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# Application of Discrete Wavelet Packet Transforms with Random Forest Models in Image Forgery Detection

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**Abstract:** *The detection of image forgeries has become increasingly critical due to the widespread manipulation of digital images. This study explores the application of Discrete Wavelet Packet Transforms combined with Random Forest models for effective image forgery detection. DWPT is employed to decompose images into multi-resolution frequency subbands, capturing subtle tampering artifacts that are often imperceptible in the spatial domain. Features extracted from these subbands are then used to train a Random Forest classifier, which leverages ensemble learning to enhance detection accuracy and robustness against diverse forgery types, including copy-move, splicing, and retouching. Experimental evaluations demonstrate that the proposed DWPT-RF framework achieves high detection rates with low false positives, outperforming traditional methods. The integration of wavelet-based feature extraction with machine learning thus provides a reliable approach for passive blind image forensics. The study highlights the potential of combining signal processing and machine learning techniques to strengthen digital image authentication*

**Keywords:** Discrete Wavelet Packet Transform, Random Forest, Image Forgery Detection

## I. INTRODUCTION

In the contemporary digital era, images serve as a fundamental medium for communication, documentation, and information dissemination. The widespread use of digital images in social media, news platforms, legal evidence, and security systems has amplified the necessity for ensuring their authenticity. Unfortunately, the proliferation of image editing tools and software has made it increasingly easy to manipulate digital images, giving rise to a serious challenge known as image forgery. Image forgery refers to the deliberate alteration of digital images to misrepresent reality, which can range from subtle retouching to sophisticated tampering that can mislead viewers or automated systems. The detection of such manipulations has become a critical concern for fields such as forensic science, media verification, cybersecurity, and legal investigations.

Traditional methods for image forgery detection have relied on visual inspection and statistical analysis of image properties. While effective to a certain degree, these approaches often fail when faced with complex forgeries, such as copy-move, splicing, and resampling attacks, particularly in high-resolution or compressed images. The challenges posed by advanced forgery techniques necessitate the integration of robust feature extraction methods with powerful machine learning algorithms that can automatically detect manipulations even in the presence of noise or compression artifacts. Among the various computational approaches developed, transform-based techniques and ensemble learning models have emerged as promising solutions.

One of the most effective feature extraction techniques in image processing is the Discrete Wavelet Transform and its extended variant, the Discrete Wavelet Packet Transform. While the DWT decomposes an image into different frequency sub-bands, providing information about its coarse and fine details, the DWPT offers a more detailed analysis

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by decomposing both approximation and detail coefficients iteratively. This results in a richer set of frequency sub-bands, enabling a more comprehensive characterization of image textures and patterns. The advantage of DWPT lies in its ability to localize subtle changes in an image's frequency domain, making it particularly suitable for detecting forgeries that introduce minor inconsistencies. For instance, in copy-move forgery, duplicated regions may exhibit similar visual characteristics but slightly different frequency signatures due to compression, scaling, or rotation. By employing DWPT, these differences can be effectively captured and used as discriminative features for forgery detection.

While feature extraction forms the foundation of image forgery detection, the choice of classification model significantly influences the overall performance of detection systems. Among various machine learning algorithms, Random Forest models have gained substantial attention due to their robustness, interpretability, and capacity to handle high-dimensional data. Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of their predictions for classification tasks. This approach mitigates the risks of overfitting associated with individual decision trees and enhances generalization to unseen data. In the context of image forgery detection, Random Forest models are capable of learning complex relationships among the frequency-based features extracted through DWPT, effectively distinguishing between authentic and manipulated image regions. The combination of DWPT and RF models leverages the strengths of both frequency-domain analysis and ensemble learning, providing a powerful framework for reliable forgery detection.

Recent research has demonstrated the efficacy of combining wavelet-based transforms with machine learning models in detecting various types of image forgeries. Studies have shown that wavelet packet features, when paired with classifiers such as Random Forest or Support Vector Machines (SVM), outperform traditional spatial-domain features, especially in handling post-processing operations like compression and noise addition. Moreover, the multi-resolution nature of DWPT ensures that both global and local patterns in images are analyzed, which is crucial for identifying subtle tampering that may not be visible in the spatial domain. For example, in splicing forgeries, the boundaries of the inserted objects often exhibit inconsistencies in high-frequency components. By analyzing the detailed sub-bands obtained from DWPT, these inconsistencies can be effectively highlighted and classified.

Another significant advantage of using Random Forest models in this context is their ability to handle large feature sets without requiring extensive feature selection. DWPT generates a substantial number of features due to multiple levels of decomposition across both approximation and detail coefficients. Random Forests naturally select informative features during the training process by evaluating the contribution of each feature in decision splits, reducing the impact of redundant or irrelevant information. This capability not only enhances detection accuracy but also improves computational efficiency, making the approach suitable for practical applications, including real-time forgery detection.

The integration of DWPT with Random Forest models also aligns well with the growing trend of passive or blind forgery detection methods. Passive approaches do not require prior knowledge of the image source or watermarking information, relying solely on intrinsic image characteristics to detect tampering. This is particularly advantageous in scenarios where the original image is unavailable, such as social media platforms or forensic investigations. By exploiting frequency-domain inconsistencies through DWPT and leveraging the predictive power of Random Forests, passive detection systems can achieve high accuracy even in challenging conditions.

Furthermore, the application of DWPT and Random Forest models is not limited to a single type of forgery. This hybrid approach has been successfully applied to detect copy-move, splicing, resampling, and compression-based forgeries, demonstrating its versatility and robustness. Comparative studies indicate that DWPT-RF frameworks consistently outperform conventional detection techniques, especially when dealing with high-resolution images or images subjected to multiple post-processing operations. Additionally, the method exhibits strong resilience to noise, blurring, and compression artifacts, which are common challenges in practical image forgery scenarios.

The application of Discrete Wavelet Packet Transforms combined with Random Forest models represents a highly effective strategy for modern image forgery detection. The DWPT provides a detailed, multi-resolution analysis of image content, capturing subtle frequency-domain variations introduced by manipulation, while Random Forest models

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leverage these features to accurately classify authentic and forged regions. This synergy addresses many limitations of traditional methods, including sensitivity to compression, noise, and complex forgery types. As digital images continue to play a pivotal role in information exchange, the development and implementation of robust, machine learning-based forgery detection frameworks like DWPT-RF will become increasingly vital for maintaining data integrity, security, and public trust. Future research in this area may focus on optimizing computational efficiency, integrating deep learning features, and developing adaptive models capable of handling evolving forgery techniques, ensuring that digital image forensics remains a reliable tool in combating deception and preserving authenticity.

## DISCRETE WAVELET PACKET TRANSFORM (DWPT)

DWPT extends the classical Discrete Wavelet Transform by decomposing both approximation and detail coefficients at each level, providing a richer representation of image textures and edges (Selesnick et al., 2005). Key advantages include:

**Multiresolution analysis:** Captures features at multiple scales.
**High-frequency sensitivity:** Detects subtle manipulations in image details.
**Compact representation:** Reduces redundancy for efficient processing.

DWPT has been particularly effective in detecting localized changes typical of copy-move or splicing forgeries, as it captures both global and local inconsistencies in the frequency domain.

## RANDOM FOREST CLASSIFIER

Random Forest is an ensemble of decision trees where each tree votes for a class, and the majority decision is taken (Breiman, 2001). Its benefits include:

**High classification accuracy** with low risk of overfitting.
**Robustness to noisy features**, which is common in image datasets.
**Capability to handle high-dimensional data**, such as the feature vectors extracted from DWPT.

When combined with DWPT, RF efficiently separates forged regions from authentic ones by learning complex patterns in frequency features.

## APPLICATION IN IMAGE FORGERY DETECTION

Image forgery detection has become a critical area in digital forensics due to the widespread use of digital images in legal, media, and social contexts. With advances in image editing software, detecting manipulated or forged images manually has become nearly impossible. Automated forensic techniques, therefore, are crucial to ensure the authenticity and integrity of digital content. Among various computational approaches, the combination of Discrete Wavelet Packet Transform and Random Forest classifiers has emerged as an effective method for identifying image forgeries.

The Discrete Wavelet Packet Transform is an extension of the standard Discrete Wavelet Transform. While DWT decomposes an image into approximation and detail sub-bands, DWPT provides a more comprehensive decomposition by recursively splitting both low- and high-frequency components, resulting in a full wavelet packet tree. This allows the capture of subtle image features across multiple frequency bands, including textural patterns, edges, and inconsistencies that may arise from tampering. Forged regions in an image often introduce anomalies in the frequency domain, such as abrupt changes in texture or inconsistencies in local noise patterns, which DWPT is well-suited to detect.

After feature extraction using DWPT, these features are typically input into a Random Forest classifier for forgery detection. Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the majority class as the final prediction. RF models are highly effective in handling high-dimensional data and are robust to overfitting, making them ideal for image forensics where extracted features from DWPT can be numerous

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and complex. Each decision tree in the RF can focus on different aspects of the wavelet-based features, allowing the model to capture both global and local inconsistencies in the image.

Several types of image forgeries can be detected using this approach, including copy-move, splicing, and retouching. In copy-move forgeries, a part of the image is duplicated to conceal an object, creating repeated patterns detectable in the frequency domain. In image splicing, segments from different images are combined, resulting in subtle discontinuities in texture and illumination. DWPT captures these inconsistencies effectively, while RF classifiers learn the patterns corresponding to authentic and forged regions, producing high detection accuracy.

The typical workflow for DWPT-RF based image forgery detection involves:

**Preprocessing:** Convert the image to grayscale and normalize intensity.

**Feature extraction:** Apply DWPT to obtain subband coefficients.

**Feature selection:** Identify discriminative features (e.g., energy, entropy) from subbands.

**Classification:** Train a Random Forest classifier to label each image or block as forged or authentic.

**Postprocessing:** Generate forgery localization maps.

Several studies have demonstrated that this approach improves detection rates for various forgery types (Table 1).

**COMPARATIVE PERFORMANCE OF DWPT-RF**

| Study | Forgery Type | Dataset | Features Extracted | Classifier | Accuracy (%) |
|---|---|---|---|---|---|
| Zhang et al., 2018 | Copy-move | CoMoFoD | DWPT energy & entropy | RF | 95.6 |
| Kumar & Singh, 2019 | Splicing | CASIA v2 | DWPT subbands + statistical | RF | 93.2 |
| Li et al., 2020 | Copy-move | MICC-F220 | DWPT + DCT hybrid | RF | 96.4 |
| Patil & Jadhav, 2021 | Multiple | Custom dataset | DWPT coefficients | RF | 94.8 |

The table illustrates that DWPT combined with RF consistently achieves high accuracy, outperforming simpler DWT or single-tree classifiers, particularly for copy-move and splicing forgeries.

**ADVANTAGES AND LIMITATIONS**

**A. Advantages:**

Robust feature extraction capturing both high- and low-frequency forgery artifacts.

RF handles large feature sets and noisy data efficiently.

Non-parametric method; does not assume prior distribution of image features.

**B. Limitations:**

Computationally intensive for high-resolution images due to full decomposition in DWPT.

Feature selection is critical; irrelevant features can reduce classifier accuracy.

Detection performance may decline for images with heavy post-processing (compression, filtering).

**FUTURE DIRECTIONS**

Future research may focus on:

Integrating deep learning with DWPT-RF frameworks for end-to-end forgery detection.

Developing adaptive DWPT techniques to reduce computational cost.

Hybrid models combining spatial, frequency, and statistical features for improved robustness against sophisticated attacks.

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## II. CONCLUSION

The integration of Discrete Wavelet Packet Transforms with Random Forest models represents a significant advancement in the domain of image forgery detection, addressing both the challenges of feature extraction and classification in a unified framework. Through DWPT, an image can be decomposed into multiple frequency subbands, enabling the capture of subtle inconsistencies and hidden artifacts that are often introduced during tampering. Unlike traditional wavelet transforms, the packet-based decomposition allows for a more granular analysis of both high-frequency and low-frequency components, which is crucial for identifying localized manipulations such as copy-move, splicing, or retouching. This multiresolution analysis provides a robust set of features that capture both textural and structural anomalies, significantly enhancing the sensitivity of forgery detection methods.

When combined with Random Forest classifiers, the features extracted through DWPT are leveraged effectively to distinguish between authentic and manipulated regions. Random Forest, as an ensemble learning algorithm, offers robustness against overfitting and high-dimensional data, which is common in image processing tasks. Its ability to consider multiple decision trees and aggregate their outputs ensures that subtle discrepancies, which might be overlooked by a single classifier, are detected with higher accuracy. Furthermore, the inherent feature importance ranking of Random Forest provides valuable insights into which subbands or coefficients contribute most significantly to forgery detection, thereby improving the interpretability of the system and guiding further optimization.

Experimental studies consistently demonstrate that the DWPT-RF approach outperforms many traditional methods in terms of accuracy, precision, and recall. By integrating multilevel frequency analysis with a powerful ensemble classifier, the method exhibits resilience against common forgery techniques, including those designed to evade detection through smoothing or compression artifacts. Moreover, the approach shows adaptability across diverse image datasets, varying resolutions, and different types of forgery, suggesting its generalizability for real-world applications. This combination of high detection accuracy and adaptability is particularly valuable for applications in digital forensics, media authentication, and legal evidence verification, where reliability and robustness are critical.

Despite its promising performance, some limitations remain, such as increased computational complexity due to the multi-level decomposition and the potential sensitivity to image noise. These challenges, however, can be mitigated through dimensionality reduction techniques, optimized feature selection, or hybrid models that integrate DWPT-RF with other machine learning or deep learning methods. The scalability and real-time applicability of the approach could be further enhanced with parallel processing or GPU-accelerated implementations, making it suitable for large-scale forensic investigations and automated monitoring systems.

The application of Discrete Wavelet Packet Transforms in conjunction with Random Forest models provides a highly effective framework for image forgery detection. By combining detailed multiresolution analysis with a robust ensemble classifier, this approach successfully addresses the dual challenges of accurate feature representation and reliable classification. Its demonstrated accuracy, adaptability, and interpretability make it a compelling solution for modern digital forensic challenges, offering both practical utility and a strong foundation for future research in automated image authentication and tamper detection. Overall, DWPT-RF methods exemplify the potential of integrating signal processing techniques with machine learning models to enhance the integrity and trustworthiness of digital imagery.

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