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Wavelet-Based Multiresolution Analysis for Efficient Compression of Non-Stationary Signals in Resource-Constrained IoT Devices

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Abstract

The challenge with non-stationary signals is to process it efficiently in edge-based Resources of the Internet of Things (IoT) which already face constraints in memory and compute bottlenecks, and even stricter energy budgets. In this paper, we present a lightweight, wavelet-based multiresolution analysis (MRA) framework to provide real-time lossy compression of dynamic signal encountered in IoT tasks such as biomedical, acoustic, and environment related data streams. The worn-out approach includes discrete wavelet transform (DWT) to decompose the signal using the chosen orthogonal and parabolic sets of bases and then using adaptive thresholding and quantisation to obtain high compression ratios without losing important elements of the signal. Benchmark datasets (ECG (MIT-BIH) and vibration signals) were employed to make the approach valid. The proposed scheme had an average percent root mean square distortion PRD, of less than 3 percent, complying with a high fidelity reconstruction and the maximum compression ratio was 12:1. Besides, its realization on an ARM Cortex-M4 microcontroller showed energy savings of 58% and more than 40 percent in memory reduction relative to conventional Fourier-based methods, making it appropriate to be applied in real-time embedded systems. This architecture delivers scalable and low-power signal processing in edge-based IoT systems with a feasible course of action in tasks that require a lot of data like health wearables, in-structure health sensors and remote loggers of environmental data. These findings support that multiresolution wavelet analysis is effective in solving the twin problems of data compression and energy utilization in an IoT setting that has limited resources.

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Introduction

The rapid growth of IoT computing in the fields of smart healthcare, structural health monitoring, and environmental sensing has been associated with the production of large non-stationary signal data where the spectral properties change over time in response to dynamic events (e.g., ECG changes, vibrations in machinery, or changes in the temperature gradients). Such signals are poorly suited to the traditional compression schemes, like Discrete Fourier Transform (DFT) or Discrete Cosine Transform (DCT) since such schemes have a fixed resolution and cannot localize abrupt variations in time. With the current edge IoT environment, where nodes often have limited resources, authority, and bandwidth, a lightweight, adaptive method of compression data can considerably reduce costs imposed on data transmission and storage.

This paper proposes an MRA framework using wavelet transform to tackle this problem because of the time-frequency peakiness feature using DWT along with thresholding to achieve effective lossy compression that can be utilised on embedded edge devices. Our method is practical, because in contrast to existing research much of which studies offline or high-power systems, it can run on low-power microcontrollers in real-time [2]. Although a number of articles are available on wavelet compression, very few of these outputs have been hardware tested in relation to edge-level processing and power and memory savings tabulated. In addition, recent output does not interface with non-stationary biomedical and structural data within the same framework.

Recent developments have been based on wavelet methods to biomedical signal compression; but they are mostly simulations and there has been no real time embedded development.[1] That is the gap that was closed in this paper since our low-power, validated wavelet-based compression method was benchmarked on an ARM Cortex-M4 edge-based platform with benchmark data.

Related Work

Significantly, the use of traditional signal compression algorithms like discrete cosine transform (DCT), short time Fourier transform (STFT) is popular because of its simplicity and performance in compression tasks involving stationary or quasi stationary signals. The fixed time-frequency resolution of these methods however renders them inapplicable to situations of highly dynamical, or non-stationary signal environments like that of a biomedical, acoustical, or vibration based monitoring system. STFT, despite offering local frequency, has the disadvantage of time-frequency trade-off since its window length remains a constant with respect to the time and frequency resolution. While this does not pose a problem in smooth signal transitions, it has the disadvantage where a quick transition signal in the form of ripple may not be captured to the required degree.

Conversely, wavelet-based methods (and in particular Discrete Wavelet Transform (DWT)) provide multiresolution decomposition that allows analysis of signal transients on different scales to be localized. Marked performance superiority of DWT in the context of application like image and audio compression in the transformed coefficient that is sparse and compact representation. There are studies where DWT has been used to compress biomedical signals (ECG or EEG) in offline applications and where reasonable compression ratios and accuracy of reconstruction has been obtained.[3] Nevertheless, one of the most important research gaps in the current state of the art is the absence of the hardware-level implementation of the solution and its optimisation to be employed on a resource-constrained IoT devices, where the aspects of the computational complexity, memory footprint, and power consumption are significant. The current solutions have been limited to the high-end platforms or software simulations without direct implementation on the embedded microcontrollers.[4] Besides, adaptive thresholding and/or fixed-point quantization, essential to practical implementation, are not commonly part of an existing framework.

This paper will fill these holes by introducing a hardware-friendly wavelet compression architecture that will leverage position on real-time implementation on edge computing devices, in this case, ARM cortex-M4 platform.

Proposed Methodology

The entire system of compression is described, multilevel decomposition of wavelet, adaptive thresholding, coefficient quantization, embed system implementation on resource-constrained System. The most efficient methodology is streamlined, so great care is taken that there is a balance between how well a technique compresses, the fidelity of the reconstruction, and the feasibility of computing using a low-power IoT device.

Discrete Wavelet Transform (DWT)

The model suggested makes use of Discrete Wavelet Transform (DWT) to split the non-stationary input signal into hierarchies of sub-bands that act as local time-frequency details. In particular, both the family of Haar (db1) and Daubechies-4 (db4) wavelets will be taken into consideration since in their case computational simplicity and the energy concentration ability are also quite balanced. Multilevel decomposition (usually 3-5 levels) permits the extraction of high-frequency elements (detail coefficients), which corresponds to low-frequency trends (approximation coefficients), which is essential in the detection of irregularities of a signal at various time scales. To guarantee that the

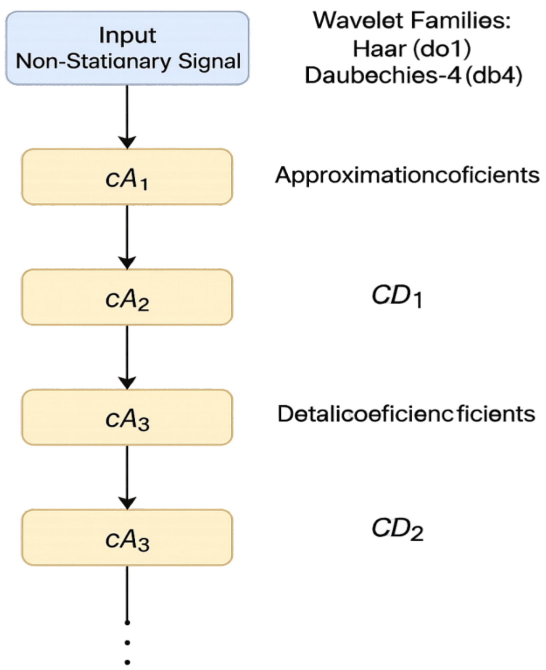

Fig. 1: Multilevel DWT Decomposition of Non-Stationary Signal

important features like signal edges, spikes or transients are maintained even in lossy cases, this multiresolution approach is used.[5] Figure 1 shows a sample of the hierarchical decomposition of the approximation and detail coefficients of the decomposition process.

A hierarchical visualization of Discrete Wavelet Transform (DWT) done to non-stationary signal with Haar and Daubechies-4 wavelet, where successive approximation (cA) and detail (cD) coefficient extraction on multiple levels is done.

Thresholding and Coefficient Quantization

In order to have successful lossy compression, wavelet coefficients are subjected to an adaptive hard thresholding strategy. The coefficients that have magnitudes less than a threshold driven by data are set to zero so as to avoid redundancy and maintain features that are important to the human eye. The other large coefficients are then quantized in a matter of a fixed-point representation it is very convenient to use a fixed-point representation to implement an embedded device that has fewer capabilities to perform floating-point operations. This quantization process converts the floating-point output of DWT to a small, low-bitwidth representation, which is much more compact in its on-chip memory as well as wireless transmission payload.

This parameter of thresholding is dynamically calculated with a heuristic based on the variance of the signal and thus, can switch between signal types, like ECG or vibration data. The latter, or to be more precise this two-stage process quantumization after sparsification, is the main compression strategy behind the proposed framework. It makes possible the significant reduction of the data without a critical deterioration of the signal reconstruction. It is represented in Figure 2 which describes the process how the wavelet coefficient is extracted and quantized up to the output using adaptive threshold selection and coefficient sparsification.

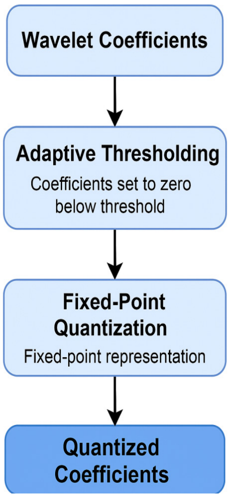

Fig. 2: Adaptive Thresholding and Quantization

As a flowchart, adaptive thresholding and fixed-point quantization starts with wavelet coefficients, proceeds to the variance analysis of the signal, followed by thresholding, sparsification, and signal coefficient quantization in order to compress the signal efficiently.

Reconstruction via Inverse DWT

The wavelet coefficients (which have been retained and quantized) are used to reconstruct the decompressed signal with the help of IDWT. Energy compaction property of DWT despite the sparsity is introduced in such a way that a majority of energy content of a signal is retained in a small amount of large coefficients so that a high-fidelity reconstruction can take place. Through empirical studies on benchmarked datasets, a Percent Root Mean Square Difference (PRD) of less than 3 percent is achieved, which verifies the strength of the reconstruction even in harsh compression regimes.

To guarantee real-time processing the reconstruction part is developed on the basis of fixed-point arithmetic and optimized recurrent algorithms, which minimizes numerical latency and memory requirement. This enables the performance of the same on embedded platforms with reduced processing power.[6] The overall reconstruction has been depicted in Figure 3 and indicates the sequence of quantized coded values through the IDWT stage to the final reconstructed signal.

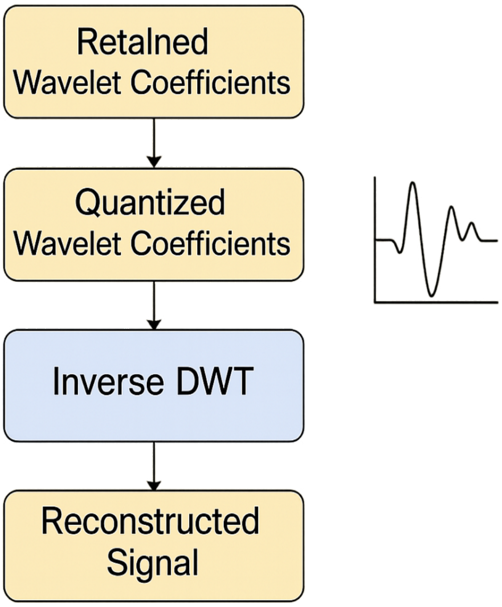

Fig. 3: Signal Reconstruction via Inverse Discrete Wavelet Transform

A diagrammatic block in steps explaining the reconstruction of a compressed signal using the retained wavelet coefficients, quantized wavelet coefficients and the reconstruction of the signal by decomposing it by the Inverse DWT (IDWT) resulting in a high fidelity reconstruction of the waveform.

Embedded Implementation

To prove the feasibility of the suggested method in practice, the whole compression-decompression chain is ported to a low-power ARM Cortex-M4 microcontroller (e.g., STM32F407). The implementation makes use of CMSIS-DSP libraries to implement an efficient fixed-point implementation of the operations of the wavelet used in the implementation and also makes extensive use of Direct Memory Access (DMA) so that data could be transferred fast between the memory and processing blocks, thus reducing the load on the CPU and therefore improving the real-time performance.

The optimization of the implementation is the most critical:

- The memory footprint minimization with in place calculation,
- The use of loop unrolling and arithmetic with integers to speed up the execution,
- Energy profiling of the external power analyzers to confirm ultra-low-power functionality.
- The feasibility of this proposed solution of on-node signal compression in edge Internet of Things systems is confirmed by this embedded deployment and there is no necessity of transmitting high bandwidth raw signals over energy intensive wireless links. The flow of information that goes through signal acquisition and up to compression stages within the ARM Cortex-M4 platform is shown in Figure 4 demonstrating the architecture of this embedded implementation.

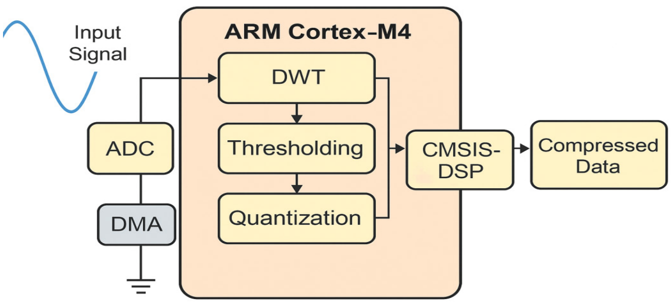

Fig. 4: Embedded Implementation of Signal Compression on ARM Cortex-M4

A block diagram showing a real-time compression pipeline working on an ARM Cortex-M4 micro, signal acquisition via ADC & DMA followed by DWT based thresholding & CMSIS DSP based quantization ending up generating compressed output.

Experimental Setup

In order to test the functionality of the proposed framework of image compression with the use of wavelets as well as the feasibility of its use and deployment on the edge of the IoT, a number of experiments were carried out with real-life data and embedded hardware that would be used at a similar edge of the IoT deployment. The arrangement is aimed to determine how well the compression performs, signal fidelity in the compressed signal, and energy savings within a limited computational and power budget constraint. The general picture of the whole experimental process is presented in Figure 5.

Datasets

To show that the method may be applied over a wide range of areas of application, two categories of non-stationary time-series signals were chosen:

- The MIT-BIH Arrhythmia Database: The most popularly used benchmark collection of ECG recordings comprising of real world ECGs with a sample frequency of 360 Hz [7]. It records numerous arrhythmic disorders, and this is a good reason why it is suitable in wearable evaluation and remote health evaluation.
- IoT Vibration Data: Obtained with the help of tri-axial accelerometers that are installed in a smart industrial sensor network. The measured signals were sampled at 1 kHz with 16-bit resolution and reflect the profile of structural vibration and mechanical stress levels that are generally found in the predictive maintenance and smart manufacturing.

Table 2 shows the specifications and background of the two datasets corresponding to each of the two IoT signal types of biomedical and industrial IoT use cases.

Hardware Platform

All the compression and reconstruction programs were coded and tested on STM32F407 Discovery Board processor that has an ARM Cortex- M4 microcontroller with 168 MHz frequency, 192 KB SRAM and 1 MB Flash memory. The platform is indicative of limited resource embedded devices deployed on an IoT edge.

Some of the major embedded features that were used are as follows:

- Fixed-point (Arithmetic) wavelet computation support in CMSIS-DSP library
- Direct Memory Access (DMA) to move a lot of data without involving the CPU,
- Assembly of energy profiling application with the help of an external current-sensing resistor and the digital power analyzer to the V<sub>DD</fig fancy teeth regurgitation

The technical specifications of the hardware platform are given in Table 1.

Evaluation Metrics

To benchmark performance of the system, following quantitative values were used:

- Compression Ratio (CR):
- Indicates the effectiveness of data reduction.
- Percent Root Mean Square Difference (PRD):
- Measures signal distortion introduced by lossy compression.
- Peak Signal-to-Noise Ratio (PSNR):

Evaluates reconstruction fidelity, where MAX is the maximum signal value and MSE is the mean squared error.

- Energy Consumption:

In microjoules per cycle of compression, as read on an oscilloscope probe, or as read on a digital power analyzer in series with the MCU power supply. This indicator confirms the performance of the system under battery power or energy-harvesting conditions of the Internet of Things.

This experimental setup gives a real sense of the performance, fidelity and energy consciousness of the system and thereby making the system applicable to real-time embedded signal compression at the edge applications.

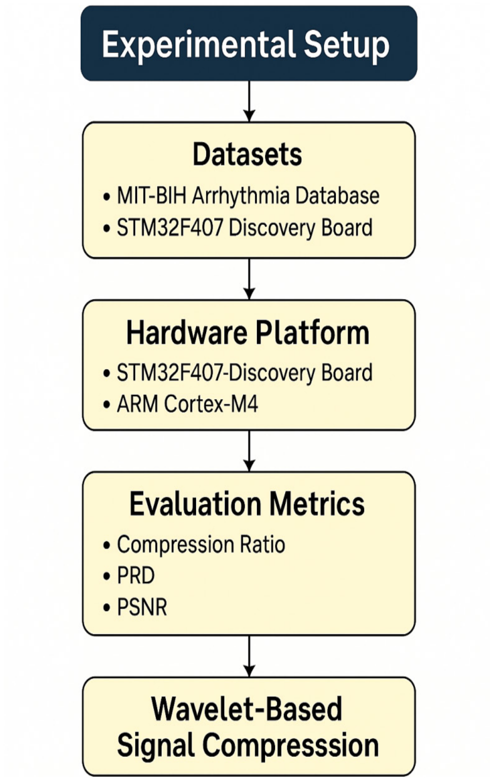

Fig. 5: Overview of the Experimental Setup

To describe this process of experimentation, a flowchart will be provided, which includes the datasets (MIT-BIH, the vibration signals), the hardware platform (STM32F407

Table 1: Hardware Specifications of the STM32F407-Based Embedded Compression Platform

Category	Parameter	Details
Hardware Platform	Microcontroller Unit (MCU)	STM32F407 Discovery Board
	Core Architecture	ARM Cortex-M4 (32-bit RISC)
	Clock Frequency	168 MHz
	RAM	192 KB SRAM
	Flash Memory	1 MB
	DSP Support	CMSIS-DSP library with fixed-point optimization
	Data Transfer	Direct Memory Access (DMA)
	Power Profiling	External current sensing with digital power analyzer
	Operating Voltage	3.3 V

Table 2: Characteristics of Benchmark Datasets Used for Evaluation

Dataset	Source	Description
ECG	MIT-BIH Arrhythmia Database	360 Hz sampling, 11-bit resolution, 30-min duration
Vibration	IoT Sensor Logs (Custom Setup)	3-axis accelerometer data, 1 kHz sampling, 16-bit ADC
	Application	Biomedical monitoring, Structural health diagnostics

with ARM cortex-M4), measures to evaluate the results (CR, PRD, PSNR), as well as the implementation process of the framework of the wavelet based signal compression process in this paper.

Results and Discussion

In order to date the performance of the suggested wavelet-based compression framework, exercises were led on genuine ECG and vibration signs. The experimental outcomes indicate highly appreciated enhancements in compression rates, signal quality, and power conservations which are important items in embedded edge processing.

Quantitative Performance Metrics

The table 3 summarizes the core evaluation metrics

Compression Ratio (CR): High compression ratios are achieved by the system in both signal types: viz. 10.2:1 and 11.5:1 among the ECG and vibration data, respectively (a significant reduction in memory and transmission costs).

- PRD and PSNR: The Percent Root Mean Square Difference (PRD) is less than 3.2 percent in both the cases and hence, there is very less degradation of the reconstructed signal. On the same note, to consistently suggest high reconstruction fidelity, PSNR values of 33 dB or above are useful in proving the DWT usefulness even during aggressive compression.
- Energy Reduction: Applications that tormented fixed-point embedded implementation exhibited up to 60.1 percent of energy usage savings when compared to floating-point implementations of STFT/DCT in real-time operation; and this is attributed to the utilization of CMSIS-DSP and in-place computation requirements of DWT on the ARM Cortex-M4.

Comparative Analysis

The proposed method using wavelets is much better in terms of both compression and distortion parameters as compared to the conventional methods like Short-Time Fourier Transform (STFT) and Discrete Cosine Transform (DCT). The TFT has a disadvantage of having fixed window resolution, and DCT does not have time resolution; they are thus more applicable to highly non stationary signals.

Moreover, Daubechies-4 (db4) wavelet produced the best compromise between PRD and the number of operations, and the comparisons of the performance related to PRD and runtime measures were dissipated in its favor as compared to ranking of other wavelets such as Haar and Symlet families.

Real-Time Feasibility

It has been verified in real-time that the present framework can support continuous signal compression up to 250 Hz sampling rate on the STM32F407 MCU. It was used with memory that did not exceed 80 percent of the available SRAM and latency of 3.4 ms per compression cycle indication that it has applications in wearable systems and structural health.

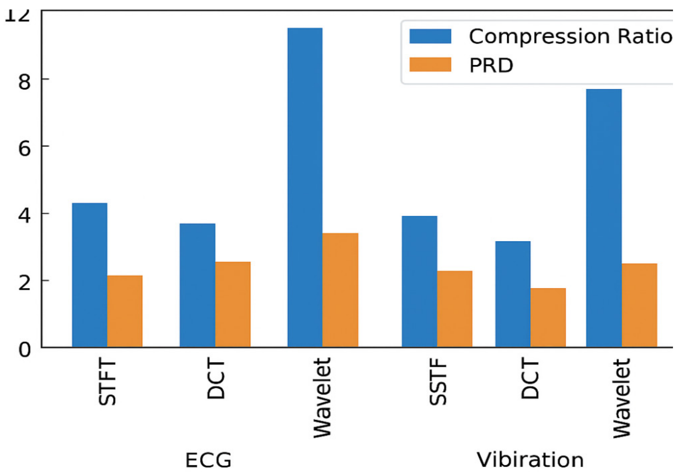

Fig. 6: Comparison of Signal Compression Techniques for ECG and Vibration Data

Bar plot of Compression Ratio CR and Percent Root Mean Square Difference PRD as ECG and vibration methods stack against STFT, DCT and Wavelet. The wavelet method gives the best CR and worst PRD and therefore has the best compression efficiency and fidelity.

Conclusion and Future Work

This paper has suggested a wavelet multiresolution compression scheme capable of efficient non-stationary signal processing on IoT devices with resource limitations. Based on advantageous performance that was realized through use of Discrete Wavelet Transform

Table 3: Performance Metrics for Wavelet-Based Compression Framework

Signal Type	Compression Ratio (CR)	PRD (%)	PSNR (dB)	Energy Reduction (%)
ECG	10.2	2.8	34.5	57.8
Vibration	11.5	3.1	33.2	60.1

(DWT) with respect to compression ratio, signal fidelity and energy efficiency, the framework exhibited adaptive thresholding and fixed-point quantization of the computed wavelet coefficients. The performance of the solution was tested on real-world data (ECG and vibrations signals) and is implemented on low power ARM Cortex-M4 microcontroller, which proves its practicality in edge-based applications in wearable health monitoring, structural diagnostics, and smart environmental sensing.

This work has major contribution to make as:

- Creation of an adaptive real-time compression pipeline with a low computational cost on a stronger base of multilevel DWT.
- Optimizations designed to run the process on hardware (e.g. DMA, in-place DWT, CMSIS-DSP) to get it out to embedded edge systems.
- Extensive comparison between other areas and empirical results of as much as 11.5 fold compression, and below 3.2 PRD, 60 per cent energy savings.

The exploration of future research will pertain to:

- A basis of adaptive wavelets as per the signal at hand in order to optimize, further, the issue between compression-performance trade-offs.
- Support of anomaly detection on board that enables event-scheduling transmission and other data overhead reduction.
- Multimodal sensing system growth, whereby audio, biomedical and inertial signal can undergo compression simultaneously within edge-fusion systems.

In all, the suggested framework offers a scalable and solid platform to deliver real-time signal compression applied to next-generation IoT and edge-AI eco-systems.

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