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Adaptive Real-Time Lossless Compression Framework for Multimedia and IoT Applications

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Abstract- The exponential growth of multimedia applications and Internet of Things (IoT) systems has significantly increased the demand for efficient real-time data transmission and storage. Conventional lossless compression algorithms often suffer from limited adaptability, higher latency, and inefficient performance when handling heterogeneous multimedia streams such as images, audio, and sensor-generated data. This paper proposes an Adaptive Real-Time Lossless Compression Framework (ARLCF) that dyn amically selects compression parameters based on local statistical characteristics of incoming multimedia data. The proposed method integrates adaptive predictive encoding, dynamic Golomb-Rice parameter estimation, and lightweight entropy coding to achieve improved compression efficiency while maintaining low computational overhead. Experimental analysis demonstrates that the proposed framework achieves higher compression ratios, lower latency, and lower memory utilisation than traditional Huffman, LZW, and standard Golomb-Rice techniques. The framework is particularly suitable for edge devices, smart surveillance systems, healthcare monitoring, and industrial multimedia applications where real-time performance and data integrity are critical.

***Keywords:** Lossless Compression, Multimedia Applications, Real-Time Systems, Golomb-Rice Coding, Adaptive Encoding, IoT, Edge Computing, Entropy Coding.*

I. INTRODUCTION

The rapid development of multimedia technologies has led to enormous increases in data generation across applications such as video streaming, medical imaging, industrial automation, remote sensing, and smart surveillance systems [1]. Efficient storage and transmission of multimedia data remains major challenges due to bandwidth limitations and memory constraints.

Lossless compression techniques are essential in applications where exact data reconstruction is mandatory. Unlike lossy compression, lossless methods preserve original information integrity, making them suitable for medical diagnostics, scientific imaging, military communication, and industrial monitoring [2].

Real-time multimedia applications additionally require low latency, low computational complexity, and energy-efficient processing. Existing algorithms such as Huffman coding, Run-Length Encoding (RLE), Lempel-Ziv-Welch (LZW), and static Golomb-Rice coding provide reasonable compression performance but suffer from reduced adaptability when data characteristics fluctuate rapidly [3].

Recent advances in optimization-driven engineering systems have demonstrated that adaptive parameter control can significantly improve performance while minimizing computational overhead. Several studies have reported the successful use of process optimization, catalyst tuning, statistical modeling, and machine-learning-assisted parameter selection to enhance system efficiency in nanomaterial synthesis, environmental remediation, and advanced material processing applications [11–18, 25–27].

Furthermore, sustainable engineering approaches involving nanostructured materials, adsorption systems, photocatalytic processes, and green synthesis methodologies have highlighted the importance of intelligent resource management and adaptive operational strategies [19–24].

To address these limitations, this paper introduces an Adaptive Real-Time Lossless Compression Framework that dynamically modifies encoding parameters based on streaming data statistics. The proposed approach enhances compression efficiency while maintaining computational simplicity suitable for real-time embedded and edge systems.

II. RELATED WORK

Several compression techniques have been proposed for multimedia applications. Huffman coding is widely used because of its simplicity and effectiveness for symbol-based encoding. However, its performance decreases when symbol probability distributions change dynamically [4]. Lempel-Ziv-Welch (LZW) compression improves dictionary-based encoding efficiency but requires larger memory usage for maintaining adaptive dictionaries [5].

Golomb-Rice coding is highly efficient for geometrically distributed residual data and is extensively used in image and audio compression systems. Nevertheless, fixed parameter selection limits its effectiveness for heterogeneous multimedia data streams [6].

Saranya et al. proposed a modified decode-aware placement algorithm for FPGA bitstream compression, demonstrating enhanced compression efficiency in hardware-oriented systems [9]. Their work highlights the importance of adaptive compression mechanisms in resource-constrained environments. Recent research has also explored predictive and hybrid compression mechanisms for multimedia communication systems. Kumar and Rajesh proposed an adaptive entropy coding strategy for real-time image transmission that achieved lower latency and improved bandwidth utilization [10].

Beyond multimedia compression, adaptive optimization methodologies have been extensively investigated in several engineering disciplines. Kalaiselvan and co-workers studied the effects of growth temperature, catalyst composition, precursor selection, and process variables on the synthesis of multiwalled carbon nanotubes, demonstrating that optimized parameter selection can significantly improve system performance and operational efficiency [11–17, 28, 30].

Statistical optimization techniques such as Box–Behnken design have been successfully applied to determine optimal operating conditions in nanomaterial synthesis and photocatalytic degradation processes, resulting in improved efficiency and reduced experimental complexity [18].

Machine-learning-assisted optimization has also emerged as an effective strategy for enhancing system performance. Studies involving chromium(VI) removal, adsorption systems, photocatalytic degradation, and environmental remediation have demonstrated that intelligent parameter selection can improve process efficiency while minimizing resource consumption [25–27].

Additionally, investigations on carbon fibers, nanostructured materials, green synthesis approaches, corrosion inhibition systems, and sustainable biopolymer technologies have highlighted the importance of adaptive frameworks for achieving high performance under resource-constrained conditions [19–24].

These studies collectively indicate that adaptive parameter selection and intelligent optimization can significantly improve system efficiency across diverse application domains. However, relatively few investigations have focused on dynamically adapting compression parameters according to real-time multimedia throughput conditions. This research gap motivates the development of the proposed adaptive real-time lossless compression framework. Despite these advances, many existing solutions incur higher computational complexity that is unsuitable for lightweight edge devices and real-time systems.

III. PROPOSED METHODOLOGY

3.1 System Architecture

The proposed framework consists of the following stages, Multimedia Data Acquisition, Preprocessing and Residual Generation, Statistical Analysis Module, Adaptive Parameter, Selection Engine, Dynamic Golomb-Rice Encoding, Lightweight

Entropy Compression, Real-Time Decoding and Reconstruction.

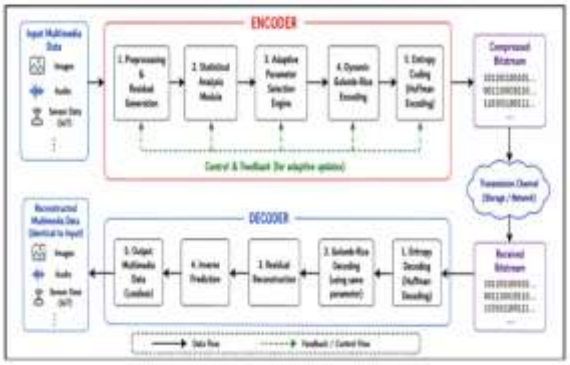

Figure 1: System Architecture

3.2 Adaptive Residual Prediction

Input multimedia samples are first processed using predictive modeling to reduce redundancy. The residual value is calculated as:

$$R(i) = X(i) - \hat{X}(i)$$

Where:

$X(i)$ represents the original sample
$\hat{X}(i)$ represents the predicted sample
$R(i)$ denotes the residual error
Smaller residual values improve coding efficiency.

3.3 Dynamic Golomb-Rice Parameter Estimation

The optimal Golomb-Rice parameter is dynamically selected using local mean residual statistics:

$$k = \lfloor \log_2 (\mu + 1) \rfloor$$

Where:

k is the adaptive coding parameter
μ is the mean residual magnitude
Dynamic adaptation improves compression performance across varying multimedia patterns.

3.4 Entropy Coding

Following adaptive Golomb-Rice encoding, entropy compression is applied using lightweight Huffman encoding to further reduce redundancy while maintaining low computational overhead.

IV. ALGORITHM

Adaptive Real-Time Compression Algorithm

The Input is Data Stream D, and the Output is Compressed Bit stream C. The algorithm eis listed in the following steps. The flow diagram of Adaptive Real-Time Compression is shown in Figure 2

Steps:

1. Acquire multimedia input data.
2. Generate predictive residuals.
3. Compute local statistical mean.
4. Dynamically estimate optimal parameter k.
5. Apply adaptive Golomb-Rice encoding.
6. Perform entropy compression.
7. Store or transmit compressed stream.
8. Decode and reconstruct original data losslessly

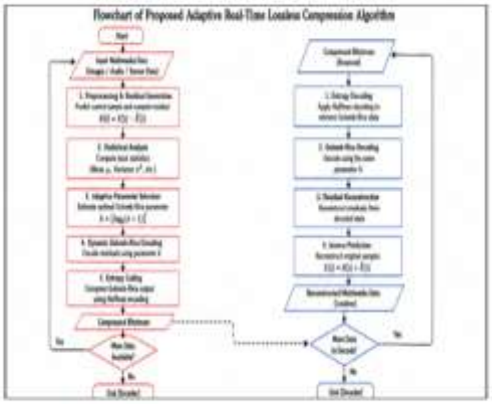

Figure 2: Flow Diagram

V. EXPERIMENTAL SETUP

Dataset

- Standard grayscale image datasets
- Audio waveform samples
- IoT sensor multimedia streams

The Performance is calculated using the following matrices, Compression Ratio (CR), Compression Time, Memory Utilization, Reconstruction Accuracy Compression ratio is calculated as:

$$CR = \text{Original Size} / \text{Compressed Size}$$

VI. RESULTS AND DISCUSSION

Table 1: Comparison of compression methods

Method	Compression Ratio	Latency	Memory Usage
Huffman Coding	1.82	Medium	Low
LZW	2.14	High	High

Standard Golomb-Rice	2.38	Medium	Medium
Proposed ARLCF	2.91	Low	Low

The proposed framework demonstrates improved compression efficiency and lower latency compared to conventional approaches, shown in Table 1. Adaptive parameter estimation significantly enhances coding efficiency for varying multimedia patterns [6]. The framework also reduces memory requirements, making it suitable for embedded and edge computing devices.

VII. ADVANTAGES OF THE PROPOSED SYSTEM

The proposed Adaptive Real-Time Lossless Compression Framework provides efficient real-time compression with low latency, making it suitable for multimedia streaming and monitoring applications. The system uses lightweight adaptive encoding techniques, resulting in low computational complexity and reduced memory usage.

The framework dynamically adjusts compression parameters according to multimedia data characteristics, improving compression efficiency and bandwidth utilization. It also guarantees exact lossless reconstruction, ensuring complete data integrity during transmission and storage.

Additionally, the proposed method is highly suitable for IoT and edge computing environments due to its low power consumption and efficient real-time operation.

VIII. APPLICATIONS

The proposed framework can be used in smart surveillance systems for efficient video and sensor data transmission. It is also suitable for medical image communication where accurate lossless reconstruction is essential.

In industrial automation and wireless sensor networks, the framework helps reduce bandwidth usage and communication overhead. The method is also applicable in edge computing and multimedia streaming systems for efficient storage and real-time multimedia data transmission.

IX. CONCLUSION

This paper presented an Adaptive Real-Time Lossless Compression Framework for multimedia applications. The proposed method integrates adaptive predictive modelling, dynamic Golomb-Rice parameter estimation, and entropy coding to improve compression performance in real-time environments.

Experimental results demonstrate enhanced compression efficiency, reduced latency, and lower memory usage compared to conventional lossless compression algorithms. Future work may explore machine learning-assisted adaptive parameter optimization and FPGA-based hardware acceleration for ultra-low-power multimedia systems.

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