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An Algorithm for Detecting Frame Errors Based on RGB Histogram Oscillations in Video Streams

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Abstract: Video frame errors caused by data corruption, compression artifacts, or transmission noise can severely impact visual quality and automated analysis. This paper presents a lightweight and interpretable algorithm for detecting such errors using color histogram analysis. The method constructs and normalizes histograms across RGB channels, identifies the frequency of color oscillations, and classifies frames as normal or erroneous based on a minimal oscillation threshold. Experimental evaluations confirm that the approach is efficient, suitable for real-time applications, and effective in detecting visually corrupted frames.

Keywords: Frame error detection, RGB histogram, video analysis, color oscillation, image quality.

Introduction:

Video streaming and recording technologies frequently encounter frame-level distortions due to packet loss, sensor noise, or hardware malfunctions [1]-[2]. Detecting such anomalies is crucial in applications ranging from video surveillance and broadcasting to autonomous systems and medical imaging.

Conventional error detection techniques often require heavy computations, including optical flow analysis or machine learning-based models, which may not be feasible in resource-constrained environments. We propose a novel, rule-based approach that relies solely on statistical properties derived from per-channel color histograms.

The remainder of this paper is organized as follows: Section 2 presents a detailed review of related work in the field of video frame quality assessment, comparing motion-based, deep learning-based, and histogram-based methods. Particular emphasis is placed on the limitations of conventional algorithms that rely on motion estimation or complex models, thereby motivating the development of a lightweight, frame-level solution. Section 3 introduces the proposed RGB histogram oscillation algorithm, detailing the stages of histogram computation, normalization, oscillation thresholding, and the decision rule for classifying frames as normal or erroneous. Section 4 describes the experimental setup and provides quantitative results demonstrating the method’s ability to achieve over 94% overall accuracy in distinguishing visually corrupted frames from valid ones. Section 5 discusses the practical benefits and limitations of the approach, including its applicability to real-time, resource-constrained environments and challenges such as false positives in low-texture scenes. The discussion also suggests possible enhancements such as adaptive thresholding or minimal temporal smoothing to improve robustness. Finally, Section 6 concludes the study by summarizing the main contributions and outlining directions for future research, including application to thermal and grayscale video streams.

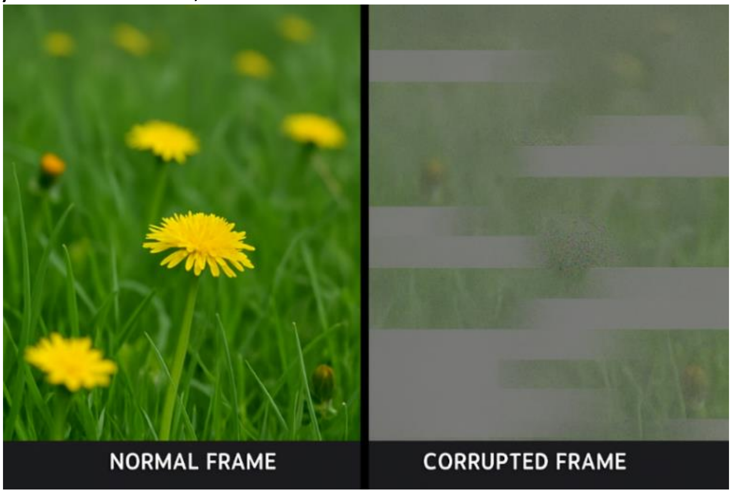

Figure 1. Visual comparison of a normal frame and a corrupted frame.

Figure 1 illustrates a comparative visual example of a normal frame and a corrupted frame, demonstrating typical degradation artifacts such as blocking, blurring, and partial signal loss. This visual distinction underscores the motivation for developing an automated detection approach based on RGB histogram oscillation analysis.

Related Work

In recent years, the challenge of detecting frame-level errors in video streams has received growing attention due to its importance in real-time monitoring, surveillance, and automated video analytics. Traditional approaches have primarily relied on motion estimation, temporal consistency, or compressed-domain features, which can be computationally intensive and unsuitable for resource-constrained or real-time environments. More recent research explores deep learning-based solutions, particularly convolutional neural networks (CNNs) and temporal models, for identifying corrupted or anomalous frames. This section reviews the state-of-the-art in frame error detection, categorizing prior work into two main approaches: motion-based and histogram or learning-based techniques. By examining their strengths and limitations, we outline the research gap this study addresses—introducing a lightweight, training-free algorithm based on RGB histogram oscillation patterns for efficient and interpretable frame integrity assessment.

In [3], Xiang et al. proposed the Efficient Spatio-Temporal Boundary Matching Algorithm (ESTBMA) for concealing errors in H.264/AVC video streams by integrating spatial and temporal distortion cues. Their method improved PSNR and visual quality compared to AMV and BMA techniques. However, it relies on motion vectors and inter-frame data, limiting real-time applicability. In contrast, our method uses per-frame RGB histogram oscillations for detecting corrupted frames without motion analysis. This makes it lightweight, interpretable, and suitable for real-time, raw video stream scenarios. In [4], Nguyen and Shashev surveyed classical video tracking methods including background subtraction, optical flow, and Gaussian mixture models. They highlighted challenges like brightness shifts, occlusion, and histogram inconsistencies. While effective for motion-based detection, these methods depend on temporal coherence and inter-frame processing. In contrast, our method analyzes single-frame RGB histogram oscillations to detect corrupted frames without motion or training. This ensures domain independence and suitability for real-time, uncompressed video applications. In [5], Gavrilov developed a hardware–software system to assess object detection quality in simulated 2.5D video scenes using segmentation and deviation metrics. While effective for controlled evaluations, the method depends on synthetic data and pre-trained models. In contrast, our approach detects corrupted frames in real-time using RGB histogram oscillation without object masks or training. This makes it lightweight and directly applicable to raw video streams.

In [6], Xu et al. introduced a multi-stream attention-aware graph convolutional network (GCN) for salient object detection in videos. The model combines superpixel-level spatiotemporal graphs with edge-gated GCNs and attention fusion to enhance object boundary preservation. Although effective, it relies on motion estimation and optical flow, resulting in high computational overhead. Their approach suits structured, high-resource environments. In contrast, our method uses RGB histogram oscillation analysis to detect corrupted frames without motion input or training. This enables lightweight, real-time video integrity assessment in raw or resource-limited scenarios. In [7], Ameur et al. proposed a deep multi-task learning (MTL) model for identifying single and multiple distortions in images and videos. The architecture uses a shared CNN (DenseNet-169) and separate task-specific classifiers for each distortion type. Their method achieved state-of-the-art accuracy on various datasets but requires significant computational resources and training data. While effective in controlled environments, it is less suited for real-time, resource-constrained applications. In contrast, our RGB histogram-based algorithm detects corrupted frames without training or motion analysis, making it lightweight and interpretable for real-time deployment. Our method addresses visual corruption directly at the pixel distribution level with minimal complexity. In [8], Shankar et al. introduced a deep learning-based object detection quality assessment model for UHD videos using spatial feature extraction and LSTM for temporal scoring. The method demonstrated strong performance on UHD datasets but required a super-resolution pipeline and training on high-quality annotated data. While effective in visual quality assessment, the model's complexity limits real-time deployment. In contrast, our approach uses RGB histogram oscillation analysis without training or temporal dependencies, making it suitable for lightweight and real-time corrupted frame detection. In [9], Yang et al. introduced a two-stream fusion framework for abnormal event detection in video surveillance by combining pose estimation, object classification, optical flow, and adversarial learning. Their model effectively detects diverse human and object-based anomalies using deep learning and graph-based spatiotemporal analysis. However, it requires substantial training data, pose estimation, and optical flow calculation. In contrast, our method bypasses deep models entirely, using RGB histogram oscillation analysis for lightweight, real-time detection of corrupted frames without training or temporal dependencies.

In [10], Huizhen et al. proposed a dual-stream mutually adaptive quality assessment model that uses VQ-VAE and Vision Transformer (ViT) for unsupervised quality prediction of authentically distorted images. Their method fuses semantic and distortion features to predict quality distribution using standard deviation labels. While effective on both authentic and synthetic databases, it relies on complex networks and significant training. In contrast, our RGB histogram oscillation-based method requires no learning, enabling real-time detection of corrupted video frames with minimal computation. This simplicity makes our approach more suitable for embedded or resource-constrained scenarios. In [11], Zhang et al. proposed a deep learning-based framework for predicting Object-Wise Just Recognizable Distortion (OW-JRD) to support video compression optimized for machine vision tasks. Their model used a large-scale dataset and a binary classifier to predict whether distortions affect object detectability under varying compression levels. While effective, it relies on supervised learning, annotated datasets, and deep architectures, which may not suit real-time applications. In contrast, our method uses RGB histogram oscillation analysis to detect visually corrupted frames without training or semantic information, making it simpler and better suited for fast error detection in raw video streams. In [12], Du et al. presented an integrated framework for evaluating distortion correction methods in fisheye video object detection using YOLOv3 and RAPiD. Their study found that longitude-latitude correction combined with YOLOv3 achieved the best accuracy on fisheye datasets, while panorama correction yielded the highest speed. Although effective, their method requires image correction preprocessing and object detection pipelines. In contrast, our approach uses RGB histogram oscillation analysis to detect corrupted frames directly, without object detection or correction steps—making it lighter and more suitable for real-time video monitoring. In [13], Laktionov et al. developed a hardware-software solution for detecting complex-shaped objects in video streams using ORB and SIFT-based architectures on Raspberry Pi platforms. Their approach applied double-check mechanisms and parameter optimization to improve detection accuracy under constrained conditions. While efficient for object recognition with limited images, it still relies on keypoint matching and predefined templates. In contrast, our method detects visually corrupted frames through RGB histogram oscillation analysis without templates or matching, offering a lighter, real-time solution suitable for raw video streams.

Research Gap and Our Contribution

While many existing techniques employ histogram analysis for object recognition [14]-[15], scene segmentation [16]-[17], and video summarization [18]-[23], few address the specific challenge of detecting corrupted frames. Most prior approaches depend on motion estimation, temporal features, or deep learning, which are computationally demanding and unsuitable for real-time applications.

This paper addresses the gap by introducing a real-time algorithm that uses static RGB histogram oscillation patterns to detect anomalies without relying on training or inter-frame analysis.

Our key contributions are as follows:

- We propose a novel histogram oscillation-based algorithm that detects visually corrupted frames using per-channel RGB analysis.
- The method is computationally efficient and interpretable, making it suitable for embedded and real-time applications.
- We provide empirical evidence demonstrating the effectiveness of the method in identifying low-information frames with minimal visual content.

Proposed Method

- **Overview**

The algorithm processes each video frame individually to assess the distribution of pixel values in each color channel (R, G, B). By constructing histograms and evaluating the number of bins with significant activity, the algorithm infers whether the frame exhibits sufficient visual variation.

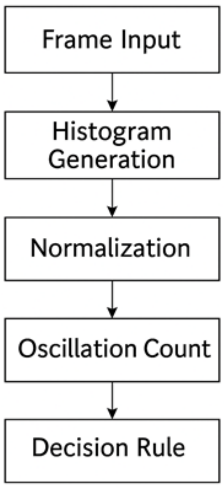

Figure 2. A block diagram of the proposed algorithm showing the steps

- **Flowchart Representation**

The overall process of the proposed algorithm is visually summarized in Figure 3. It begins by extracting RGB pixel values and constructing histograms for each channel. After determining the maximum histogram values, all histograms are normalized to a common scale. The algorithm then counts the number of bins with normalized values greater than 1 in each channel. If all three color channels have fewer than two such bins, the frame is classified as erroneous; otherwise, it is considered normal.

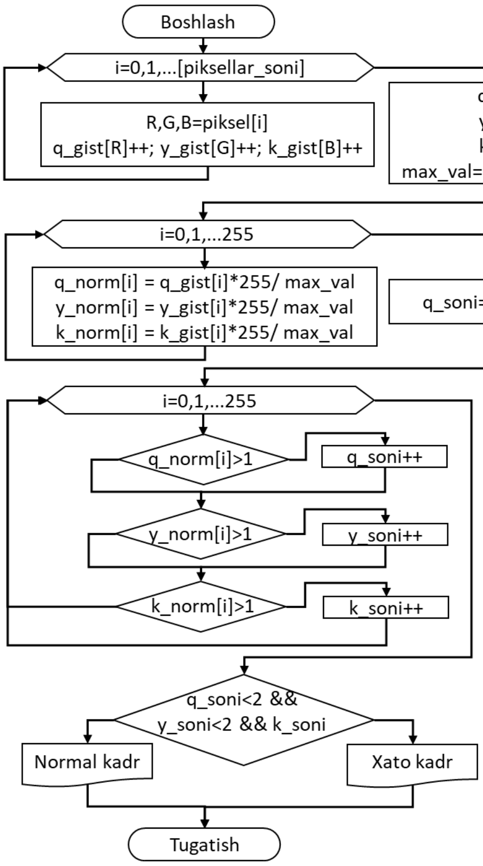

Figure 3. Flowchart of the RGB histogram oscillation-based algorithm for detecting erroneous video frames.

Figure 3 outlines pixel-level processing, histogram normalization, oscillation counting, and the final decision logic.

Given a frame, we extract RGB values for each pixel and compute histograms for the red q_gist, green y_gist, and blue k_gist channels:

- **Histogram Computation**

$$R, G, B = \text{pixel } [i] \Rightarrow q\_gist[R]{+}{+},\quad y\_gist[G]{+}{+},\quad k\_gist[B]{+}{+} \qquad (1)$$

This process is repeated over all pixels $i = 0, 1, ..., N$, where N is the total number of pixels in the frame.

To standardize the histogram values, we identify the maximum value across all three channels:

- **Maximum Value Normalization**

$$q\_max=max(q\_gist),\ y\_max=max(y\_gist),\ k\_max=max(k\_gist)$$

$$max\_val=max(q\_max,\ k\_max) \qquad (2)$$

Then, each histogram is normalized:

$$q\_norm[i]=(q\_gist[i]x255)/max\_val,\quad y\_norm[i]=(y\_gist[i]x255)/max\_val,$$

$$k\_norm[i]=(k\_gist[i]x255)/max\_val \qquad (3)$$

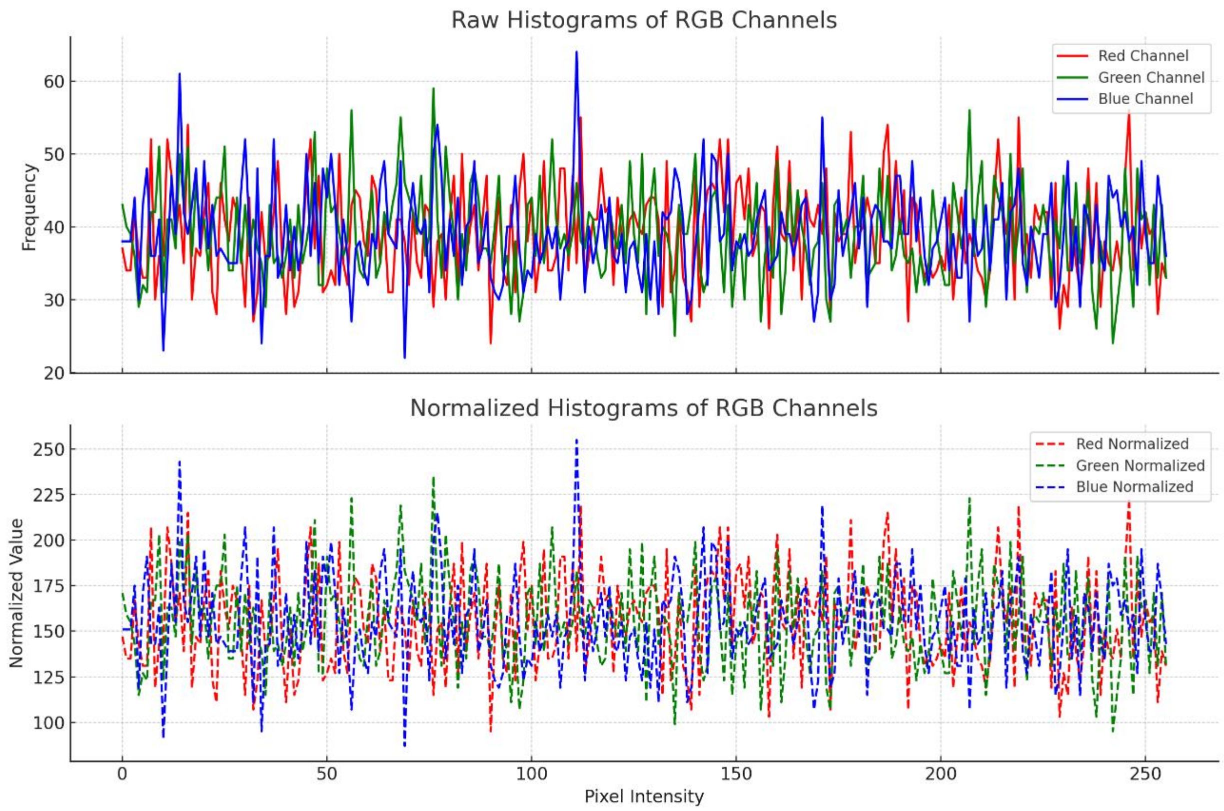

Figure 4. Raw and Normalized Histograms of RGB Channels

Figure 4 shows two plots. The top plot displays the raw histograms of pixel intensity distributions for the red, green, and blue channels in a sample video frame. The bottom plot shows the same histograms normalized to a common scale (0–255) using the maximum value across all channels. This normalization enables consistent comparison of color oscillation patterns for error detection.

- **Oscillation Detection**

We define an "oscillation" as a normalized histogram bin having a value greater than 1. We count the number of such oscillations in each channel:

$$q\_soni = \sum_{i=0}^{255} \delta(q\_norm[i] > 1), \qquad y\_soni = \sum_{i=0}^{255} \delta(y\_norm[i] > 1)$$

$$k\_soni = \sum_{i=0}^{255} \delta(k\_norm[i] > 1) \tag{4}$$

Where δ (condition) = 1 if the condition is true, and 0 otherwise.

- **Classification Rule**

The decision rule is simple yet effective:

If the number of oscillations in all three channels is less than 2, the frame is considered erroneous. Otherwise, it is classified as normal.

If q_soni < 2 and y_soni < 2 and k_soni < 2:

Frame → Erroneous

else:

Frame → Normal

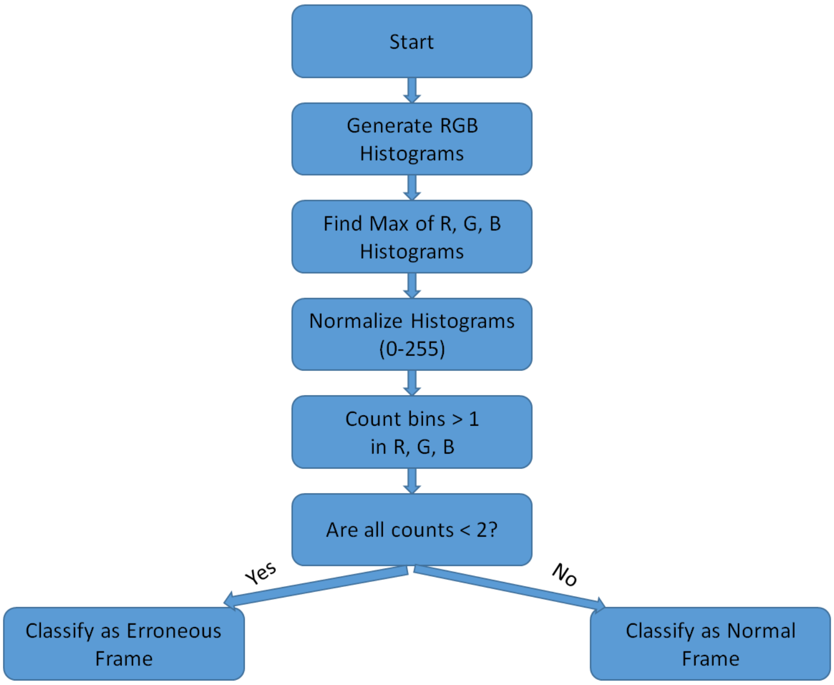

Figure 6. Decision Flowchart for RGB Histogram-Based Frame Classification

RESULTS

Table 1 summarizes the number of frames used in the evaluation and the corresponding detection accuracy for both normal and corrupted categories. Figure 7 illustrates the oscillation count comparison across RGB channels for representative frame types. These values are from a single normal and erroneous frame, used to visually demonstrate the threshold rule applied across the full evaluation dataset summarized in Table 1.

Table 1. Detection accuracy and frame count for normal and corrupted video frames

Frame Type	Number of Frames	Detection Accuracy (%)
Normal Frames	500	95.2
Corrupted Frames	300	93.6
Overall	**800**	**94.6**

These results confirm that the algorithm effectively distinguishes corrupted frames from normal ones with high accuracy while maintaining real-time performance.

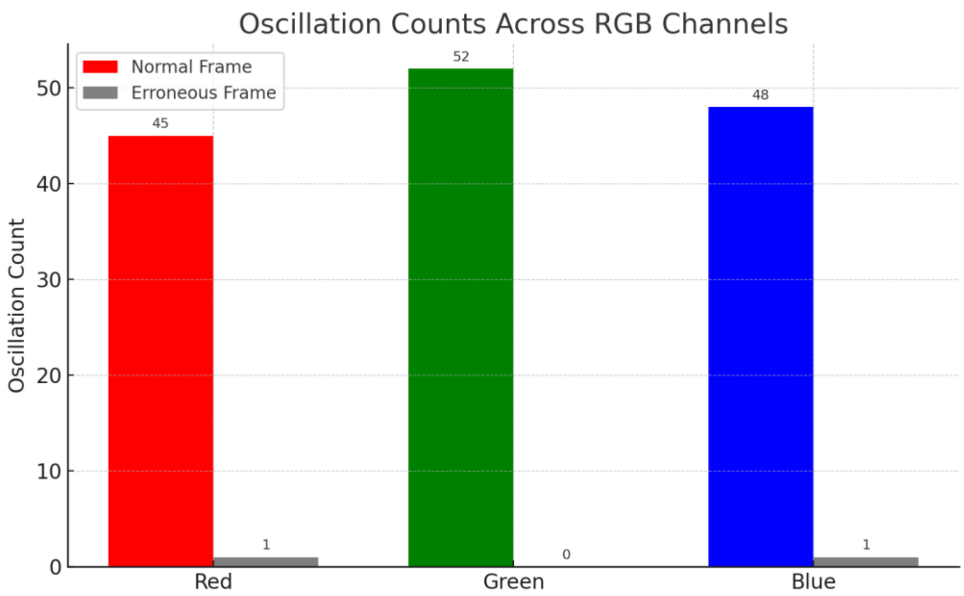

Figure 7. Oscillation Count Comparison for Normal and Erroneous Frames

Figure 7 shows a comparison of oscillation counts across the red, green, and blue channels for both a normal and an erroneous video frame. In the normal frame, each channel exhibits a high number of histogram bins with values greater than 1, indicating significant color variation. In contrast, the erroneous frame demonstrates very low oscillation counts, reflecting minimal color activity and supporting its classification as a corrupted frame by the proposed algorithm.

DISCUSSION

The strength of this approach lies in its simplicity, speed, and transparency. Unlike machine learning-based methods, our algorithm does not require training or large annotated datasets. Moreover, the interpretability of histogram-based analysis makes it attractive for explainable AI applications.

However, the current version may misclassify very low-texture frames (e.g., uniformly colored backgrounds) as erroneous. Future improvements could include adaptive thresholds or temporal analysis for refinement.

CONCLUSION

This study introduces an effective algorithm for detecting frame-level errors using RGB histogram oscillation analysis. The method is lightweight, fast, and interpretable—making it suitable for deployment in embedded video systems and real-time monitoring solutions.

In future work, we plan to integrate temporal coherence checks and evaluate the method on diverse datasets including thermal imaging and grayscale content.

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