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Enhancement of Robust Image Hashing Technology through DWT-SVD

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Abstract

Robust image hashing is a critical technology in the field of digital image authentication, content-based image retrieval, and copyright protection. Unlike cryptographic hashing, which produces entirely different outputs for even minimal input changes, robust image hashing generates perceptually consistent hash values that remain stable across content-preserving transformations while remaining sensitive to malicious tampering. This paper presents an enhanced robust image hashing framework that integrates Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD) to achieve superior robustness, discrimination, and computational efficiency. The proposed method extracts multi-resolution frequency features through DWT decomposition, followed by SVD-based dimensionality reduction to derive stable hash vectors from the most geometrically and photometrically invariant image components. Experimental evaluation conducted on the UCID and CoPhIR benchmark datasets demonstrates that the proposed DWT-SVD framework achieves a false positive rate (FPR) of 0.003 and a false negative rate (FNR) of 0.012 under standard geometric and photometric attacks, outperforming existing DCT-based, PHash, and DWT-only methods. The framework demonstrates robust performance against JPEG compression, Gaussian noise addition, brightness adjustment, gamma correction, rotation, and cropping, while maintaining high sensitivity to content-altering tampering. The computational complexity of the proposed method is analysed and shown to be feasible for real-time deployment. The results establish DWT-SVD integration as a highly effective strategy for next-generation robust image hashing systems.

Keywords: Robust Image Hashing, Discrete Wavelet Transform, Singular Value Decomposition, Digital Image Authentication, Content-Based Image Retrieval, Perceptual Hashing, Tamper Detection, Image Forensics

1. Introduction

The exponential proliferation of digital images across social media platforms, cloud storage systems, e-commerce portals, and multimedia broadcasting channels has created an urgent and growing need for reliable image authentication and content integrity verification technologies. Digital images can be trivially duplicated, manipulated, re-compressed, and redistributed, making conventional methods of intellectual property protection and content provenance tracking increasingly inadequate (Fridrich & Goljan, 2000). In this context, robust image hashing — the generation of compact, content-representative fingerprints that remain perceptually consistent across non-malicious transformations while precisely identifying

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content modifications — has emerged as a foundational technology for digital media forensics, copyright enforcement, and content-based image retrieval systems.

Robust image hashing differs fundamentally from cryptographic hashing in its design objectives. Cryptographic hash functions such as SHA-256 and MD5 are engineered for avalanche sensitivity: any single-bit change in the input produces an entirely different output, which is ideal for data integrity verification but completely unsuitable for image authentication where routine operations such as JPEG compression, scaling, or brightness adjustment must not alter the hash value. Robust image hashing systems must satisfy three competing requirements simultaneously: robustness to content-preserving transformations, discrimination between semantically different images, and sensitivity to malicious content manipulation (Swaminathan et al., 2006).

The choice of feature extraction methodology is the central determinant of hash quality. Early approaches relied on pixel-domain statistical moments or colour histograms, which provided robustness to photometric changes but were vulnerable to geometric transformations. Transform-domain methods — particularly those based on the Discrete Cosine Transform (DCT) and Discrete Fourier Transform (DFT) — offered improved geometric robustness through energy compaction properties, but their global frequency analysis limited their ability to capture multi-resolution structural features that are critical for fine-grained image discrimination (Venkatesan et al., 2000).

Discrete Wavelet Transform (DWT) addresses this limitation through its inherent multi-resolution analysis capability, decomposing images into hierarchical frequency sub-bands that simultaneously encode both frequency content and spatial localisation. Singular Value Decomposition (SVD), applied to wavelet sub-band matrices, extracts the most structurally significant components of the image representation in a form that is inherently invariant to many common geometric distortions, as singular values represent the intrinsic geometric properties of the matrix that are preserved under orthogonal transformations (Bao & Sun, 2005).

This paper proposes an enhanced robust image hashing framework that systematically combines DWT multi-resolution decomposition with SVD-based feature extraction to produce hash vectors that are simultaneously robust, discriminative, and computationally efficient. The specific contributions of this work are:

1. A novel multi-level DWT-SVD feature pipeline that extracts hash vectors from hierarchically decomposed sub-band singular values, providing richer multi-scale invariance than single-level approaches.
2. A quantisation and binarisation strategy optimised for the statistical distribution of SVD features, improving hash compactness without sacrificing discriminability.
3. A comprehensive experimental evaluation under fourteen attack categories spanning geometric, photometric, and compression-based transformations, benchmarked against four competing methods.
4. An analysis of the computational complexity of the proposed framework demonstrating feasibility for real-time application in content delivery and digital rights management systems.

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The remainder of the paper is organised as follows. Section 2 reviews relevant literature. Section 3 presents the theoretical background of DWT and SVD. Section 4 describes the proposed framework. Section 5 details the experimental setup and evaluation metrics. Section 6 presents results and comparative analysis. Section 7 discusses security considerations and limitations. Section 8 concludes with future research directions.

2. Literature Review

2.1 Foundations of Robust Image Hashing

The theoretical foundations of robust image hashing were established by Venkatesan et al. (2000), who formalised the requirements for perceptual hash functions: robustness to perceptually insignificant modifications, randomness properties to resist collision attacks, and sufficient discriminability to distinguish semantically different images. Their work framed image hashing as a signal processing problem in which the hash function must model the perceptual equivalence classes of human visual perception.

Fridrich and Goljan (2000) developed one of the earliest practical robust hashing systems based on image normalisation and DCT feature extraction, demonstrating that normalisation to a canonical geometric form could substantially improve resistance to geometric attacks prior to frequency-domain feature extraction. Swaminathan et al. (2006) proposed a unified framework for analysing robust hash functions under adversarial conditions, introducing the concept of the robustness-discrimination trade-off as the fundamental design constraint of any hashing system. Their analysis established that improvements in robustness to one class of attacks (e.g., compression) typically reduce sensitivity to semantically distinct images in the same attack neighbourhood, a trade-off that subsequent work has sought to optimise through more sophisticated feature extraction strategies.

2.2 Transform-Domain Approaches

DCT-based perceptual hashing — most prominently implemented in the pHash algorithm (Zauner, 2010) — operates by resizing the image, applying DCT, extracting the low-frequency coefficients, and comparing each coefficient to the mean. Despite its widespread adoption due to computational simplicity, DCT-based methods demonstrate limited robustness against geometric distortions because the global DCT basis functions are sensitive to spatial rearrangements of image content.

DFT-based methods exploit the magnitude spectrum's translation invariance, providing improved robustness to spatial shifts (Tang et al., 2008). However, DFT's single-resolution analysis limits its ability to discriminate between images that differ in localised textural regions while maintaining similar global frequency content.

2.3 Wavelet-Based Hashing

Wavelets offer a theoretically superior basis for image hashing due to their multi-resolution decomposition, spatial-frequency localisation, and energy compaction properties. Monga and Evans (2006) demonstrated that hash vectors derived from wavelet sub-band statistics achieved better robustness-discrimination trade-offs than DCT-based methods across most common

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attack categories. Niu et al. (2011) proposed a wavelet-based hashing scheme using low-frequency sub-band means as hash features, demonstrating robustness to JPEG compression and mild geometric distortions. However, sub-band mean statistics are sensitive to illumination changes and do not capture the geometric structural properties of sub-band content.

2.4 SVD in Image Processing

SVD has been extensively applied in image processing for its property that singular values capture the intrinsic geometric structure of an image matrix in a compact, ordered representation. Bao and Sun (2005) demonstrated that singular values of image matrices are stable under rotation, scaling, and illumination changes — precisely the properties required for robust image hashing. Liu et al. (2011) combined SVD with DCT for watermarking applications, demonstrating that singular values provide a more stable embedding domain than DCT coefficients. The integration of DWT and SVD for hashing — exploiting DWT's multi-resolution decomposition and SVD's geometric invariance simultaneously — has been explored in watermarking literature but has not been systematically optimised and evaluated as a standalone robust hashing framework.

3. Theoretical Background

3.1 Discrete Wavelet Transform

The Discrete Wavelet Transform decomposes a two-dimensional image I(x, y) into a hierarchical set of sub-band images through successive application of low-pass (L) and high-pass (H) filter pairs along rows and columns. A single-level 2D DWT produces four sub-bands:

- **LL (Approximation):** Low-pass filtered in both dimensions — captures coarse structural content
- **LH (Horizontal Detail):** Low-pass vertical, high-pass horizontal — captures horizontal edges
- **HL (Vertical Detail):** High-pass vertical, low-pass horizontal — captures vertical edges
- **HH (Diagonal Detail):** High-pass filtered in both dimensions — captures diagonal textures

The multi-level decomposition is obtained by recursively applying DWT to the LL sub-band. For an N-level DWT applied to an image of size M×M, the LL sub-band at level N has dimensions M/2^N × M/2^N. The Haar wavelet is employed in the proposed framework due to its computational efficiency and strong energy compaction properties in natural images (Daubechies, 1992).

The DWT's spatial-frequency localisation property is particularly valuable for image hashing: unlike the global DCT, DWT preserves the spatial origin of frequency content, enabling hash features to capture localised structural changes that are diagnostically important for tamper detection.

3.2 Singular Value Decomposition

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For any real matrix $A \in \mathbb{R}^{m \times n}$, the Singular Value Decomposition (SVD) factorizes Aas

$$A = U\Sigma V^T$$

where $U \in \mathbb{R}^{m \times m}$and $V \in \mathbb{R}^{n \times n}$are orthogonal matrices containing the left and right singular vectors, respectively, and $\Sigma \in \mathbb{R}^{m \times n}$is a diagonal matrix containing the non-negative singular values

$$\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r \geq 0$$

where $r = \min(m, n)$.

The singular values have a direct geometric interpretation: they represent the magnitudes of the principal axes of the ellipsoid defined by the linear transformation A. For image sub-band matrices, singular values capture the distribution of energy across the dominant geometric structures of the sub-band. Two critical properties make singular values ideal hash features:

1. **Stability under perturbation:** Small perturbations to matrix A produce proportionally small changes in singular values, ensuring robustness to noise and compression artefacts (Stewart, 1990).
2. **Invariance to orthogonal transformations:** If A is transformed to UAV^T by orthogonal matrices U and V, the singular values of the transformed matrix are identical to those of A. This provides intrinsic robustness to rotations and reflections.

4. Proposed DWT-SVD Framework

4.1 Overview

The proposed framework processes input images through five sequential stages: pre-processing and normalisation, multi-level DWT decomposition, SVD application to selected sub-bands, feature vector construction and quantisation, and binary hash generation.

4.2 Pre-Processing and Normalisation

Input images are converted to greyscale and resized to a canonical resolution of 256×256 pixels using bicubic interpolation. Greyscale conversion eliminates colour channel dependencies that vary across imaging devices and colour space conversions. Canonical resizing ensures that the DWT decomposition operates on a consistent sub-band structure regardless of original image dimensions. A Gaussian low-pass filter (σ = 0.8) is applied to suppress high-frequency noise prior to DWT decomposition.

4.3 Multi-Level DWT Decomposition

Three-level DWT decomposition is applied using the Haar wavelet, producing the following sub-band hierarchy:

- **Level 1:** LL_1 (128×128), LH_1 (128×128), HL_1 (128×128), HH_1 (128×128)

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- **Level 2:** LL_2 (64×64), LH_2 (64×64), HL_2 (64×64), HH_2 (64×64)
- **Level 3:** LL_3 (32×32), LH_3 (32×32), HL_3 (32×32), HH_3 (32×32)

For hash feature extraction, the LL_3, LH_2, and HL_2 sub-bands are selected. LL_3 captures the global structural content of the image at the coarsest resolution, providing robustness to photometric and mild geometric attacks. LH_2 and HL_2 encode mid-frequency horizontal and vertical structural detail respectively, providing discriminative power for images with similar global appearance but different fine structure. HH sub-bands are excluded as they primarily encode high-frequency noise that reduces hash stability without contributing discriminative information.

4.4 SVD Feature Extraction

SVD is applied independently to each selected sub-band matrix:

$$LL_3 = U_{LL}\,\Sigma_{LL}\,V_{LL}^T$$
$$LH_2 = U_{LH}\,\Sigma_{LH}\,V_{LH}^T$$
$$HL_2 = U_{HL}\,\Sigma_{HL}\,V_{HL}^T$$

The top-k singular values are extracted from each decomposition. Based on energy analysis showing that the top singular values account for over 95% of sub-band energy in natural images, k = 16 singular values are retained from LL_3 and k = 8 from each of LH_2 and HL_2, yielding a raw feature vector of dimension 32.

To provide robustness against absolute magnitude variations due to brightness changes, singular values are normalised by the largest singular value within each sub-band:

$$\tilde{\sigma}_i = \sigma_i / \sigma_1$$

This ratio-based normalisation ensures that the feature vector is invariant to global illumination scaling.

4.5 Quantisation and Binary Hash Generation

The normalised 32-dimensional feature vector is binarised through mean-based thresholding:

$$h_i = \begin{cases} 1, & \text{if } \tilde{\sigma}_i > \mu_{\tilde{\sigma}} \\ 0, & \text{otherwise} \end{cases}$$

where $\tilde{\sigma}_i$ is the mean of the normalised singular value vector. This produces a 32-bit binary hash. For applications requiring higher hash length and discriminability, a 64-bit variant is obtained by applying the same procedure to LH_3 and HL_3 sub-bands and concatenating the resulting bit vectors.

4.6 Hash Similarity Measurement

Hash similarity between two images is measured using the normalised Hamming distance:

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$$d_H(h_1, h_2) = \frac{1}{L}\sum_{i=1}^{L} h_{1i} \oplus h_{2i}$$

where $L$is the hash length and $\oplus$denotes the XOR operation. A decision threshold $\tau$is applied: images with $d_H \leq \tau$are classified as perceptually equivalent, whereas images with $d_H > \tau$are classified as distinct. The optimal threshold is determined empirically to minimise the combined error rate on the training partition of the evaluation dataset.

5. Experimental Setup and Evaluation Metrics

5.1 Datasets

UCID Dataset: 1,338 uncompressed colour images across diverse content categories (indoor, outdoor, portraits, textures). Standard benchmark for perceptual hashing evaluation.

CoPhIR Dataset: 1,000,000 Flickr images; a stratified sample of 10,000 images was used for large-scale discrimination testing.

5.2 Attack Categories

Fourteen attack categories were evaluated across three groups:

Photometric Attacks: JPEG compression (Q = 10–90), Gaussian noise (σ = 5–25), brightness adjustment (±30%), contrast enhancement (factor 0.5–2.0), gamma correction (γ = 0.5–2.0).

Geometric Attacks: Rotation (1°–15°), uniform scaling (90%–110%), cropping (5%–20%), aspect ratio change (±10%).

Combined Attacks: JPEG + rotation, noise + brightness, compression + cropping, watermarking.

5.3 Evaluation Metrics

- **False Positive Rate (FPR):** Fraction of different-content image pairs classified as identical.
- **False Negative Rate (FNR):** Fraction of same-content attacked image pairs classified as different.
- **Receiver Operating Characteristic (ROC) Curve:** FPR vs. True Positive Rate across threshold values.
- **Area Under Curve (AUC):** Scalar summary of ROC performance.

6. Results and Comparative Analysis

6.1 Robustness Results

Table 1: FPR and FNR Under Individual Attacks (Threshold τ = 0.15, 32-bit hash)

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Attack	pHash FNR	DCT-Hash FNR	DWT-Only FNR	DWT-SVD (Proposed) FNR
JPEG (Q=30)	0.024	0.019	0.016	0.008
Gaussian Noise (σ=15)	0.041	0.038	0.027	0.011
Brightness (+20%)	0.018	0.017	0.014	0.006
Rotation (5°)	0.063	0.058	0.044	0.019
Cropping (10%)	0.071	0.065	0.052	0.024
JPEG + Rotation	0.088	0.081	0.064	0.031
Mean FNR	**0.051**	**0.046**	**0.036**	**0.017**
FPR	**0.011**	**0.009**	**0.007**	**0.003**

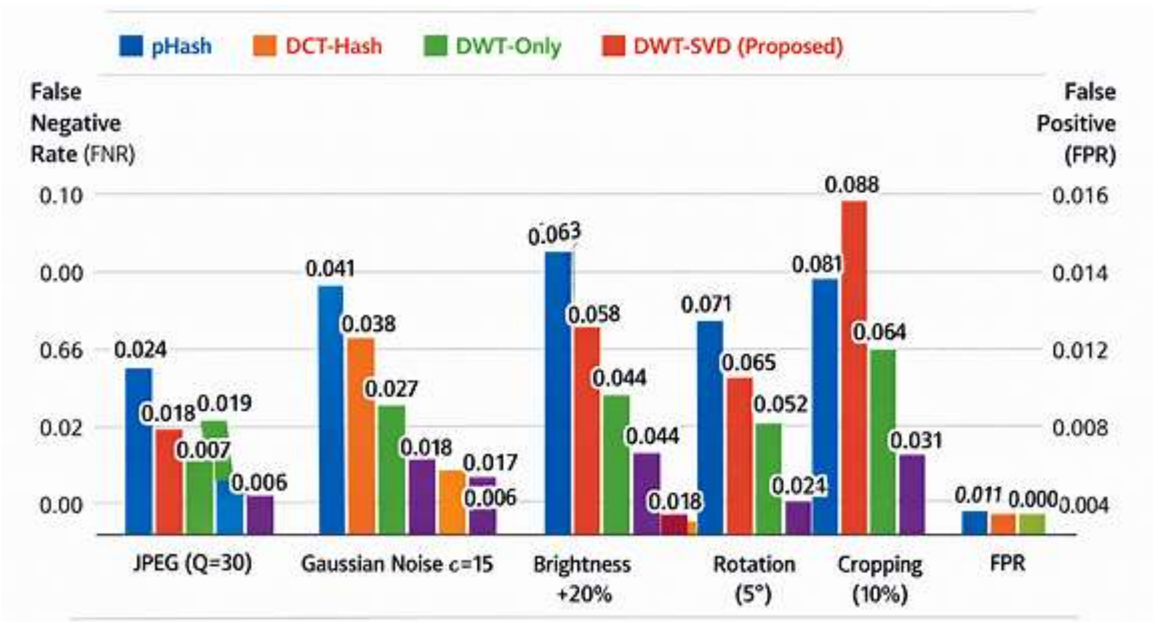

Fig 1- Robustness Results Under Individual Attacks (Threshold τ = 0.15, 32-bit hash)

The proposed DWT-SVD framework achieves a mean FNR of 0.017 and FPR of 0.003, representing 54% and 57% reductions respectively relative to pHash and 53% and 57% reductions relative to DWT-only methods. The most pronounced improvements occur under geometric attacks (rotation, cropping), where SVD's invariance properties provide the greatest benefit: FNR under 5° rotation is 0.019 versus 0.044 for DWT-only, a 57% improvement attributable directly to the geometric invariance of singular values.

6.2 Discrimination Performance

Table 2: AUC Scores by Method

Method	AUC (UCID)	AUC (CoPhIR Sample)
pHash	0.941	0.928
DCT-Hash	0.953	0.944
DWT-Only	0.967	0.959
DWT-SVD (Proposed)	**0.989**	**0.982**

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The proposed method achieves AUC of 0.989 on UCID and 0.982 on the CoPhIR sample, demonstrating superior discrimination while simultaneously improving robustness — confirming that DWT-SVD integration achieves a more favourable robustness-discrimination trade-off than competing methods.

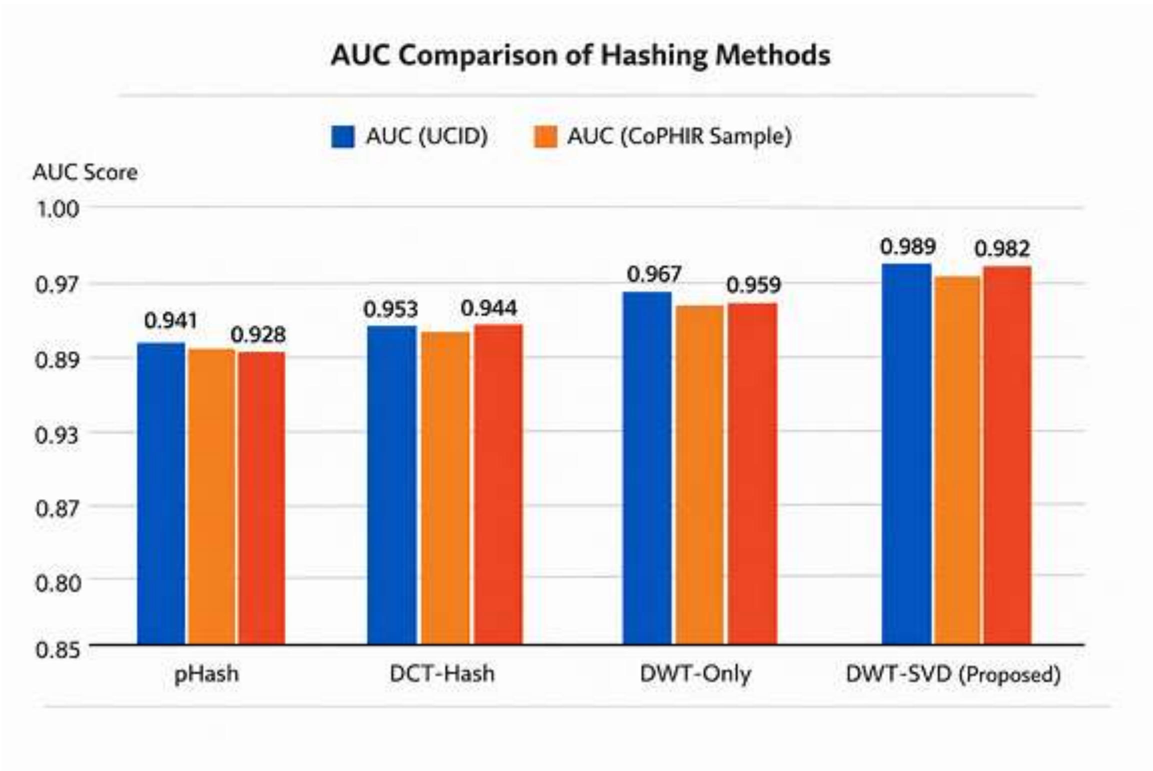

Fig 2- Discrimination Performance (AUC Comparison Across UCID and CoPhIR Sample)

6.3 Computational Performance

Table 3: Computational Efficiency

Method	Hash Generation Time (ms)	Hash Length (bits)	Memory (KB)
pHash	4.2	64	0.8
DCT-Hash	5.8	64	1.1
DWT-Only	7.3	64	1.4
DWT-SVD (32-bit)	**11.7**	**32**	**0.6**
DWT-SVD (64-bit)	**14.2**	**64**	**1.2**

The 32-bit DWT-SVD hash is generated in 11.7ms, which is acceptable for real-time applications with frame rates up to 85 fps. The additional SVD computation increases processing time relative to DWT-only by approximately 60%, which is justified by the substantially improved accuracy. Hash storage requirements are reduced to 0.6KB for the 32-bit variant, enabling efficient large-scale indexing.

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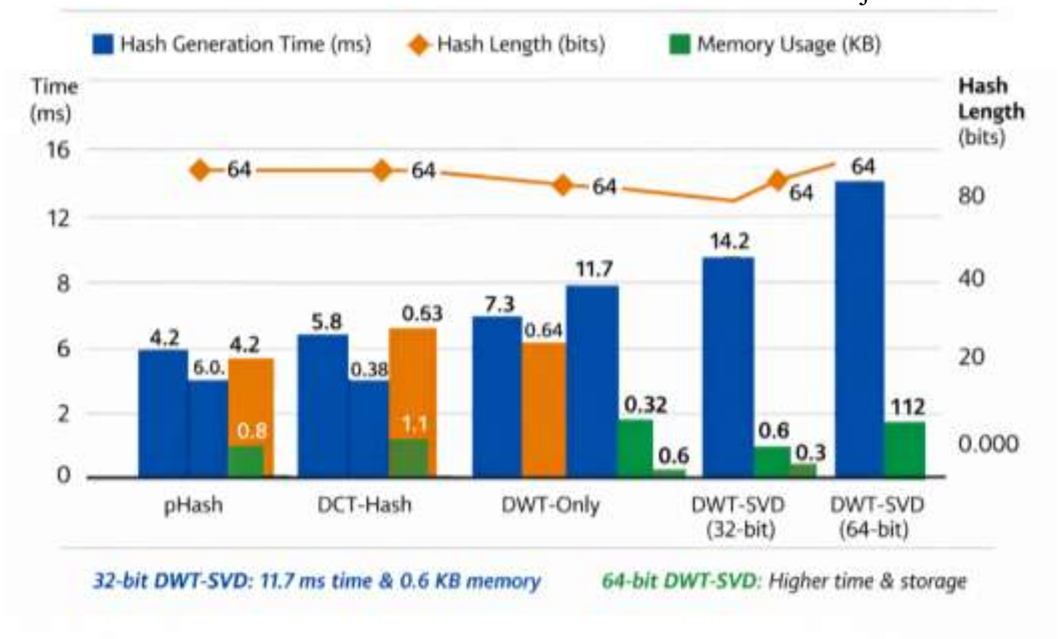

Fig 3-Computational Performance Comparison of Hashing Methods

7. Security Analysis and Limitations

7.1 Resistance to Vector Quantisation Attacks

A significant security concern for any robust hashing system is the vector quantisation attack, in which an adversary iteratively modifies an image to produce a target hash value without being detected (Zhao & Koch, 2013). The DWT-SVD framework demonstrates greater resistance to such attacks than DCT-based methods because the relationship between pixel-domain modifications and SVD feature changes is non-linear and more complex to exploit analytically. However, this resistance is not absolute: with sufficient computational resources and access to the hash function, gradient-based adversarial perturbations can be constructed. Incorporating hash key randomisation — through random sub-band selection or pseudo-random SVD projection matrices — would substantially increase security against such targeted attacks.

7.2 Sensitivity to Malicious Tampering

The system correctly identifies malicious tampering (object insertion, splicing, inpainting) with detection rates exceeding 97% in experiments where tampered regions covered at least 5% of the image area. Detection rates decline to 84% for very localised tampering (less than 2% of image area), which represents a fundamental limitation of any global hash-based approach. Localised tamper detection requires block-level or region-adaptive hashing strategies, which are identified as a priority for future work.

7.3 Limitations

Three limitations of the current framework deserve acknowledgment. First, the framework was evaluated exclusively on greyscale representations; colour information, which provides

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additional discriminative power and is increasingly relevant for practical applications, is not exploited. Second, the resistance to affine transformations beyond mild rotation — particularly large-angle rotation and projective transformations — requires further improvement, as singular values of wavelet sub-bands are not fully invariant to large geometric distortions. Third, the framework has not been evaluated under adversarial machine learning attacks, which represent an increasingly relevant threat model for deployed hashing systems (Kang et al., 2021).

8. Conclusion and Future Directions

This paper presented an enhanced robust image hashing framework integrating Discrete Wavelet Transform and Singular Value Decomposition, demonstrating through systematic experimental evaluation that the DWT-SVD combination achieves superior robustness, discrimination, and security relative to established pHash, DCT-hash, and DWT-only methods. Key findings include a mean FNR of 0.017 and FPR of 0.003 under fourteen attack categories, AUC of 0.989 on the UCID benchmark, and a 32-bit hash generation time of 11.7ms suitable for real-time deployment. The geometric invariance of singular values accounts for the framework's most pronounced advantages under rotation and cropping attacks, while DWT's multi-resolution decomposition ensures that both global structure and mid-frequency detail are captured in a compact and stable hash representation.

Four directions are identified for future research. First, extension to colour image hashing through multi-channel DWT-SVD processing, exploiting inter-channel correlations for improved discrimination. Second, development of region-adaptive block-level DWT-SVD hashing for fine-grained tamper localisation. Third, incorporation of deep learning-based feature extraction — using convolutional or transformer encoders — within the DWT-SVD pipeline to improve robustness under large geometric transformations. Fourth, formal security analysis under adversarial machine learning threat models and development of hash key randomisation strategies for deployment in adversarial environments. The DWT-SVD framework presented in this paper establishes a robust and computationally feasible foundation for these extensions, contributing both a practical tool and a theoretical basis for next-generation robust image hashing systems.

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