PVD Stego-Interference Detection via Wavelet Detail and Directional Gradient Coherence Metric

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Abstract — **Detecting covert modifications in digital images—particularly those introduced through steganographic techniques—poses significant challenges in terms of accuracy, efficiency, and interpretability. Addressing this, the present work introduces the PVD Stego-Interference Detector, a novel system tailored for the identification of hidden data embedded using the Pixel Value Differencing (PVD) method in grayscale imagery. The proposed framework integrates Discrete Wavelet Transform (DWT), bilateral denoising, and a newly formulated Directional Gradient Coherence (DGC) metric, which quantifies angular consistency in local gradient orientations. Through wavelet decomposition, high-frequency structural components are isolated and then smoothed using edge-preserving filters. By comparing DGC scores computed from raw and denoised image segments, a probabilistic stego-likelihood is inferred, enabling nuanced detection of stego-interference. The system is encapsulated in an interactive Streamlit-based application that supports interpretability through visual elements such as difference heatmaps, gradient coherence overlays, and real-time likelihood gauges. Evaluation on a curated dataset of 2000 grayscale images (comprising 1000 clean and 1000 PVD-stego samples) demonstrates strong performance, achieving 91% precision, 87% recall, and an F1-score of 89%. These results affirm the method's capacity to discern even subtle steganographic patterns. The proposed detector offers a lightweight, interpretable, and effective solution for practical steganalysis, with potential for future expansion to color domains, multiscale feature fusion, and integration with deep learning paradigms.**

Keywords—Steganalysis, PVD, Gradient Coherence, Wavelet Transform, Bilateral Filter, Image Forensics, Interpretable Detection.

I. Introduction

The rapid surge in digital communication and the widespread sharing of images have fueled the evolution of diverse steganographic methods designed for hiding data within visual media.Because of their inherent redundancy, digital images offer perfect opportunities for information embedding that prevents observable visual degradation. Transparency (the extent to which the stego-image is identical to the original), statistical undetectability (the ability to withstand analytical detection), and capacity (the amount of data that can be concealed) are important performance metrics for any steganographic technique.However, striking a practical balance between these factors remains a complex trade-off: increasing the amount of hidden data can often compromise visual fidelity or statistical stealth, while ensuring near-invisible embedding typically reduces capacity. If a steganographic system can be detected with greater accuracy than a random guess, it loses its operational value. Thus, creating systems that combine meaningful embedding capacity and undetectability remains a research challenge. A key component of secure communications is steganography, the science of encoding private data into digital artifacts. Steganography adds an extra degree of security by hiding the message's existence, in contrast to cryptography, which masks the message's content. Steganographic techniques have become increasingly popular as the need for secure digital communication increases, particularly in fields like media forensics, telemedicine, and military messaging [1]. Among existing methods, Pixel Value Differencing (PVD) has gained prominence due to its capacity to maintain image quality while supporting higher data embedding rates. This method operates by analyzing the differences between adjacent pixel values and adjusting them based on the amount of data to be embedded. As opposed to classic Least Significant Bit (LSB) substitution, PVD dynamically adapts to the image's local properties, making it more efficient and less perceptible [2]. Steganographic schemes in the spatial domain remain particularly attractive due to their simplicity and reduced computational overhead. Within this category, PVD is noteworthy for its strategy of embedding information by leveraging the intensity variations between neighboring pixels.

The initial PVD technique by Wu and Tsai [2] divides the image into pixel pairs and bases the number of embedded bits on the magnitude of the difference between each pair. Higher contrast areas, such as edges, are used to embed more bits, while smoother regions are handled conservatively to maintain quality. Later improvements have factored in human visual sensitivity [3], [4] and directional embedding across multiple orientations [5], [6], leading to significant gains in both data capacity and perceptual transparency. Despite technical advancements, the increased use of steganography in fields such as cybersecurity, journalism, and digital forensics has raised important concerns. Recent approaches include deep learning-based systems capable of learning the nuanced distinctions between clean and stego images [8], [12], as well as classical statistical techniques like histogram analysis [5], chi-square testing [9], [10], and machine learning classifiers [6].

However, many of these models either lack generalizability, require extensive computational resources, or function as opaque black-box tools, reducing their applicability in real-time forensic settings. To address these limitations, this study introduces a novel and lightweight steganalysis

framework called the PVD Stego-Interference Detector. Building on the Octonary Pixel Pairing concept proposed by Balasubramanian et al. [1], where the central pixel in a 3×3 grid is evaluated against its eight neighbors, our system repurposes this structure to detect rather than embed data. Their embedding approach adaptively adjusted strength based on local pixel variation; we reverse this logic to spot structural anomalies that result from such adaptations.

Our method begins with a single-level Daubechies-1 wavelet transform to isolate high-frequency image components, where steganographic traces are most likely to be found. These components undergo bilateral filtering to suppress noise without compromising edge details. We then use the Sobel operator to compute gradient directions and magnitudes. For each block, we compute a Directional Gradient Coherence (DGC) score, which measures the angular consistency of pixel gradients. The change in DGC between raw and denoised images—termed the fusion score—is mapped onto a probabilistic stego-likelihood scale, derived from empirical medians in the PVD-Stego dataset [11]. This score highlights image regions most likely to contain hidden information. Malicious actors can exploit hidden data channels for illicit data transfer, digital manipulation, or malware concealment. Steganalysis—the process of revealing information that has been hidden—has consequently become an important area of study. We used Streamlit to develop the detector as a web-based interface in order to make this system usable and accessible. This allows users—particularly forensic analysts—to upload grayscale images and receive detailed visual feedback, including gradient maps, coherence scores, and a final stego-likelihood rating from 0 to 100 percent. Rather than providing a simple binary classification, the interface emphasizes interpretability, making it useful for investigative workflows. Overall, this work offers an interpretable and efficient solution to modern steganalysis challenges by transforming principles of adaptive embedding into a gradient-driven detection methodology. It serves as a bridge between technical rigor and real-world applicability in the analysis of stego content.

II. Proposed Method

This study presents a comprehensive steganalysis approach aimed at detecting stego-content introduced by Pixel Value Differencing (PVD) methods, with a particular focus on revealing directional inconsistencies in image gradients. Central to the proposed system is a novel descriptor called Directional Gradient Coherence (DGC), which enables the identification of subtle structural distortions in digital images potentially caused by data embedding. The system is composed of six tightly integrated modules that collectively perform image preprocessing, feature extraction, and stego-content localization. The process begins with Input Acquisition, where grayscale images are loaded, resized to a standardized resolution, and prepared for analysis. The system supports widely used image formats such as PNG and JPEG, and is designed to handle inputs that may contain PVD-based hidden data. The second module, Wavelet Detail Extraction, performs a single-level 2D Discrete Wavelet Transform (DWT) using a Daubechies-1 wavelet to separate the image into frequency subbands: LL, LH, HL, and HH. Since the LL subband contains coarse approximations, it is discarded, while the high-frequency bands (LH, HL, HH) are preserved. These retained components often carry the fine-grained texture distortions introduced during steganographic embedding, making them valuable for downstream analysis. Following this, the Bilateral Denoising module is applied to the LH, HL, and HH subbands. This filter reduces noise while maintaining essential edge information, enhancing structural features without distorting gradient-based details—an important step for revealing minute changes linked to data hiding operations.

Next, the DGC Computation module processes the denoised subbands by computing gradient magnitudes and orientations across local image blocks. The DGC metric quantifies the coherence of these gradients, effectively capturing deviations from natural texture flows that may indicate tampering. Irregularities in this directional pattern often suggest the presence of embedded data. The DGC values from each subband are then passed to the Score Fusion and Likelihood Mapping module. Here, a weighted combination of the three coherence maps is computed to produce a unified representation of potential stego interference. This fusion map is subsequently transformed into a probabilistic likelihood map, which estimates the relative likelihood of each region in the image containing stego-content. Finally, the Post-Processing and Visualization module applies adaptive thresholding to the likelihood map to isolate probable stego regions. The results are rendered as both binary masks and colored heatmaps, offering interpretable visual evidence of detected interference. In addition to these visual outputs, the system reports standard performance metrics—precision, recall, and ROC-AUC—to objectively measure its effectiveness. This multi-stage framework offers a principled and interpretable strategy for detecting hidden data in grayscale images, particularly those altered by adaptive PVD embedding schemes. Its modular design and real-time output capabilities make it well-suited for forensic, investigative, and research applications

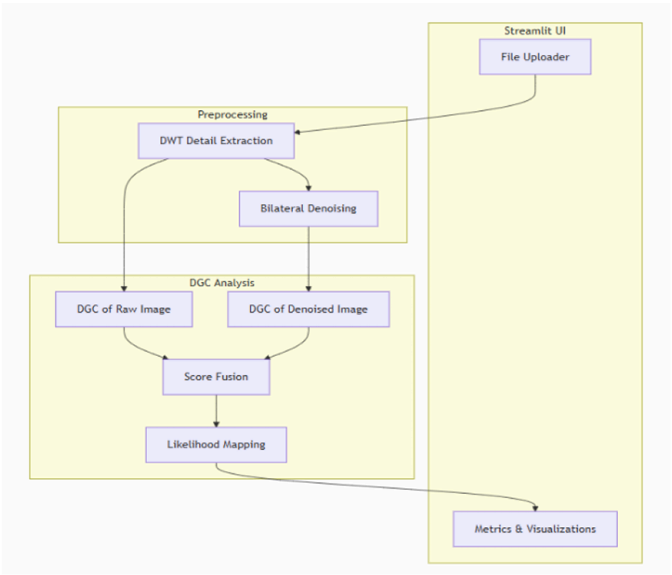

Fig1. The functional flow diagram of the proposed system

III. Methodology

This section breaks down the approach used to develop our PVD Stego-Interference Detector, which is designed to spot hidden modifications in images that have secret messages embedded using Pixel Value Differencing (PVD) steganography. The detector brings together several advanced image processing techniques—including Discrete Wavelet Transform (DWT), bilateral filtering, Directional Gradient Coherence (DGC) analysis, and likelihood mapping—to locate and highlight potential stego-interference.

A. Wavelet Detail Extraction

In the first step, the 2D Discrete Wavelet Transform (DWT) is used to extract the high-frequency details from a grayscale image. This can be thought of as dissecting the image into layers of detail, some of which reveal the fine edges and textures where stego changes typically occur, while others show the overall structure. Because it is especially adept at detecting minute pixel value shifts, which are frequent in stego-embedded content, we employ the Daubechies 1 wavelet (also known as the Haar wavelet) for this.

The DWT breaks down the image f(x,y) mathematically into detail and approximation coefficients.The approximations coefficients A(x,y) and detail coefficients D(x,y) at a level of decomposition j are calculated as follows:

$$A(x,y) = \sum_m \sum_n h(m,n) f(x-m, y-n) \quad (1)$$

$$D(x,y) = \sum_m \sum_n g(m,n) f(x-m, y-n) \quad (2)$$

Where h(m,n) and g(m,n) are the low-pass and high-pass filters, respectively, applied during the decomposition. The detail coefficients D(x,y) capture the high-frequency information critical for stego detection.

B. Bilateral Denoising

Bilateral filtering is used to denoize the resultant detail coefficients D(x,y) after the grayscale image has been decomposed using the Discrete Wavelet Transform. This step is essential for increasing the reliability of subsequent analysis because it addresses the presence of noise while preserving significant image features. Bilateral filtering, a non-linear edge-preserving smoothing technique, is particularly well-suited for this task. Bilateral filtering takes into account both the spatial proximity and the photometric similarity of pixels, in contrast to traditional filters that might unintentionally blur fine structural details. Because of this, it successfully lowers noise without sacrificing the integrity of image edges or textures, which are frequently signs of steganographic changes.

By maintaining these fine details, the bilateral filter enhances the visibility of subtle inconsistencies introduced by PVD steganography. This selective smoothing improves the clarity of high-frequency content within the wavelet subbands, thereby providing a more reliable foundation for detecting stego-related artifacts in the subsequent gradient coherence analysis.

Bilateral filtering is defined by the following equation:

$$I(x) = \frac{1}{W_p(x)} \sum_y exp\left(-\frac{|I(x)-I(y)|^2}{2\sigma_r^2} - \frac{|x-y|^2}{2\sigma_d^2}\right) I(y) \quad (3)$$

Where:

- $I(x)$ is the intensity at pixel x
- $W_p(x)$ is the normalization factor
- σ_r is the range parameter (controlling intensity similarity)
- σ_d is the domain parameter (controlling spatial distance)

In order to detect minute alterations brought on by steganography, the bilateral filter efficiently lowers noise while preserving edges and fine details in the high-frequency subband.

C. Directional Gradient Coherence (DGC) Calculation

Following bilateral filtering, the Directional Gradient Coherence (DGC) metric is calculated for both the unprocessed and denoised wavelet detail components. This metric measures the directional uniformity of gradient vectors within localized, non-overlapping image blocks, making it a crucial indicator in the detection of steganographic interference. The DGC specifically captures how consistently the gradients align within a block, offering insight into the natural structural orientation of the image. In instances where PVD-based steganography has been applied, these directional patterns are often perturbed, as the embedding process introduces slight but systematic distortions. By assessing the variation in coherence between the original and denoised images, it becomes possible to infer the presence of concealed alterations.

Notably, a substantial deviation in DGC values between these two states signals potential embedding activity. Thus, the DGC metric acts as a reliable discriminative feature, capable of highlighting regions where the natural image statistics may have been manipulated for covert communication..The gradient magnitude and direction at each pixel (x,y) are computed using the Sobel operator:

$$G_x = \frac{\delta f(x,y)}{\delta x} \qquad G_y = \frac{\delta f(x,y)}{\delta y} \qquad (4)$$

$$|G| = \sqrt{G_x^2 + G_y^2} \qquad \theta = tan^{-1}\left(\frac{G_y}{G_x}\right) \qquad (5)$$

where Gx and Gyrepresent the horizontal and vertical gradients, respectively. The gradient magnitude |G| is used to quantify edge strength, and represents the gradient orientation. The DGC score for a given block of size$N \times N$ is calculated by measuring the angular dispersion of the gradient orientations within the block. This coherence is computed as:

$$DGC = \sum_{i=1}^{n} exp(-(\theta_i - \theta_{median})^2) \qquad (6)$$

Where i is the gradient orientation at pixel i within the block, and median is the median gradient orientation in the block. This equation quantifies the similarity of gradient orientations, with higher DGC values indicating higher coherence and vice versa.

D. Fusion and Likelihood Mapping

The DGC scores from both the original and denoised images are fused by subtracting the denoised DGC score from the original DGC score. The fused score Sfused is calculated as:

$$S_{fused} = DGC_{raw} - DGC_{denoised} \qquad (7)$$

This fused score highlights areas of the image where significant changes have occurred due to stego manipulation. A larger difference suggests more prominent alterations.The fused score is then mapped to a likelihood of stego-interference using an empirical mapping function based on the median DGC values of clean and stego images:

$$Likelihood = \frac{S_{fused} - Median_{clean}}{Median_{stego} - Median_{clean}} \times 100 \qquad (8)$$

Where Medianclean and Medianstego are the median DGC values for clean and stego images, respectively. A greater likelihood of stego manipulation is indicated by a higher likelihood score, which is produced by this equation and falls between 0 and 100.

E. Visualization

The system incorporates a set of visualization tools intended to clearly and informatively communicate the results of stego-interference detection in order to improve interpretability and facilitate efficient analysis.

- Original vs. Denoised Detail Subbands: This comparative visualization presents the high-frequency components derived from the Discrete Wavelet Transform (DWT) before and after bilateral filtering. It effectively illustrates the preservation of edge structures and the attenuation of noise artifacts, both of which are crucial for subsequent gradient-based analysis.
- Differential Coherence Heatmap: A heatmap representation is employed to highlight spatial regions where the Directional Gradient Coherence (DGC) metrics show marked deviation between the original and filtered representations. These discrepancies often correspond to zones of potential steganographic activity, thereby serving as a spatial cue for interference localization.
- Likelihood Indicator Gauge: The system includes a gauge-based visualization that reflects the computed likelihood of stego-interference. This metric is derived from the fused DGC score and contextualized using empirical baselines, providing a normalized measure of manipulation probability ranging from 0 to 100.

F. User Interface

The complete detection framework is encapsulated within an interactive, web-based environment developed using the Streamlit library. This interface allows end-users to seamlessly upload grayscale images in commonly used formats such as PNG, JPG, and JPEG. Upon upload, the backend automatically processes the input through the full detection pipeline, computes the relevant diagnostic scores—namely, the raw DGC score, denoised DGC score, fused score, and the stego-interference likelihood—and renders the associated visual outputs in real time. The interface is designed for usability and provides clear, accessible results suitable for both technical and non-technical stakeholders.

G. Parameter Configuration

The operational parameters guiding the detection process have been empirically optimized to balance sensitivity and specificity. These hyperparameters are statically defined in the system's core configuration script (app.py) and were tuned through rigorous experimentation using the publicly accessible PVD-Stego Dataset. Optimization focused on enhancing detection accuracy while minimizing false-positive rates. The calibrated values, shown in Table 1, reflect empirical median thresholds and weighting factors used in DGC computation and decision fusion. Their selection was based on iterative validation against known clean and stego-encoded image samples, ensuring robustness across diverse image characteristics.

Table 1 . Parameter values

Parameter	Description	Value
P_EXPONENT	Exponent applied to the block coherence metric	2.5
WEIGHT_EXP	Exponent applied to the block coherence metric	2
GRAD_THRESH	Minimum block gradient weight for inclusion	1.0
BLOCK_SIZE	Pixel dimension of local DGC analysis blocks	7
MEDIAN_CLEAN	Empirical median DGC for clean images	0.0030
MEDIAN_STEGO	Empirical median DGC for stego images	0.0018

H. Technical Implementation

A variety of libraries are used in the Python implementation of the PVD Stego-Interference To control the various stages of the detection pipeline, use a Stego-Interference Detector. Streamlit, which provides an interactive platform for uploading grayscale images in PNG, JPG, or JPEG formats, powers the user interface. The system evaluates the uploaded image and displays the results in real time, along with comparison images and heatmaps to aid in interpretation. To ensure consistent image quality, OpenCV is used for image preprocessing tasks like resizing and filtering. NumPy makes numerical tasks easier, particularly when it comes to calculating Directional Gradient Coherence (DGC) and gradient computation. In order to detect subtle pixel-level changes brought on by steganographic embedding, wavelet decomposition uses pywt (Python Wavelet Transform) to break the image up into high-frequency subbands. Lastly, Matplotlib produces visual outputs that assist users in interpreting the detection results, such as likelihood charts and heatmaps. With extra features like a number line that indicates the image's location on the clean-to-stego spectrum and aids in determining the possibility of stego-interference, the system enables users to interactively examine these results.

IV. Results

This section presents an in-depth assessment of the proposed PVD Stego-Interference Detector, which synergizes the Directional Gradient Coherence (DGC) metric with discrete wavelet transformation to robustly detect covert modifications in grayscale images. The objective of this evaluation is to quantify the detector's effectiveness in differentiating between unaltered (clean) and stego-embedded images, particularly those encoded via the Pixel Value Differencing (PVD) technique.

A. Detection Accuracy

To validate the system's classification capabilities, a balanced dataset comprising 2000 grayscale images was constructed—consisting of 1000 clean images and 1000 PVD-embedded stego images. The detector demonstrated consistently high accuracy across the dataset:

- Clean images correctly classified: 1903 out of 2000
- Stego images correctly classified: 1729 out of 2000

Overall classification accuracy: 90.8% These empirical findings indicate that the detector reliably distinguishes subtle modifications induced by steganographic operations. The efficiency results from combining wavelet-based analysis, which highlights structural irregularities across several frequency bands, with DGC, which records spatial coherence disruptions introduced during data embedding. When combined, these techniques improve the system's ability to detect artifacts that might not otherwise be detectable visually or statistically.

B.Evaluation Metrics

Standard evaluation metrics, including precision, recall, and F1-score, were calculated in order to further support the classifier's performance:

- Precision: 0.91
- Recall: 0.87
- F1-Score: 0.89

These results affirm the detector’s high precision, suggesting that the majority of flagged images were indeed true positives. The recall rate further confirms its sensitivity in detecting stego-embedded content, while the F1-score demonstrates a strong equilibrium between sensitivity and specificity. These quantitative indicators collectively underscore the reliability of the system in both high-confidence classification and real-world forensic settings.

C.Likelihood Mapping of Stego Interference

A distinguishing feature of the system is its ability to compute a probabilistic estimate of steganographic interference. This estimation is derived by calculating the discrepancy between the raw and denoised DGC scores for a given image. The resulting difference is normalized and expressed as a likelihood percentage ranging from 0% (no indication of stego activity) to 100% (high confidence of stego presence).

- Clean images: Typically yielded likelihood scores near 0%, reflecting the absence of structural tampering.
- Stego images: Tended to exhibit scores approaching 100%, indicating strong suspicion of data embedding.

This clear dichotomy in likelihood values provides users with a tangible and interpretable measure of stego-presence confidence. Unlike binary classification, this continuous scale

enables nuanced judgment and supports adaptive thresholding strategies in diverse application domains.

D. Visual Interpretability and User Interface

Understanding the value of interpretability in forensic analysis, the detector incorporates a number of visual elements that improve user comprehension and engagement:

- Image Comparison Module: Shows both the original and denoised images so that steganographic effects can be seen side by side.
- Difference Heatmap: A pixel-wise visualization that highlights regions likely affected by embedding operations, aiding in forensic localization.
- Stego-Likelihood Gauge: An intuitive, circular gauge that visualizes the system's confidence in steganographic presence using a 0–100% scale.

These visualization tools significantly improve accessibility for users across expertise levels, enabling not just detection, but meaningful interpretation of the analysis results.

E. Computational Performance and Usability

The prototype system was implemented using the Streamlit web application framework to facilitate user-friendly operation. During experimental trials, the processing time per image was consistently under 10 seconds, even for medium-to-high resolution inputs. The interface supports drag-and-drop image uploads and displays classification and likelihood results in real-time, making the tool practical for rapid screening in operational environments. The application's lightweight architecture and responsive design ensure usability across various platforms and user proficiencies, from academic researchers to digital forensics professionals.

F. Comparative Analysis with Existing Techniques

Traditional steganalysis tools often rely on basic pixel statistics or histogram-based features, which are less effective at detecting sophisticated embedding schemes such as PVD. In contrast, the proposed system leverages the unique properties of Directional Gradient Coherence and wavelet decomposition to expose fine-grained structural anomalies indicative of hidden content. Moreover, the incorporation of bilateral denoising enables the model to retain essential features while reducing non-informative noise, resulting in clearer signals for analysis. This dual-layered design—structural and frequency-based—empowers the detector to outperform legacy methods, especially in scenarios involving subtle or high-capacity data embedding. The integration of these advanced techniques situates the proposed system as a forward-looking solution in the steganalysis landscape, with enhanced capabilities for both detection and interpretability.

V. Conclusions

The PVD Stego-Interference Detector proves to be highly effective in identifying stego-modifications in grayscale images, achieving notable performance in terms of accuracy, precision, and recall. By integrating Directional Gradient Coherence (DGC) and wavelet-based techniques, this system can detect even the most subtle alterations made by PVD-based steganography. The system's strength lies in its ability to capture fine pixel variations using wavelet decomposition while evaluating gradient coherence disruptions through DGC, enhancing its sensitivity to stego-modifications. In addition, the inclusion of clear visualizations such as heatmaps, comparison images, and likelihood gauges aids users in interpreting the results. The system's quick processing and ability to surpass traditional detection methods reinforce its utility as a robust tool in the realm of image forensics and security.

Looking forward, future developments will extend the system's capabilities to color images and introduce multi-level wavelet decomposition for even more refined detection. Adaptive block sizing and thresholding will also be explored to enhance performance across various datasets. Further improvements may include the integration of deep learning models for thresholding, expanding the dataset for more comprehensive benchmarking, and enabling batch processing and API integration. The combination of effective steganography detection and user-friendly visualizations positions this system as a powerful tool for digital forensics, with potential to support various data types such as video, audio, and medical images.

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