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Common Gabor Features for Image Watermarking Identification

Ismail Taha Ahmed [1], Baraa Tareq Hammad [1] and Norziana Jamil [2,*]

1 College of Computer Sciences and Information Technology, University of Anbar, Anbar 55431, Iraq; ismail.taha@uoanbar.edu.iq (I.T.A.); baraa.tareq@uoanbar.edu.iq (B.T.H.)
2 College of Computing and Informatics, University Tenaga Nasional, Kajang 43000, Selangor, Malaysia
* Correspondence: Norziana@uniten.edu.my

Abstract: Image watermarking is one of many methods for preventing unauthorized alterations to digital images. The major goal of the research is to find and identify photos that include a watermark, regardless of the method used to add the watermark or the shape of the watermark. As a result, this study advocated using the best Gabor features and classifiers to improve the accuracy of image watermarking identification. As classifiers, discriminant analysis (DA) and random forests are used. The DA and random forest use mean squared energy feature, mean amplitude feature, and combined feature vector as inputs for classification. The performance of the classifiers is evaluated using a variety of feature sets, and the best results are achieved. In order to assess the performance of the proposed method, we use a public database. VOC2008 is a public database that we use. The findings reveal that our proposed method's DA classifier with integrated features had the greatest TPR of 93.71 and the lowest FNR of 6.29. This shows that the performance outcomes of the proposed approach are consistent. The proposed method has the advantages of being able to find images with the watermark in any database and not requiring a specific type or algorithm for embedding the watermark.

Keywords: watermarking identification; Gabor feature; discriminant analysis (DA) classifier; Random_forest classifier

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1. Introduction

Digital photos on electronic websites are easy to manipulate, modify, edit, and distribute. This occurs as a result of advancements in multimedia technology. Therefore, there are two critical factors to consider: image security and privacy. Digital watermarking is a fascinating data concealment technology that is used to secure multimedia files.

The fundamental goal of digital watermarking is to embed or hide specific unseen extra details (watermark) in another signal, such as an image, audio, or video [1,2], which is referred to as a host or cover. The visual quality of the embedded host signal should not be decreased greatly. The two fundamental operations in a watermarking system are embedding and extracting. Figure 1 depicts the embedding and extraction procedure. As demonstrated in Figure 2, the strategies were used to integrate the Hat image within the Lena image.

Across various multimedia and domain kinds, Figure 3 displays a generic taxonomy of digital watermarking techniques.

Watermarking is divided into two categories, visible and invisible watermarking, according to human perception. The phrase "visible watermarking" refers to the addition of a watermark to multimedia that is visible to all viewers. The TV channel log and the brands log are two examples while the second type is a distinctive type that hides the watermark in the multimedia in order to verify purity and possession. Copyright is an example of this [3,4].

Watermarking techniques can be classed as watermarking based spatial, watermarking based transform, and watermarking based hybrid domain, according to domain. In spatial domain, the technique adds invisible watermark data into pixel values of the host image. These techniques are significantly simpler, more efficient, and faster to implement [3]. Incorporating a watermark in the host image's least significant bits (LSBs) [5] is the simplest spatial domain image watermarking technique. Image watermarking can also be accomplished with a variety of approaches, such as intermediate significant bits (ISB) [6] or patchwork algorithms, as well as spread spectrum and correlation-based algorithms. The approach in [7] presents spatial image watermarking based on the widely used LSB substation technique. The LSB approach is the most well-known for watermarking based spatial domains. However, it is insufficiently robust to safeguard watermark data from many types of attacks. As a result, significant bit (ISB) methods have been created to increase the watermarking system's robustness and maintain its quality.

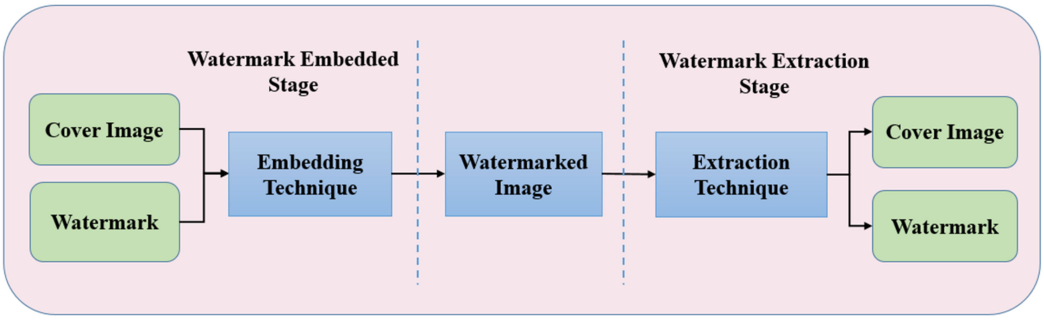

Figure 1. The general process of embedding and extraction operation.

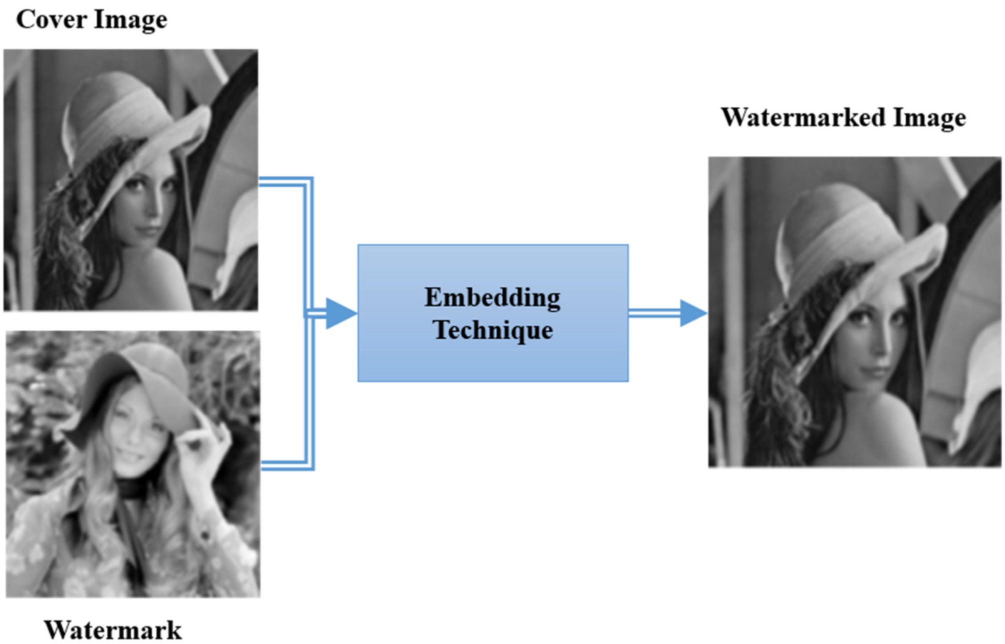

Figure 2. The Structure of watermarking.

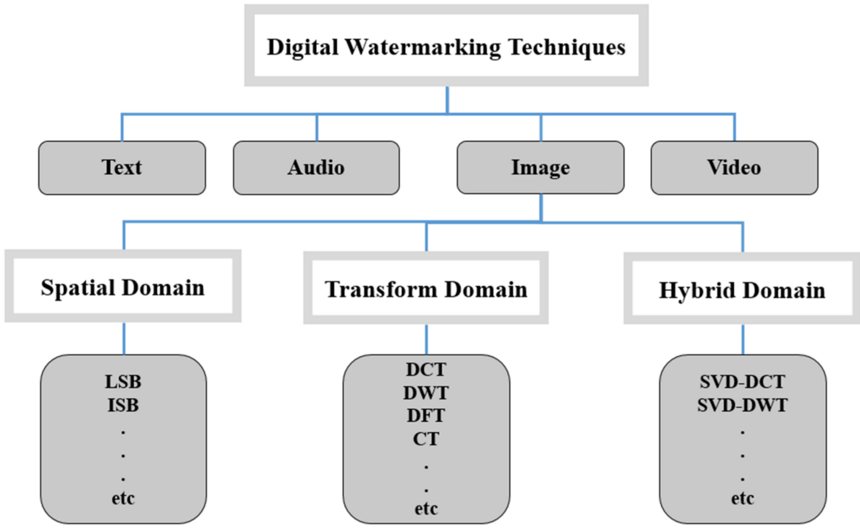

Figure 3. Watermarking techniques classification.

In the transform domain, the method begins by converting and representing the original image in the frequency domain using a forward transform. The watermark should then be inserted into the transform domain coefficients. The techniques used in the hybrid domain are usually a mixture of spatial and transform-domain techniques. Liu et al. [8] proposed a watermarking based on DCT and fractal encoding. They have good PSNR and improve security. Vaishnavia et al. [9] presented a singular value decomposition (SVD)-based watermarking. They maintain image quality but are not resistant to rotation and scaling. Roy et al. [10] proposed watermarking based on DCT and repetition code. They have a better PSNR rating. Wang et al. [11] proposed a watermarking based on DWT and Haar wavelet. They are resistant to lossy compression as well as Gaussian noise. Singh et al. [12], presented a watermarking based on the DCT domain to overcome the false positive detection problem. Vishwakarma et al. [13] presented a watermarking based on the DCT transform, a differential evolution and kernel extreme learning machine (DE-KELM). However, the watermarked image quality is unaffected. Poljicak et al. [14] presented a simple watermarking based on the DFT-based with an optimal implementation radius. The watermarked image's quality degradation was demonstrated to be modest. Cedillo-Hernandez et al. [15] introduced a simple watermarking system for maintaining medical photographs based on the DFT domain, which achieved good robustness and image quality. Hemdan et al. [16] proposed a hybrid watermarking technique based on DWT-SVD. Sridhar 109 proposed watermarking based on a combination of DCT, DWT, and SVD to improve robustness and invisibility. Savakar et al. [17], proposed watermarking based on the combination of DWT and SVD to improve robustness and invisibility. Hu et al. [18] proposed the watermarking technique based on combination of the DWT and DCT to improve robustness and invisibility. Assini et al. [19] proposed watermarking based on the combination of DWT, DCT, and SVD to improve robustness and invisibility. Zhou et al. [20] presented a robust image watermarking technique based on DWT, APDCBT, and SVD. They produce higher-quality images. Wang et al. [21] presented an adaptive image watermarking technique based on a combination of singular value decomposition (SVD) and the Wang–Landau (WL). It has been demonstrated that this approach achieves a balance of resilience and invisibility.

As previously stated, the findings are promising, but there are several drawbacks, including (1) high computational costs of embedding and extracting the watermark, (2) few methods designed for watermark identification, (3) low TPR, and (4) high FNR. As a result of these drawbacks, we focus our efforts on efficient features that have the least amount of complexity while also assisting the classifier perform better. Gabor features are one of these beneficial characteristics. The Gabor can be used to define texture abnormality. Because of its spatial selectivity and orientation, the 2D Gabor filter with multi-orientation and multiscale is used to extract texture information of the host image [22]. Therefore, this research proposed to increase the accuracy image watermarking classification using the best Gabor features. Discriminant analysis (DA) and random forests are used as classifiers. The remainder of this paper is organized as follows. The Gabor features are discussed in Section 2. The suggested methods are described in Section 3. Observations and analyses are discussed in Section 4. Finally, in Section 5, conclusions can be drawn.

2. Gabor Features

Daugman [23] developed Gabor filtering for image textural analysis. Because of their spatial localization, orientation selectivity, and frequency characteristic, Gabor filters have been frequently employed in a variety of image analysis and classification applications [22]. They are complicated band-limited filters that have optimal localization in both the spatial and frequency domains. In the spatial domain, the family of 2D Gabor filters can be formulated (1) as having:

$$\begin{gathered} G_{\theta,f,\sigma 1,\sigma 2}(x,y) = exp\left[\frac{-1}{2}\left(\frac{x'^2}{\sigma_1^2}+\frac{y'^2}{\sigma_2^2}\right)\right]\ \cos(2\pi f x' + \varphi) \\ x' = x\ \sin\theta + y\ \cos\theta \\ y' = x\ \cos\theta + y\ \sin\theta \end{gathered} \tag{1}$$

where:

f = the spatial frequency of the wave at an angle θ with the x axis;
$\sigma 1$ and $\sigma 2$ = the standard deviations of the 2D Gaussian envelope;
φ = the phase.

The textural abnormality in an image is caused by inserting any watermark into a host image. Therefore, the texture analysis may be able to quickly detect these watermarks. Gabor filters have been frequently employed in a variety of image analyses and classification applications. Therefore, Gabor filtering plays a unique role in the image watermarking classification by detecting textural abnormalities within the host image that are harder to identify with the human eye. Across various orientations and scales, two common Gabor features [24,25], namely mean squared energy and mean amplitude, are extracted.

To further understand the Gabor, we applied the Gabor filter to the image in Figure 4 and extracted certain features.

Figure 4. An Image example.

In order to compute Gabor features at varied scales and orientations, Figure 5 displays the 2D Gabor filters with varied eight orientations and five scale [26].

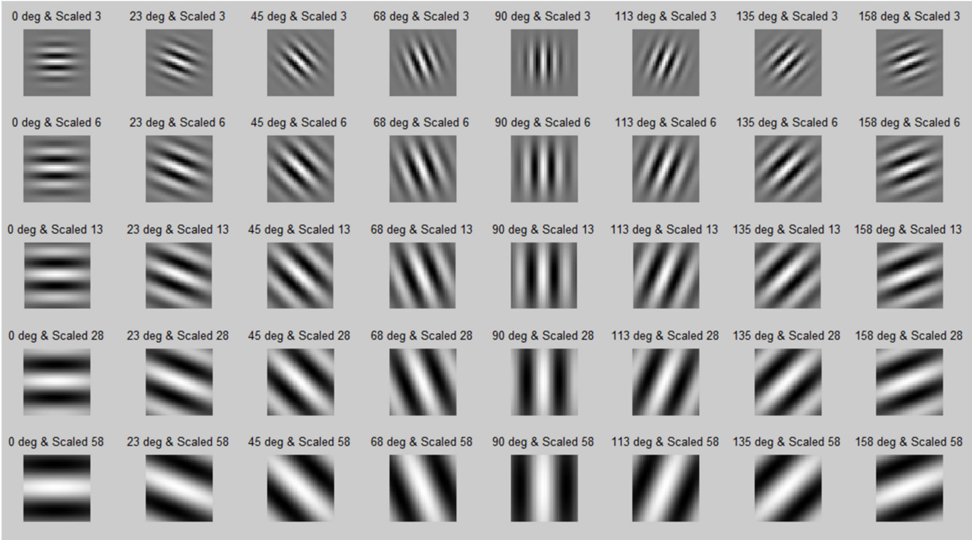

Figure 5. A two-dimensional Gabor filter with eight orientations and five scale [26].

Then, as illustrated in Figure 6, we convolved each filter with the image to generate 40 ($8 \times 5 = 40$) alternative representations (response matrices) of the same image.

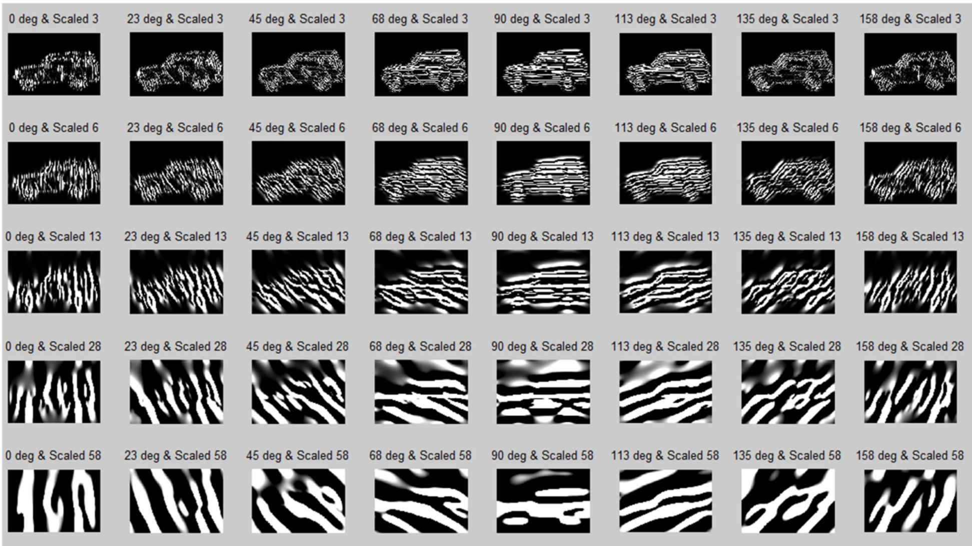

Figure 6. The convolution operation of a Gabor filter with an image.

Finally, mean squared energy and mean amplitude are extracted as feature vectors from those response matrices in order to obtain feature vector [27]. The squared value of each matrix value in a response matrix was summed together to calculate mean squared energy. The sum of absolute values of each matrix value in a response matrix was used to calculate the mean amplitude. [27] is recommended to read to learn more about Gabor features.

3. The Proposed Methods

Figure 7 shows the three main steps in the proposed method: pre-processing, feature extraction, and watermarking identification. The proposed technique steps are depicted in detail below.

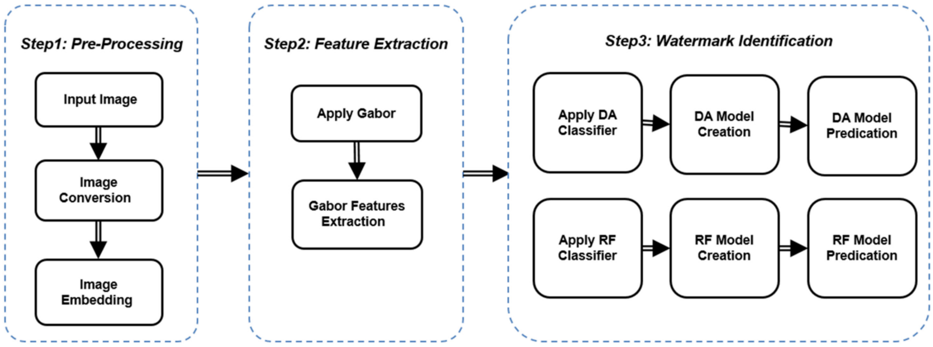

Figure 7. Proposed method Flowchart.

Step 1: Preprocessing

Here, for all images in the VOC2008 Database, three preprocessing operations were performed: (1) input the image, (2) image conversion, and (3) image embedding.

Step 1.1: Input Image First, the image can be entered by using Matlab function I = Imread (image).

Step 1.2: Image Conversion

To reduce overall computing complexity, convert the RGB image to gray scale image (I′) using Matlab function (rgb2gray (I)) [28].

Step 1.3: Image Embedding

For each gray scale image (I′), we generated the watermarked image using uMark (https://www.uconomix.com/Products/uMark/Default.aspx, accessed on 27 August 2021). uMark is a free utility for embedding a watermark into an image that is accessible for both Windows and Mac systems. The benefit of this software is that it allows for batch watermarking, which allows for the processing of 100 photos at once. In the generating procedure, the randomization was the randomization factor was considered.

Step 2: Feature Extraction

One of Gabor's advantages is that it reduces computing time. The Gabor filter's scale and orientation have a significant impact on classification accuracy. Mean squared energy and mean amplitude are derived throughout sale 3 and orientation 2 in our experiments. A gray-scale image's Gabor features are computed using the function "PHASESYM".

Step 2.1: Apply Gabor

As previously stated, apply 2D Gabor filters to each watermarked gray scale image I′ of size M $\times$ N pixels using formula (1). The following are the Gabor filter bank parameters: nscales = 3, norientions = 2. Then, convolve each filter gu,v (x, y) with the image I′ to generate the set of (3 $\times$ 2 = 6) alternate representations of each image (response matrices).

Step 2.2: Gabor Features Extraction

Finally, mean squared energy and mean amplitude are extracted as feature vectors from those response matrices in order to obtain feature vector. The squared value of each matrix value in a response matrix is summed together to calculate mean squared energy. The sum of absolute values of each matrix value in a response matrix is being used to calculate the mean amplitude. The dimension of obtained mean squared energy feature vector is 1 $\times$ 6. The dimension of obtained mean amplitude feature vector is 1 $\times$ 6. The dimension of obtained combined features vector is 1 $\times$ 12.

Step 3: Watermark Identification

Identification of image watermarking is a two-class problem, including host and watermark classes. As a result, we must figure out how to classify such images. Discriminant analysis (DA) and random forest are used to classify images.

Step 3.1: Apply DA Classifier

The DA classifier was chosen as the first classifier for this research, and it is usually a decent first choice for developing classifiers. In many applications, discriminant analysis (DA) [29,30] is one of the most used methodologies for classification. It is assumed that data is produced using distinct Gaussian distributions for various classes. DA creates a group membership prediction model. In order to produce optimum discrimination, the model discriminant function based on linear combinations of the predictor variables. The feature vectors are divided into two portions (training and testing data sets) that will be utilized to develop and train the DA model as well as the test and evaluate the final DA model.

Step 3.1.1: DA Model Creation

To build a model, mean squared energy, mean amplitude, and combined feature vectors are used as training data. Then, the DA model trained on the training set.

Step 3.1.2: DA Model Prediction

Test the trained DA model to determine whether the image is host or watermarked.

Step 3.2: Apply Random_forest Classifier

LeoBreiman proposed random forest (RF) in 2001 [31], which is a decision tree-based machine learning technique. By creating a large number of decision trees for each tree prediction, RF plays an important role in regression, classification, and other tasks. RF outperforms the traditional machine learning approaches such as artificial neural networks and support vector machines in terms of efficiency [32]. It outperforms single decision trees in terms of performance. The feature vectors are divided into two portions (training and testing data sets) that will be utilized to develop and train the Random_forest model as well as the test and evaluate the final Random_forest model.

Step 3.2.1: Random_forest Model Creation

To build a model, mean squared energy, mean amplitude, and combined feature vectors are used as training data. Then, the Random_forest model trained on the training

Step 3.2.2: Random_forest Model Prediction

Test the trained Random_forest model to determine whether the image is host or watermarked.

4. Results and Discussion

This section focuses on assessing the proposed method. The VOC2008 dataset is described first. The performance metrics are then addressed briefly. The experimental results are then analyzed, and the proposed approach is then compared to other methods. The proposed technique is developed in MATLAB version R2020a on an HP laptop with an Intel Core i7 processor operating at 2.60 GHz and 8 GB of RAM running Microsoft Windows 10 64-bit (OS).

4.1. Dataset

Finding and creating a data set of images with and without watermarks is critical for proposing an effective watermark detection method. Several experiments were performed using a public database named Visual Object Classes 2008 challenge MOC2008 [33] to evaluate the performance of the proposed technique. This database has a significant aspect in that it is diversified in terms of including images of people, sceneries, animals, and items, which makes it ideal for detecting watermarks. Figure 8 shows a number of samples from the database.

For each image in VOC 2008 data set [33], we generated watermarked image using uMark (https://www.uconomix.com/Products/uMark/Default.aspx, 21 July 2021). The reason for this is that the database lacked watermarked images. uMark is a free utility for embedding a watermark into an image that is accessible for both Windows and Mac systems. The benefit of this software is that it allows for batch watermarking, which allows for the processing of 100 photos simultaneously. In the generating procedure, the randomization factor was considered. Figure 9 shows the original and watermarked images samples. Images containing watermarks were given a target of "1," while those without were given a target of "0" in order to construct the ground truth labels. The detection method will return a value between 0 and 1, indicating that it either contains a watermark or not. To avoid the model from merely learning whether images had and did not have watermarks, the original images and their matching images with watermarks were both used in the training data set. There was a total of 10,192 images (5096 host and watermarked).

Figure 8. Image Samples of the VOC2008 Database [33].

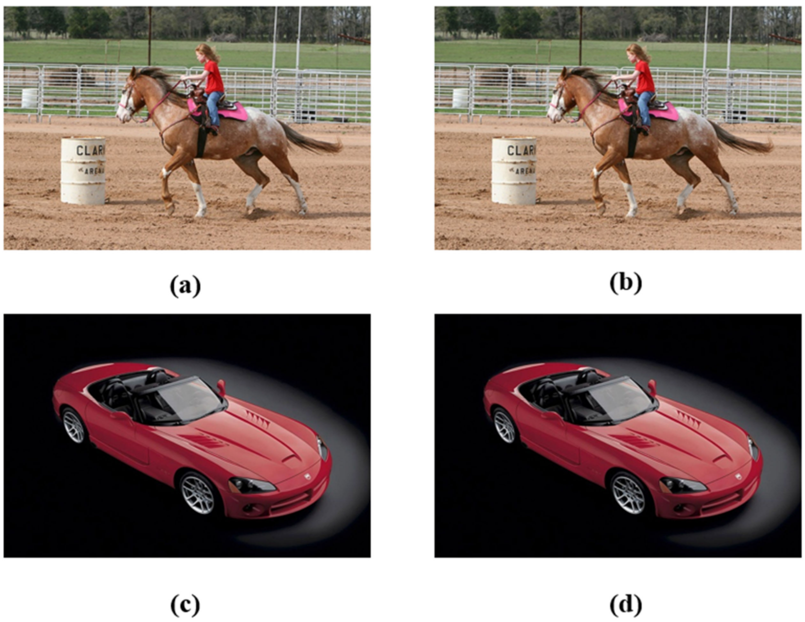

Figure 9. The first row: (**a**) original image; (**b**) watermarked image; Second Row: (**c**) original image; (**d**) watermarked image.

4.2. Performance Measures

Two metrics are utilized to assess the robustness of our proposal: (1) true-positive rate (TPR), and (2) false-negative Rate (FNR) [34]. Equation (2) calculates true positive (TP), which reflects correctly identified embedded watermarks. Equation (3) calculates the false-negative rate (FNR), which indicates watermarks that were identified while they were not truly embedded.

$$TPR = \frac{(TP\ detected)}{(Total\ of\ Detections)} \times 100\% \tag{2}$$

$$FNR = 1 - TPR \tag{3}$$

4.3. Evaluation Results

Because different classifiers have differing classification performance, we employ the discriminant analysis (DA) and random forests classifiers to classify distinct Gabor features vectors such as mean squared energy, mean amplitude, and combined feature. In order to obtain accurate findings, we used 10-fold cross-validation. Table 1 shows the outcomes of the proposed evaluation measures (TPR and FNR) over the VOC2008 database.

Table 1. The Results of TPR and FNR of two classifiers across the VOC2008 Database.

Classifiers	Mean Squared Energy Feature		Mean Amplitude Feature		Combined Feature	
	TPR (%)	FNR (%)	TPR (%)	FNR (%)	TPR (%)	FNR (%)
Discriminant analysis (DA)	82.15	17.85	88.54	11.46	**93.71**	**6.29**
Random_forest (RF)	78.82	21.18	82.92	17.08	86.35	13.65

Despite that all classifiers use the same feature vector, they yield different outputs. This is due to each classifier having its own set of characteristics. Figures 10 and 11 depict the visual impact of various feature types on various classifiers.

The TPR value for DA classifier fluctuates between mean squared energy, mean amplitude, and combined feature, with values of 82.15, 88.54, and 93.71, respectively. The TPR value for Random_forest classifier fluctuates between mean squared energy, mean amplitude, and combined feature, with values of 78.82, 82.92, and 86.35, respectively. The TPR for both classifiers increased significantly, showing significant variations in those three features.

The FNR value for DA classifier fluctuates between mean squared energy, mean amplitude, and combined feature, with values of 17.85, 11.46, and 6.29, respectively. The FNR value for Random_forest classifier fluctuates between mean squared energy, mean amplitude, and combined feature, with values of 21.18, 17.08, and 13.65, respectively. For both classifiers, the FNR declined considerably, indicating significant differences in those three features.

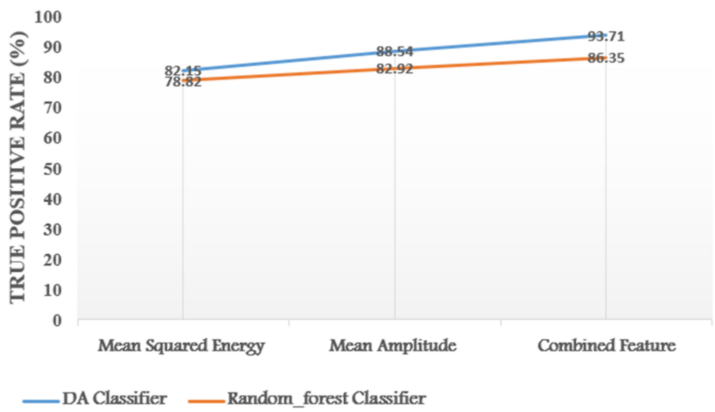

Figure 10. Effect of Feature kind on TPR values for different classifiers.

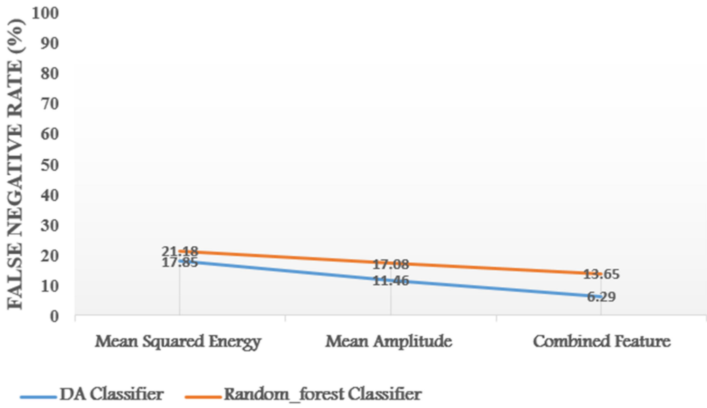

Figure 11. Effect of Feature kind on FNR values for different classifiers.

The proposal attained a highest TPR of 93.71 and a lowest FNR of 6.29 when the feature combination of mean squared energy and mean amplitude feature was applied. As a result, it is natural to conclude that the DA classifier outperforms the random forest classifier in all three features vectors. According to the results, the DA classifier with combined features is the best of our proposed method. This demonstrates that the performance outcomes of the proposed approach are relatively stable.

4.4. Performance Comparison of Methods

As illustrated in Table 2, the proposed method is compared to other state-of-the-art image watermarking approaches [35–38]. The spatial domain is used in both [37,38] watermarking detection methods. The techniques [37,38] are based on singular value (SV) decomposition and shell based pixel selection, respectively. The transform domain is used in both [35,36] watermarking detection methods. The techniques [35,36] are based on discrete wavelet transform (DWT) and discrete shearlet transform (DST), respectively. The present approaches in [35,36] have the maximum accuracy. However, as seen in Table 2, they have the disadvantage of being time intensive. The fundamental reason is that the transform domain is being used. Our proposed outperforms other spatial based watermarking methods [37,38]. Figures 12 and 13 show how the proposed method, which does not use the transform domain, outperforms other current methods in terms of TPR and FNR rates. In comparison to both of other current spatial and transform domain techniques, the proposed method had a maximum TPR of roughly 93.71 percent and a minimum FNR of around 6.29 percent.

Table 2. Performance comparison with previous methods.

Methods	Features Type	DB/Image No	Perception	Domain	Robust Methodology		Evaluation Metrics	
					Embedded	Extraction/ Detection	TPR (%)	FNR (%)
Mathur et al. [38]	shell based pixel	Their images:20 images	Invisible	spatial	Yes	Yes	73.5	36.93
Ghazy et al. [37]	SVD	Cameraman image	Invisible	spatial	Yes	Yes	85.43	14.57
Elbasi et al. [35]	DWT	3 images	Invisible	Transform	Yes	Yes	92.93	7.07
Ahmaderaghi et al. [36]	DST	Their images:30	Invisible	Transform	Yes	Yes	93.53	22.49
Ours	Gabor	VOC 2008: 5096 images	Invisible	Spatial	Yes	Yes	93.71	6.29

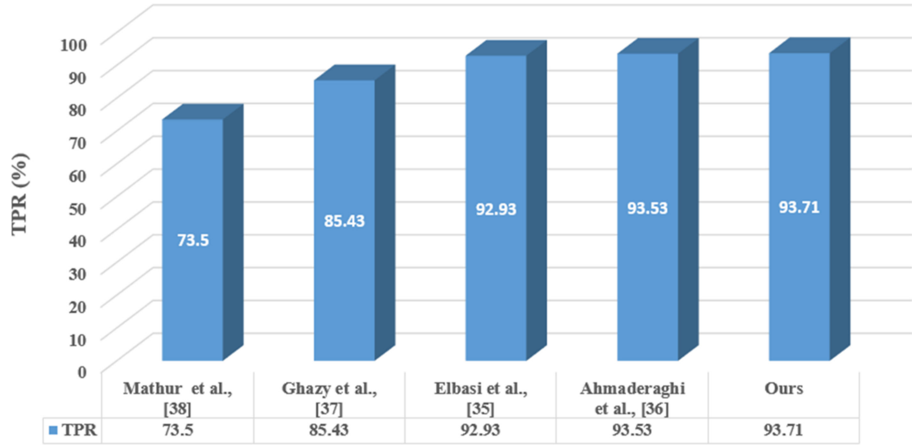

Figure 12. TPR results of different methods comparison.

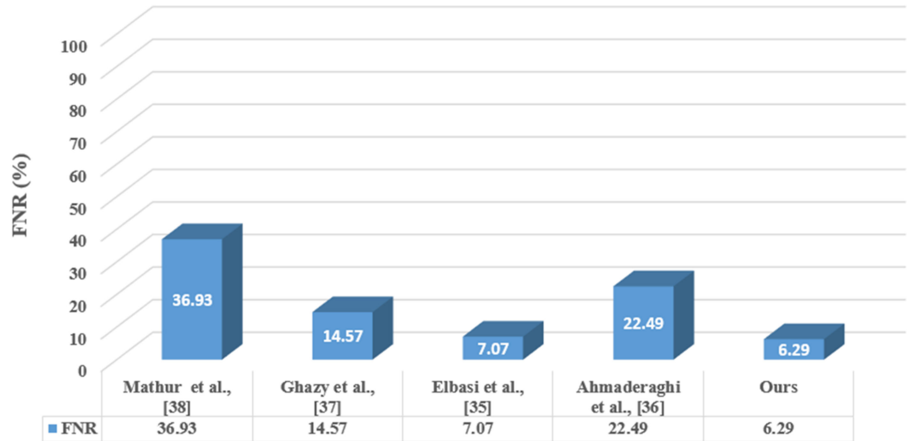

Figure 13. FNR results of different methods comparison.

5. Conclusions

The majority of existing approaches have the following drawbacks: (1) high computational costs of embedding and extracting the watermark, (2) few watermark identification methods, (3) low TPR, and (4) high FNR. As a result, we proposed image watermarking identification using one of the Gabor features, such as mean squared energy feature, mean amplitude feature, or combined features, in this paper. As classifiers, discriminant analysis (DA) and random forests are used. When mean squared energy and mean amplitude feature were combined, the proposal had the greatest TPR of 93.71 and the lowest FNR of 6.29. As a consequence, in all three feature vectors, the DA classifier outperforms the random forest classifier. According to the results, our suggested method's DA classifier with combined features is the best. This demonstrates that the performance outcomes of the proposed approach are generally stable. In the future, one challenge will be to improve the TPR and FNR outcomes by searching for a more effective feature extraction approach in another domain, as well as looking for a more effective classifier, such as deep learning.

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