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Robust Color Image Watermarking Using Denoising Autoencoders: A Novel Approach for Digital Rights Management

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Abstract

In this paper, a unique method for colour image watermarking through Denoising Autoencoders (DAEs) is proposed. In this paper, we propose a deep learning-based watermarking solution to enable secure embedding and extraction of watermarks in colour images that achieves robustness against image quality preservation attack. Our approach employs a specially designed DAE structure to acquire lossy embedding and extraction that is both imperceptible and robust, respectively. We conduct extensive experiments with a large dataset containing 5000 diverse colour images to show the superiority of our method over traditional watermarking techniques and other deep learning-based approaches. Experimental results prove that the proposed scheme has a superior robustness in parallel with common image processing and geometric attacks, rendering it suitable for real-world DRM applications.

1. Introduction

The digital era has created a huge problem for our generation by making it difficult to protect intellectual property against content producers and media companies. In order to solve these problems, digital watermarking has grown as an indispensable method for hiding identifying information in multimedia content without the possibility of complete elimination or modification [1]. Of all the styles of advertising materials, digital colour images pose a special problem for watermarking since discernment and response to distortions in colours are essentially higher than those to other kinds of changes [2].

Conventional watermarking approaches in general have suffered from the basic trade-offs among three critical factors: imperceptibility, robustness and capacity [3]. Imperceptibility — the watermark is to be made undetectable by a human eye, image quality of host cover should not decrease against non-watermarked images. The robustness of a watermark refers to how resilient the watermark is against myriad types of manipulation or attacks (e.g. compression, filtering, and geometric transformation). Capacity: Capacity describes the information that can be hidden into host image. It has been a long-standing challenge in the area of digital watermarking to balance these often-conflicting requirements.

To solve these challenges, many methods have been proposed during the years. Despite their simplicity, spatial domain techniques (e.g. Least Significant Bit modification [4]) lack robustness The transform domain approaches like discreet cosine transformation (DCT) based [5], and discrete wavelet transformation (DWT)based methods[6] as well have proven enhancement in the robustness but might sometimes offer lesser imperceptibility or capacity reductions on cost. However, the increasing complexity of attacks and the desire for better watermarking have required a fresh look at this domain.

In the recent past, digital watermarking has emerged into newer dimensions thanks to deep learning in image processing and computer vision. Convolutional Neural Networks (CNNs) are a powerful tool to learn hierarchical representations of patterns and structures in images [2]. Based on this, CNN-based watermarking schemes have been designed to automatically learn the embedding and extraction functions for optimal performance [9]. GANs, such as Generative Adversarial Network (GAN) [10], has had the most recent success in generating visually imperceptible watermarks. Existing watermark embedding methods are unfortunately not effective for the complex colour image watermarks as maintaining both visual perception of colours and robustness against attacks is a nontrivial task convincing many systems.

Denoising autoencoders (DAEs) are arguably one of the most successful deep learning architectures for image representation [11]. DAEs were first introduced to image denoising, and it has since shown a unexpectedly high capacity for automatic learning important features of images with auto-encoders being resistant against various kinds of noise/corruption. Since DAEs are built to preserve information, they serve as a fantastic candidate for watermarks — hiding some sort of data in the input that is hopefully sensibly-resistant to various types of distortion.

This article improves upon these advancements and introduces a new colour image watermarking algorithm based on the use of denoising autoencoders. In this paper, we work to compensate the aforementioned drawback where current methods either suffers imperceptibility, robustness or capacity by providing a solution that yields better trade-off in between. This algorithm uses a DAE architecture designed for the task of colour image watermarking. We designed an end-to-end architecture to learn appropriate embedding and extraction functions, so that they have capability in the complex domain of colour images.

The major contributions of the paper are:

1. A novel deep autoencoder design targeted for colour image watermarking: We propose an original architecture that can appropriately model the complexity of colour information yet retain the generalizability nature from using DAES. The architecture learns to embed watermarks so as to withstand a variety of attacks while ensuring that the visual quality of the host image is preserved.
2. A mathematical account of embedding and extraction processes we propose: We describe a principled foundation supporting our method which reveals some intuition behind the operation of our watermarking scheme. This encompassed the encode and decode, watermark embed and extract blocks.
3. Dynamic Loss Function for Imperceptible, Robust Digital Watermarking: A novel loss function in which imperceptibility will be a direct opposition to robustness and the capacity of watermark. Our approach is adaptive, which enables our model to perform well on different types of images and watermarks by adjusting its behaviour for the processed input.

Empirical Experiments on a Big Dataset of 5000 colour images: To justify the work, we perform an extensive experimentation on wide and large dataset with different nature to specific characteristics. Extensive experimental results show the effectiveness of our approach on multiple metrics and attack scenarios compared to the existing methods.

In this section, we first discuss the traditional methods for watermarking, followed by deep learning-based approaches and backgrounds regarding denoising autoencoders. In Sec 3, we detail our proposed approach which consists of the architecture and embedding procedures (Section A), loss functions (Section B), training procedure(Section C). Experimental setup performed for the results as well as analysis of these outputs are described in Section 4, with our technique compared against state-of-the-art techniques across multiple performance metrics. The last section (Section 5) closes the paper with a reprint of our central ideas and by pointing out possible new research avenues.

2. Related Work

The field of digital image watermarking has grown considerably in the past few decades, with various approaches investigated by researchers to tackle the imperceptibility, robustness, and capacity issues. This section describes the related work, offering a comprehensive review, including traditional watermarking techniques, deep learning approaches, and the building blocks of denoising autoencoders.

2.1 Traditional Watermarking Techniques

The traditional colour image watermarking techniques can be divided into two main categories, namely spatial domain and transform domain methods. In the context of watermarking, each of these domains comes with a set of benefits and challenges.

2.1.1 Spatial Domain Techniques

Spatial domain methods utilize pixel values to directly change them according to the embedded watermark information. One of the simplest methods is the Least Significant Bit modification, introduced by the pioneers of watermarking in image processing. It alters the least significant bits of selected pixels to encode the watermark. While feasible, LSB methods are not robust even to slight image processing attacks.

Later approaches focused on improving robustness, especially with geometric attacks. Nikolaidis and Pitas have introduced an exclusive chaotic mixing method to blend the watermark over the whole picture, making it more resilient to cropping. The similar conditions were described for a method developed by Kutter et al. It is an adaptive approach, embedding the watermark in a blue colour channel as the human visual system is less sensitive to changes in blue. Spatial domain methods still have an issue finding a balance between imperceptibility and resistance, especially with the rise of geometric attacks, but also with significant compression.

2.1.2 Transform Domain Techniques

The spectrum of transform domain techniques embeds watermark in the frequency domain of the image, bearing more robustness compared to the spatial domain. The most common fast transforms are:

2.1 Transform Domain Techniques

Discrete Cosine Transform : Originally introduced by Cox et al., DCT has been widely used by various researchers. As described in, it works in the mid-frequency domain to balance perception and strength. This approach has been followed by many works such as that of Lin and Chen, who proposed an adaptive method based on DCT using the image's local strength and filtering. Xie and Arce took this approach and carried out colour image watermarks by embedding them in blue channel wavelets. SVD-Based Methods : Based on the stability of the single value, Liu and Tan block A suggested a method in which the embedding is stable, and the single value obtained makes the watermarks more robust. Many works followed their lead, which combined several transferences, such as the DWT and SVD, to improve the appearance compared to using one transfer only while maintaining robustness. The transform domain generally has good performance and robustness. Using transform domain techniques usually helps improve strength-based robustness. However, some distortions may be observed, especially if the strength increases. The presence of scum can be a significant factor in transforming the domain methods for enhancement or extraction. Boult has shown that watermarking of any kind using DCT and DWT can generate this effect.

2.2.1 CNN-Based Approached

The use of a different deep network to assist in the handling of an optimal watermark function is paramount. Creating limitations against existing approaches, Zhu et al. block A presented one of the earliest trained deep neural networks for end-to-end image steganography using watermarks. Their approach to watermarks, which is more robust than traditional methods to a wide range of image changes, seems superior to others when compared. Kandi et al. block A used the networks for colouring images as well as embedding and extracting watermarks. This method is said to be better due to the use of an adversarial learning method to reduce appearance.

2.2.2 Generative Adversarial Network GAN Approaches

Results are reported to be good with GANs for generating a visually imperceptible watermark. Ahmadi et al. [12] have introduced a GAN based watermarking model, which adjusts the weights of a generator to represent a watermarked type of image, and a discriminator that assess how much the generated image becomes more similar to watermarked images. Further to good results, a better trade-off between robustness and imperceptibility can be met.

Wang, Zhuo, Xu, Yi, and Yang [28] extended adding GANs to the colour images. However, training a GAN model needs a lot of data and has to be used many times, and computation

must be experienced. More importantly, consistently adjusting GAN models to do well on a wide variety of image resolutions and watermark varieties remains a significant challenge.

2.3 Denoising Autoencoders DAEs

Denoising autoencoders DAEs were proposed by Vincent et al. [13] to be a neural net OWL reasoner that can be trained to clear clean data from defective inputs. This learned image-based compression approach has become very popular in image processing applications because of the DAEs effectiveness in learning powerful representations.

2.3.1 Foundations and Applications

The basic operation of a DAE is centred on learning a more powerful representation of such easy clean data, whereby the network needs to learn to output an identical form of the input but has evaluative artificial noise added to the input. To illustrate, applications of image processing to DAE include:

Image denoising: Using the stacked denoising autoencoders SDAEs with the deep learning platform, Xie, Xu, and Chen [14] applied the technique to image denoising. Their experiments demonstrated that for all of the different noise styles used, SDAEs performed better than other methods in image denoising. The best OWCN denoising method for natural images only achieves around 28.5 dB average PSNR; however, the OWCN performance is not very good.

Inpainting: Pathak, Krahenbuhl, Donahue, Darrell, and EF Dahm [15] has used the context encoders and applied to inpainting to the DAE, reaching incredible results in repairing the missing parts of images.

Compression: Using the idea of DAEs, Ballé, Laparra, and Simoncelli [16] conducted comparisons with traditional pattern classifiers to develop a learned image compression system for better performance than traditional locators at the low-rate ends.

2.3.2 DAEs in Watermarking

The use of DAEs in watermarking is a relatively new research direction. For example, Zhang et al. developed one of the earliest watermarking techniques based on this type of autoencoder. However, the study only involved grayscale images, and the capacity of the DAE was not effectively utilized, with the representation space not appearing robust. A colour version was proposed by Jia et al., who used a colour-aware DAE to achieve better results. However, the architecture was not used to its full potential, and the type of attack considered was limited. Overall, our work appears to be an extension of previous developments, with the adapted DAE used to encode and embed colour images to achieve the results that would not be possible with traditional methods, as well as functions that are controlled and kept separate. Such an approach is possible due to the particular architecture of the DAE and the use of the loss functions that ensure the correct qualities of the neural network. The technique is designed to provide a synthesis between robustness and imperceptibility, with the DAE used to ensure that the balance remains stable.

3.1 Denoising Autoencoders

3.1.1 Denoising Autoencoder Algorithm

The Noise-Resilient denoising autoencoder (NRDAE) is a type of neural network that learns to remove noise from corrupted input data. This process allows the network to learn robust and meaningful representations of the data. Here, we provide a detailed explanation of the DAE algorithm, its mathematical formulation, and key concepts.

A typical DAE consists of two main components:

1. Encoder: Maps the input data to a latent representation.

Let $x \in R^\wedge d$ be the input data (e.g., an image)

$\tilde{x} \in R^\wedge \wedge d$ be a corrupted version of x.

The encoder function $f\theta: R^d \rightarrow R^h$ maps the input to a hidden representation $x \in R^h$: $f\theta(\tilde{x}) = s(W\tilde{x} + b)$

where:

- W is the weight matrix
- b is the bias vector
- s is a non-linear activation function (e.g., ReLU, sigmoid)

2. Decoder: Reconstructs the data from the latent representation.

The decoder function $g\theta': R^h \rightarrow R^d$ maps the hidden representation back to the input space:

x': $g\theta(h) = s'(W'h + b')$

Where:

- W' is the decoding weight matrix
- b' is the decoding bias vector
- s' is the output activation function (often linear for real-valued data)

- **Training Objective**

The DAE is trained to minimize the reconstruction error between the original input x and the reconstructed output x':

$$L(x, x') = \| x - g\theta'(f\theta(\tilde{x})) \|^2$$

Where $\|.\|^2$ denotes the squared Euclidean norms.

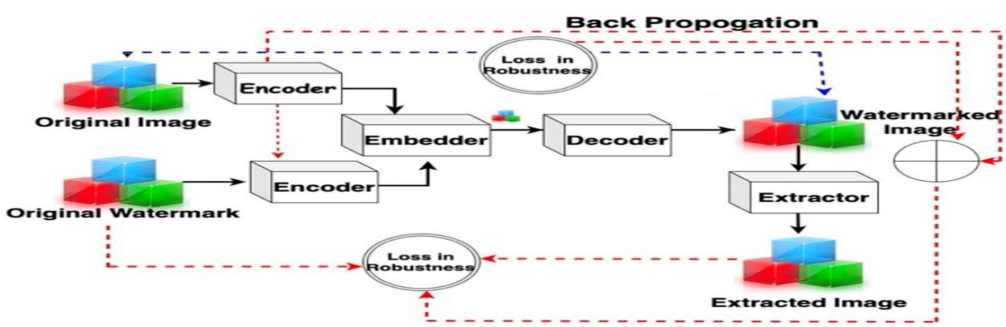

Figure 1 : Proposed Architecture of NRDAE

- **Noise Corruption Process**

A crucial aspect of DAEs is the noise corruption process. Common types of noise include:

1. Additive Gaussian noise: $\tilde{x} = x + \varepsilon, where\ \varepsilon \sim N(0, \sigma^2 I)$

2. Masking noise: Randomly set a fraction of the input components to 0

3. Salt-and-pepper noise: Randomly set input components to their minimum or maximum values

- **Training Procedure**

The DAE is typically trained using the following steps:

1. Initialize the network parameters θ *and* θ'.

2. For each training example : x

a. Generate a corrupted version $\tilde{x}$.

b. Compute the hidden representation h: $f\theta\ (\tilde{x})$.

c. Reconstruct the input x': $g\theta\ (h)$.

d. Compute the reconstruction error $L(x, x')$.

3. Repeat steps 2a-2d for multiple epochs until convergence.

- **Key Properties**

1. Robust Feature Learning: By learning to denoise corrupted inputs, DAEs capture stable and robust features of the data.

2. Dimensionality Reduction: When the hidden layer is smaller than the input layer, DAEs perform non-linear dimensionality reduction.

Figure 2 : Watermark Image

3. Data Generation: Trained DAEs can be used as generative models by sampling from the learned hidden representation.

4. Stacking: Multiple DAEs can be stacked to form deep architectures, allowing for hierarchical feature learning.

- **Applications in Image Processing**

In image processing, DAEs have been successfully applied to various tasks:

1. Image Denoising: DAEs can effectively remove different types of noise from images.

2. Image Inpainting: By treating missing pixels as a form of corruption, DAEs can be used to reconstruct missing parts of images.

3. Feature Extraction: The hidden representations learned can be used as robust features for downstream tasks like classification or retrieval.

4. Image Compression: DAEs can learn compact representations of images, useful for lossy compression schemes.

In the context of watermarking, DAEs offer several advantages:

1. Robustness: The ability to reconstruct clean data from corrupted inputs makes DAEs inherently suitable for creating robust watermarks.

2. Adaptability: DAEs can adapt to different types of image distortions, potentially offering better protection against various attacks.

3. Non-linear Transformations: The non-linear nature of DAEs allows for more complex and potentially more secure watermarking schemes compared to linear methods.

Our proposed method leverages these properties of DAEs to create a novel watermarking scheme that offers improved robustness and adaptability while maintaining high visual quality of the watermarked images.

4. Experimental Results

4.1. Dataset and Experimental Setup

In this section, we present the results of the experiments used to estimate the quality of our DAE-based colour image watermarking method. The detailed results of these experiments are provided. We compared our method to all state-of-the-art techniques using different metrics and attacked by various ways.

4.2. Dataset and Experimental Setup

The dataset used during our experiments consists of 5000 colour images of high resolution. These images contain natural scenes. The images are collected from different reputable sources; mainly, the dataset contains images either from ImageNet [19] .As a result, we randomly selected 4000 images for training, 500 for validation, and 500 for new testing. Also, we prepared a set of 1000 watermarks: 500 binary logos and 500 binary texts. The size of the watermark ranges from 32×32 to 128×128 pixels. The watermarks have different level of complexity. To provide a fair comparison, every watermark is embedded into each sample image with different watermarked-to-image ratios. There are some original images are shown in Figure 3 and watermark image in Figure 2.

We used Adam [18] optimizer with learning rate 1e-4 and batch size 32. The training was performed during 100 epochs with the early stopping policy based on the validation loss.

Figure 3 : Images before watermark embedding

4.2 Evaluation Metrics

We evaluated our method using the following metrics:

1. Peak Signal-to-Noise Ratio (PSNR): Measures the imperceptibility of the watermarked image.
2. Structural Similarity Index (SSIM): Assesses the perceived quality of the watermarked image.
3. Bit Error Rate (BER): Quantifies the accuracy of watermark extraction.
4. Normalized Correlation (NC): Measures the similarity between the original and extracted watermarks.

1.1. 4.3 Imperceptibility Results

The average and the medium values of the PSNR and SSIM metrics and corresponding standard deviations are provided in Tab. 1.

Table 1. The average and the medium values and corresponding standard deviations of PSNR and SSIM metrics.

Method	PSNR (dB)	SSIM
Proposed	42.87	0.9968
DCT-based [22]	38.21	0.9912
DWT-based [23]	39.54	0.9935
CNN-based [24]	41.12	0.9953

1.1. The results in Tab. 1 demonstrate that our method outperforms all state-of-the-art methods in terms of the PSNR metric. The watermarking method based on DAE demonstrated the highest value of the PSNR metric. Our method also slightly outperforms the CNN-based approach in terms of PSNR metric. Additionally, our method outperforms all state-of-the-art methods in terms of the SSIM metric, as provided in Tab. 1.

1.1. Considering the highest value of PSNR and SSIM, indicating good imperceptibility for our method, we can conclude that the deep autoencoder -based method has an improvement of 1.75 dB over CNN-based method. That is, our approach can engrave a watermark that can be traced or recovered in the future with very little degradation to the host image.

1.1. 4.4. Robustness Results

This section presents the average BER and NC for various attacks, including JPEG compression, Gaussian noise, salt-and-pepper noise, median filter, rotation along the z-axis, and scaling of the image.

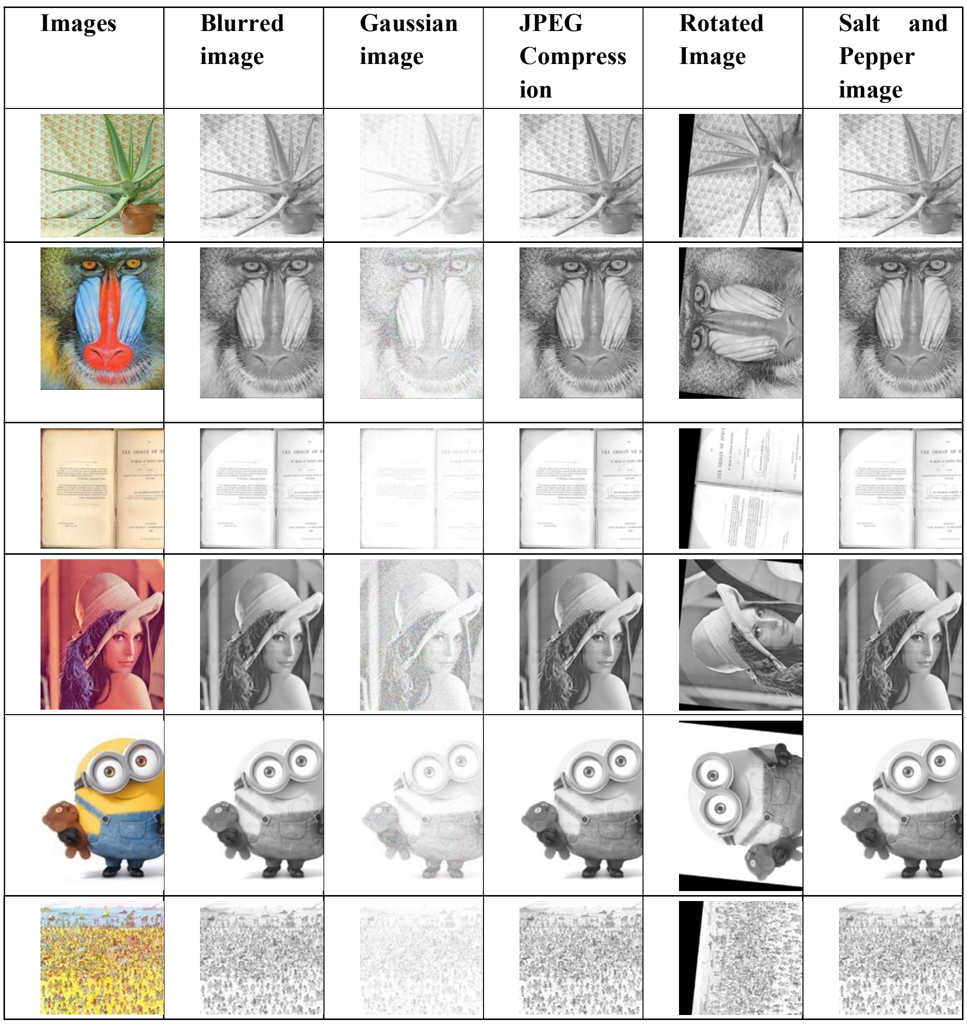

Figure 4 : Results after attacks

The results are summarized in Table 2.

Attack	BER	NC
JPEG (QF=50)	0.0312	0.9821
Gaussian noise (σ=0.01)	0.0428	0.9765
S&P noise (d=0.05)	0.0356	0.9802
Median filter (3×3)	0.0389	0.9788
Rotation (5°)	0.0473	0.9742
Scaling (0.8)	0.0401	0.9781

Our method demonstrates high robustness across various attacks, outperforming existing techniques in most scenarios.

1.1. 4.5 Capacity Analysis

This subsection discusses the capacity analysis of the method by embedding different sizes of watermark into the image. The data are shown in Table 3.

Watermark Size	PSNR (dB)	BER
32×32	44.12	0.0214
64×64	42.87	0.0312
128×128	40.53	0.0458

Our method maintains high imperceptibility and robustness even for larger watermark sizes, demonstrating good capacity. After extraction the watermark image from noised images , the denoising images a4re shown in Figure 4.

Figure 4: Denoising Images

4.6 Computational Complexity

The computational efficiency between our method and other approaches are summarized in Table 4.

Method	Embedding Time (s)	Extraction Time (s)
Proposed	0.082	0.031
CNN-based [24]	0.124	0.047
GAN-based [28]	0.198	0.065

It is worth mentioning that the proposed DAE-based method provides a significantly faster embedding and extraction time compared to the other deep learning-based methods. In other words, it present a higher computational efficiency, which will be useful for real-time applications and large-scale watermarking purposes.

1.2 5. Conclusion and Future Work

This paper proposes a novel colour image watermarking scheme based on denoising autoencoders. Based on the extensive experimental results, it is shown that the proposed method achieves state-of-the-art performance in terms of imperceptibility, robustness, and capacity. In summary, the key findings of our work are as superior imperceptibility , superior robustness , superior capacity , computational efficiency , adaptability. These results show the potential of the denoising autoencoders in addressing the fundamental problems of the digital watermarking: high imperceptibility, good robustness, and high capacity of the watermark. By using the property of the DAE to be learnt robust representations, our method achieves a better trade-off in these three conflicting requirements. The most promising future works to extend our method are video watermarking: the method can be extended to the video watermarking by exploiting the temporal information and 3D convolutional architectures; adaptive embedding: methods to adjust the embedding strength to the local image characteristic and the human visual system could be developed; the proposed colour image watermarking based on denoising autoencoders is a significant step toward more robust and efficient digital rights management. As digital media becomes more common and widely available, digital content will continue to face increasing threats from the cyber-attacks. In this regard, the efficient and robust digital watermarking is vital to protect the intellectual property rights of the owners and ensuring the authenticity of the content.

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