analyses various architectures, optimization techniques, and integration strategies, providing a comprehensive understanding of current research trends and future challenges.

Literature Review

Zhang et al. proposed an FFT-based deep learning model for EEG classification. The study demonstrated that transforming EEG signals into the frequency domain significantly improves classification accuracy. FFT-based feature extraction enhances neural network learning capability. Hsu et al. introduced a multi-path pipelined FFT architecture that improves throughput and reduces power consumption. Their design uses parallel processing techniques to achieve efficient real-time signal processing.

Liu et al. proposed an SDF-based FFT processor that minimizes memory usage and hardware complexity. The architecture is suitable for low-power biomedical devices due to its compact design. Ding et al. developed CirCNN, which uses FFT-based computation to accelerate deep neural networks. The model reduces computational complexity and improves energy efficiency in AI systems.

Kumar et al. designed a low-power Radix-4 FFT processor using optimized arithmetic units. The study showed significant improvements in energy efficiency and processing speed. Chen et al. (2021) proposed an energy-efficient FFT processor architecture specifically designed for wearable biomedical devices. The study incorporated clock gating and optimized arithmetic units to minimize dynamic power consumption. The results demonstrated that the proposed architecture significantly reduces energy usage while maintaining high processing speed, making it suitable for continuous physiological signal monitoring systems.

Gupta et al. (2021) developed a Radix-4 pipelined FFT processor with optimized butterfly units. By reducing the number of complex multipliers, the architecture achieved lower hardware area and improved computational efficiency. The design is particularly beneficial for embedded biomedical systems requiring compact and efficient implementations. Park et al. (2021) introduced a parallel FFT architecture using multi-core processing techniques. The system distributes FFT computations across multiple cores, achieving high throughput and reduced latency. This approach is highly effective for real-time biomedical applications such as EEG signal analysis and brain-computer interfaces.

Hsu and Chen (2021) focused on pipeline optimization techniques in FFT processors. Their design minimized memory access delays and improved data throughput by balancing pipeline stages. The architecture demonstrated improved real-time processing capabilities for biomedical signal applications. Zhang et al. (2021) proposed an FFT-based feature extraction method integrated with CNNs for EEG classification. The study showed that frequency-domain transformation improves neural network performance, resulting in higher classification accuracy and robustness against noise.

Verma et al. (2022) developed an area-efficient FFT processor using single-path delay feedback (SDF) architecture. The design minimized memory requirements and hardware complexity, making it highly suitable for low-power biomedical applications. Sharma et al. (2022) proposed a hybrid FFT-deep learning model for ECG signal classification. FFT was used for feature extraction, while deep neural networks performed classification. The system achieved improved diagnostic accuracy and reduced noise sensitivity.

Li et al. (2022) introduced a high-speed FFT processor using parallel pipeline architecture. The design significantly reduced latency and improved throughput, making it suitable for real-time biomedical imaging applications such as

MRI and CT scan processing. Mehta et al. (2022) proposed a reconfigurable FFT processor architecture that dynamically adjusts pipeline stages based on input requirements. This approach improves hardware utilization and reduces power consumption in adaptive biomedical systems.

Roy et al. (2022) developed a deep learning-assisted FFT model for ECG classification. The study demonstrated that FFT-based feature extraction enhances the performance of neural networks in detecting cardiac abnormalities. Das et al. (2022) introduced an approximate computing-based FFT processor aimed at reducing power consumption. The architecture achieved significant energy savings by allowing controlled accuracy trade-offs, making it suitable for wearable biomedical devices.

Banerjee et al. (2023) proposed a hybrid Radix-4/2 FFT architecture that balances computational complexity and hardware efficiency. The design improved processing speed while reducing hardware requirements. Kulkarni et al. (2023) implemented a 1024-point pipelined FFT processor on FPGA for biomedical applications. The architecture achieved high throughput and reduced resource utilization, demonstrating its effectiveness in real-time healthcare systems.

Yadav et al. (2023) developed an FFT-based deep learning model for EEG classification. The system improved classification accuracy by combining spectral feature extraction with neural networks. Zhou et al. (2023) proposed a hardware-software co-designed FFT accelerator. The architecture improved flexibility and performance by integrating programmable logic with optimized FFT algorithms.

Meng et al. (2023) introduced a compact FFT chiplet design for real-time signal processing. The architecture improved computational efficiency and reduced hardware footprint. Leitersdorf et al. (2023) developed a Processing-in-Memory (PIM) FFT architecture that reduces memory bottlenecks. The system achieved higher throughput and improved energy efficiency.

Singh et al. (2023) proposed a deep learning-assisted FFT processor for biomedical signal denoising. The model improved signal clarity and reduced noise interference. Patel et al. (2023) designed an optimized Radix-4 FFT processor with reduced pipeline stages. The architecture achieved lower delay and improved hardware efficiency.

Reddy et al. (2023) proposed a low-power FFT processor for wearable biomedical systems. The architecture achieved significant energy savings and real-time processing capability. Wang et al. (2020) introduced a mixed-radix FFT processor that reduces computational complexity and improves processing speed. The architecture is suitable for high-performance biomedical systems.

Liu et al. (2020) developed a memory-efficient SDF FFT architecture that reduces buffer requirements and hardware complexity. Hsu et al. (2020) proposed a multi-path FFT architecture that improves throughput and reduces power consumption through parallel processing.

Ding et al. (2020) introduced the CirCNN model, which uses FFT to accelerate deep learning computations, significantly reducing computational complexity. Kumar et al. (2021) proposed a low-power Radix-4 FFT processor using optimized arithmetic units, achieving improved energy efficiency and performance.

Comparative Table

No.	Author (Year)	Method / Architecture	Application	Key Contribution	Advantages	Limitations
1	Zhang et al. (2021)	FFT + CNN	EEG	Feature extraction	High accuracy	High computation
2	Hsu et al. (2020)	Multi-path FFT	DSP	Parallel processing	High throughput	Complex design
3	Liu et al. (2020)	SDF FFT	Biomedical	Memory optimization	Low area	Limited scalability
4	Ding et al. (2020)	FFT-based DL	AI systems	Complexity reduction	Energy efficient	Accuracy trade-off
5	Kumar et al. (2021)	Radix-4 FFT	Embedded	Low power design	Energy efficient	Slight delay
6	Chen et al. (2021)	Low-power FFT	Wearable	Clock gating	Reduced energy	Complexity
7	Gupta et al. (2021)	Radix-4 FFT	DSP	Optimized butterfly	Reduced area	Delay

8	Park et al. (2021)	Parallel FFT	EEG	Multi-core system	High speed	Hardware cost
9	Hsu & Chen (2021)	Pipeline FFT	Real-time	Latency reduction	Efficient flow	Overhead
10	Zhang et al. (2021)	FFT-CNN	EEG	Frequency learning	High accuracy	Training cost
11	Verma et al. (2022)	SDF FFT	Biomedical	Area efficient	Low memory	Pipeline delay
12	Sharma et al. (2022)	FFT + DL	ECG	Classification	High accuracy	Complexity
13	Li et al. (2022)	Parallel FFT	Imaging	High speed	Low latency	Power use
14	Mehta et al. (2022)	Reconfigurable FFT	Adaptive	Dynamic pipeline	Efficient	Control complexity
15	Roy et al. (2022)	FFT + DL	ECG	Feature extraction	Robust detection	Model size
16	Das et al. (2022)	Approx FFT	Wearable	Low power	Energy saving	Accuracy loss
17	Banerjee et al. (2023)	Hybrid FFT	DSP	Radix mix	Balanced design	Complexity
18	Kulkarni et al. (2023)	FPGA FFT	Biomedical	1024-point FFT	High throughput	Resource usage
19	Yadav et al. (2023)	FFT + DL	EEG	Classification	High accuracy	Computation
20	Zhou et al. (2023)	HW-SW FFT	DSP	Co-design	Flexible	Complex
21	Meng et al. (2023)	FFT Chiplet	Signal	Compact design	Efficient	Integration
22	Leitersdorf et al. (2023)	PIM FFT	AI	Memory optimization	Fast processing	Cost
23	Singh et al. (2023)	DL + FFT	Biomedical	Noise reduction	Improved clarity	Training
24	Patel et al. (2023)	Radix-4 FFT	DSP	Reduced stages	Faster	Trade-offs
25	Reddy et al. (2023)	FPGA FFT	Wearable	Low power	Efficient	Limited scaling
26	Wang et al. (2020)	Mixed-radix FFT	Imaging	Speed improvement	Efficient	Complex
27	Liu et al. (2020)	SDF FFT	DSP	Memory reduction	Compact	Limited
28	Hsu et al. (2020)	Multi-path FFT	DSP	Parallelism	High throughput	Complex
29	Ding et al. (2020)	FFT DL	AI	Acceleration	Efficient	Approximation
30	Kumar et al. (2021)	Radix-4 FFT	Embedded	Low power	Efficient	Delay

Comparative Analysis

The comparative analysis of the 30 selected studies highlights a progressive evolution in FFT processor architectures for biomedical applications. Early works (2020–2021) primarily focused on optimizing hardware architectures such as Radix-4, mixed-radix, and SDF-based FFT processors. These approaches significantly improved computational efficiency and reduced hardware complexity, making them suitable for real-time biomedical signal processing. However, they often suffered from increased power consumption and scalability limitations. In 2021–2022, research shifted toward energy-efficient and area-optimized architectures. Techniques such as clock gating, approximate computing, and pipeline reconfiguration were introduced to reduce power consumption and improve hardware utilization. These designs were particularly beneficial for wearable and implantable biomedical devices. However, trade-offs between accuracy and power efficiency were

observed, especially in approximate computing methods.

From 2022 onwards, the integration of deep learning with FFT architectures became a dominant trend. Hybrid models combining FFT-based feature extraction with deep neural networks such as CNNs significantly improved classification accuracy for biomedical signals like EEG and ECG. Additionally, emerging architectures such as Processing-in-Memory (PIM) and chiplet-based FFT processors addressed memory bottlenecks and enhanced throughput. Overall, while traditional FFT architectures excel in speed and efficiency, modern deep learning-integrated approaches provide superior performance in biomedical applications, albeit with increased computational complexity.

Discussion

Recent advancements in FFT processor design have significantly improved biomedical signal processing capabilities. The integration of deep learning techniques with FFT architectures has enabled more accurate and efficient analysis of complex physiological signals. Traditional FFT designs primarily focused on improving computational efficiency and reducing hardware complexity; however, modern approaches emphasize intelligent data processing. Hybrid FFT-deep learning models, particularly those using convolutional neural networks (CNNs), have demonstrated superior performance in signal classification and noise reduction. These models leverage frequency-domain features extracted by FFT to improve learning accuracy. Additionally, innovations in hardware design, such as pipelined architectures, SDF models, and PIM-based systems, have enhanced processing speed and energy efficiency.

Despite these advancements, challenges remain in balancing power consumption, computational complexity, and accuracy. Deep learning models require significant computational resources, which may limit their applicability in low-power biomedical devices. Furthermore, achieving efficient hardware-software integration remains a critical issue. Future research should focus on developing lightweight deep learning models and optimizing FFT architectures to achieve efficient and scalable biomedical systems.

Conclusion

The development of area-efficient FFT processors has become increasingly important in biomedical signal processing applications. This survey highlights the significant advancements in 1024-point pipelined Radix-4 FFT processors and their integration with deep learning techniques. These technologies have enabled improved performance in applications such as EEG classification, ECG analysis, and medical imaging. Traditional FFT architectures, particularly Radix-4 and pipelined designs, have demonstrated superior computational efficiency compared to earlier methods. These architectures reduce arithmetic complexity and enable continuous data processing, making them suitable for real-time applications. Additionally, techniques such as SDF architecture, mixed-radix designs, and pipeline optimization have improved hardware utilization and reduced latency.

Recent advancements have introduced deep learning techniques into FFT-based systems, enabling enhanced feature extraction and classification accuracy. Hybrid models combining FFT and CNN have shown significant improvements in biomedical signal analysis. Furthermore, emerging technologies such as PIM and chiplet-based FFT architectures have addressed memory bottlenecks and improved energy efficiency. However, challenges remain in achieving a balance between performance, power consumption, and hardware complexity. Deep learning models introduce additional computational overhead, which may limit their use in resource-constrained environments.

Future research should focus on developing efficient and scalable architectures that integrate deep learning with FFT processing. Additionally, advancements in edge computing and hardware acceleration technologies are expected to further enhance biomedical signal processing systems. In conclusion, deep learning-based FFT processors represent a promising direction for developing advanced biomedical applications. Continued research in this field will lead to more efficient, accurate, and real-time healthcare systems.

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