Robust Feature Based Image Watermarking Process

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ABSTRACT
A digital image watermarking scheme must be robust against a variety of possible attacks. In the proposed approach, a new rotation and scaling invariant image watermarking scheme is proposed based on rotation invariant feature and image normalization. The rotation invariant features are extracted from the segmented areas and are selected as reference points. Sub-regions centered at the feature points are used for watermark embedding and extraction. Image normalization is applied to the sub-regions to achieve scaling invariance. In the scheme, first, the image is segmented into a number of homogeneous regions and the feature points are extracted. Then the circular regions for watermark embedding or extraction are defined. Based on the image normalization and orientation assignment, the rotation, scaling, and translation invariant regions can be used for watermark embedding and extraction. The segmented image is modeled as mixture generalized Gaussian distribution and this model is the basis of mathematical analysis of various aspects of the watermarking processes such as probability of error, embedding strength adjustment. The watermark embedding strength is adjusted adaptively using the noise visibility function.The original image is not needed for the watermark detection. The effectiveness and accuracy of the proposed scheme is established through experimental results.

Keywords
Image normalization, watermarking, Noise visibility function, segmentation

1. INTRODUCTION
The digital watermarking is the process of possibly irreversibly embedding information into a digital signal. The signal may be audio, pictures or video, for example. If the signal is copied, then the information is also carried in the copy. The rapid development of new information technologies has improved the ease of access to digital information. It also leads to the problem of illegal copying and redistribution of digital media Quite a number of rotation and scaling invariant watermarking algorithms have been proposed [1].

The Fourier Mellin transform (FMT) [2] has the property of rotation and scaling invariance. Once the discrete Fourier transform (DFT) and the FMT are applied to an image, the image will be transformed to the rotation, scaling, and translation (RST) invariant domain. The watermark embedded into this domain can be RST invariant. However, the implementation difficulties hinder the research of watermarking schemes based on this principle. Another strategy for detecting watermarks after geometric distortion is to identify what the distortions are, and apply the inverse transform before watermark extraction. This can be done by embedding a template along with the watermark [3] into the cover image. The researchers proposed to embed two watermarks, a template and a spread spectrum message containing the information or payload. The template contains no information itself, but is used to detect the transformations undergone by the watermarked image. This type of template is applicable for all images. However, they can also be easily removed [4],[5] since they usually represent peaks in a transform domain. This fact may increase collusion attempts to discern the registration pattern and, once found, the registration pattern could be removed from the watermarked image, thus restricting the invertible ability of any geometric distortions [6].

Based on the template-based approaches, it is quite straightforward to come up with the idea that if we can identify some kind of pattern that the cover image bears with inherently, it can be used as the reference template. Because this pattern has to be recognizable, normally we use salient features of the cover image as the desired pattern. Therefore, we can identify the pattern even when the cover image is severely distorted. Meanwhile, image normalization has been widely used in pattern recognition and image registration [7]. It also helps researchers achieve scaling invariance in watermarking schemes. Some of such feature-based watermarking schemes have been proposed in literature. In [8], the geometric invariant watermarking scheme is based on moments and image normalization. Geometric moments were used to geometrically normalize the image before watermark embedding at the encoder and before watermark extraction at the decoder.

In [9], the authors extracted features of the cover image and used the disk regions centered at the feature points for watermark embedding and extraction. Meanwhile, image normalization was applied in the scheme to make those disk regions invariant to rotation and scaling. It was stated that the extracted feature points can survive a variety of attacks and can be used as reference points for both watermark embedding and extraction. In [9], although the image normalization was used to grant the rotation and scaling invariance to the disk regions, the performance of the watermarking scheme is not good against rotation. Through experiments, we find out that the feature points cannot be located accurately, if the watermarked image goes through distortions and geometrical transforms. The results cannot be improved much even if higher order moments are calculated.

Considering these problems, we propose our watermarking scheme based on the rotation invariant feature and image normalization [11]. In the scheme, the Bayesian image segmentation is used to segment the cover image into several homogeneous regions. For each region, one feature point is extracted using Gaussian scale model. These points are robust against rotation, scaling, and noise. Using the method addressed in [10], the orientation of the feature points are calculated. For each disk region centered at the feature point, the region is first rotated to align with the orientation of the feature point.

Then the image normalization is applied to transform the disk region to its compact size, which is scaling invariant. In this way, the disk region for watermark embedding and extraction is rotation and scaling invariant. To analyze the watermarking processes, a mathematical model is very important. In this paper, after the image segmentation, each homogeneous region is approximated as a generalized Gaussian distribution with the parameters estimated using expectation maximization (EM).

Using the noise visibility function, the watermark embedding strength is adjusted adaptively based on the characteristics of the embedding region.

2. PROPOSED WORK

A digital image watermarking scheme must be robust against a variety of possible attacks. In the proposed approach, a new rotation and scaling invariant image watermarking scheme is proposed based on rotation invariant feature and image normalization.

In the scheme first the image is segmented into a number of homogeneous regions and the feature points are extracted. Then the circular regions for watermark embedding are defined. Based on the image normalization and orientation assignment ,the rotation ,scaling and translation invariant regions can be used for watermark embedding and extraction. The segmented image is modeled as mixture generalized Gaussian distribution and this model is the basis of mathematical analysis of various aspects of the watermarking processes such as probability of error , embedding strength adjustment. The original image is not needed for the watermark detection.

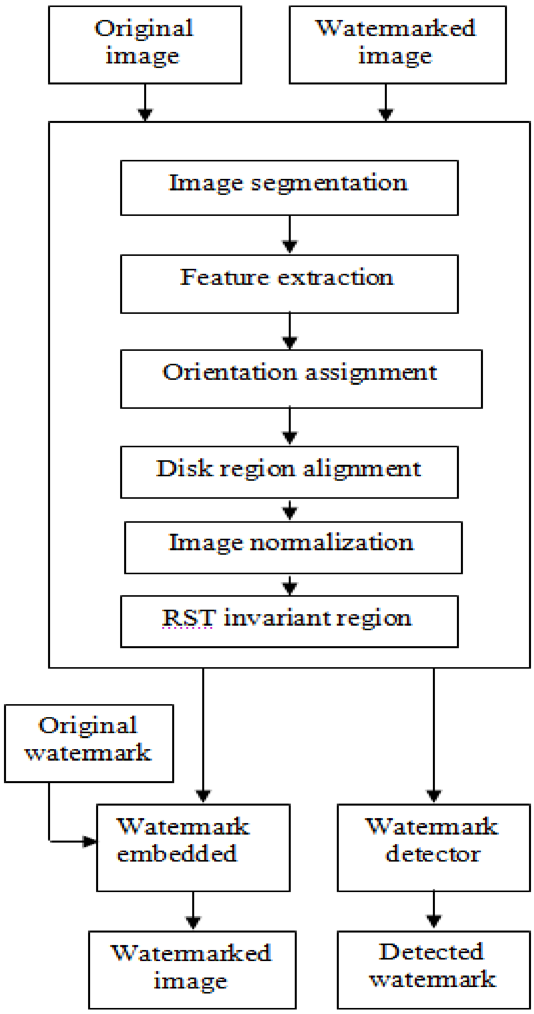

Figure 1. Watermark embedding and extraction scheme

2.1 Image Segmentation

In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries in images.

The result of image segmentation is a set of segments that collectively cover the entire image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. In statistics, an expectation-maximization (EM) algorithm is used for finding maximum likelihood estimates of parameters in probabilistic models, where the model depends on unobserved latent variables.

The image segmentation algorithm used is EM (expectation maximization) algorithm. Assume the observed image is y and the segmentation is x, for each sub region Xs of the segmentation, the conditional distribution of Ys given is a Gaussian distribution with mean and variance

$$p_{y_s|x_s}(y_s \mid x_s) \approx N(\mu_{y_s}, \sigma_{y_s}) \quad (1)$$

Here, the mixture Gaussian distribution is used to model the observed image y . The density is

$$p_{y|x}(y \mid x) = \sum_{s \in S} m_s \, p_{y_s|_{x_s}}(y_s \mid x_s) \quad (2)$$

Where m is the mixture weighting factor and

$$\sum_{s \in S} m_s = 1 \quad (3)$$

To get the parameters of the mixture generalized Gaussian distribution, the expectation-maximization (EM) algorithm is used. First, for each distribution, the mean vector and covariance are set to the initial values. The covariance can be set to be the identity matrix and the mean is calculated by finding the mean of different regions of the image. For example, the image can be divided evenly into a certain number of sub regions and the mean values can be calculated from these sub regions as the initial value. Then the probability of the pixel falling into one of the Gaussian distribution can be calculated

$$p(s \mid y_j) = \frac{m_s p_s(y_j)}{\sum_{s \in S} m_s p_s(y_j)} \quad (4)$$

The update of the parameters is based on the iteration. The EM iteration will continue until

$\log \prod_{k=1}^{N} p(y_k)$ 1% for one iteration. Based on the maximum a posteriori (MAP) probability, the segmentation can be estimated.

To solve the above equations, the iterative conditional modes (ICM) can be used to get the segmentation result. Furthermore, the mean and variance can be calculated to adjust the watermark embedding strength.

The original image is segmented into different homogeneous regions. Each segmented region is represented in one color.

The darker the segmented region, the larger the variance of the region which indicates that it contains more high-frequency components. Moreover, each segmented region can be modeled using one generalized Gaussian distribution. Now, the image can be proximated using the mixture generalized Gaussian distribution.

2.2 Feature Extraction

Gaussian scale model uses the difference of Gaussian to approximate the filtering effect of the laplacian of Gaussian second order derivative. It is used to locate the geometrical-transform-invariant feature points. The feature points with strong edge responses will be removed due to their sensitivity to noise. Gaussian filter defined as

$$G_\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{x^2+y^2}{2\sigma^2}\right] \quad (5)$$

where f(x,y) is the original image. g(x,y) is the original image.The expression is given as

$$g_1(x,y) = G_\sigma * f(x,y) \quad (6)$$

$$g_2(x,y) = G_{k\sigma} * f(x,y) \quad (7)$$

g1(x,y) and g2(x,y) are different from each other in scale by a constant factor k.The DoG filtered image computed as

$$DoG = g_2(x,y) - g_1(x,y) \quad (8)$$

Each segmented region , one feature point is selected and the circular region centered at the selected feature point with radius R will be used for the watermark embedding and detection. For the detected feature points, the circle regions with the same radius centered at the feature points is defined. Once the reference feature points are selected , then assign the rotation and scaling invariant properties to the circular regions centered at the selected feature points.

3.3 Orientation assignment and circular region alignment

The orientation assignment is used to make the circular regions rotation invariant. To do so, a window centered at the selected feature points is defined. The gradients of all the pixels in this windows are computed using the first order erivative. Then the histogram of the gradient are calculated and the peak of the histogram is assigned as the orientation of the feature point. In this way, the orientation would not be affected by noise, small local distortion or some displacement of the feature point position.

The gradient of pixel (x_0,y_0) in the image I is computed as

$$\nabla I(x_0, y_0) = \left[\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right]_{(x_0,y_0)} \quad (9)$$

The magnitude of the gradient is given by $\sqrt{((\partial I/\partial x))^2 + ((\partial I/\partial y))^2}$ and orientation is given by $\tan^{-1}((\partial I/\partial x)/\partial I/\partial y))$.

To generate the histogram, two weighting factors are taken into consideration: the magnitude of the gradient and a Gaussian 2-D filter centered at the feature points. In this way, the gradient with larger magnitude contributes more to the histogram and the point closer to the center feature point contributes more.

2.4 Image Normalization

Scaling normalization is employed to acquire the scaling invariance for the circular region. It transforms the image into its standard form by translating the origin of the image to its centroid.

With the scaling normalization, the aligned circular regions can be transformed to its compact size. Therefore, the selected circular regions are scaling invariant and are ready for watermark embedding. Based on the above analysis, the rotation and scaling invariant regions can be located in the image for watermark embedding.

2.5 Watermark Embedding

The noise visibility function (NVF) characterizes the local features of the image and is one way to do the texture masking in spatial domain. NVF to guide the calculation of watermark embedding strength. For each segmented region, the local variance can be used to compute the NVF. For the pixel x(i,j) belonging to the distribution Ps.

$$NVF(x(i,j)) = \frac{h(i,j)}{h(i,j)+\sigma^2} \quad (10)$$

Where $h(i,j) = \rho_s(\eta(\rho_s))^{\rho_s} \dfrac{1}{|r(i,j)|^{2-\rho_s}}$ (11)

where Ps is the shape parameter ranging from 0.3 to 2 for most real images.

$$y_s = x_s + (1-NVF).\alpha.w \quad (12)$$

where xs denotes the original image data in the circular region, NVF is used to adaptively control the embedding strength, and w presents the random watermark sequence which is generated under normal distribution and is the same size as one circular region.

2.6 Watermark Detection

During the watermark detection, the linear correlation described by is used to detect the existence of the watermark in the circular regions.

$$rlc = \frac{1}{s_s} \sum_{x,y\in s} w.f_s^{'}(x,y) \quad (13)$$

where s is one of the circular regions, Ss is the area of region, and w is the watermark generated by using the same key used in watermark embedding process. The watermark detection includes the following steps. Use PN generator to generate the same watermark as the one used for watermark embedding. Locate the RST invariant regions for watermarking using the Gaussian scale model. Calculate the linear correlation between the watermark and the watermarked data. The watermark is detected in one circular region when the result is larger than a predefined threshold. Multiple circular regions can also work as a redundancy to increase the robustness of the watermark. Four types of distortions are tested. They are rotation, scaling, compression and Gaussian noise pollution.

3. EXPERIMENTAL RESULTS

The input image is converted into segmented image. If the residual covariance is not low , then the clear image will not be got. So update the mean and variance to minimize the residual covariance. After getting the clear image the data is being embedded.

By using NVF, the data is embedded within the image. That image is represented as watermarked image.

Content from the watermarked image is removed to get the original image. The figure 2 shows the input image of the project. Size of the input is 256×256 gray level image.

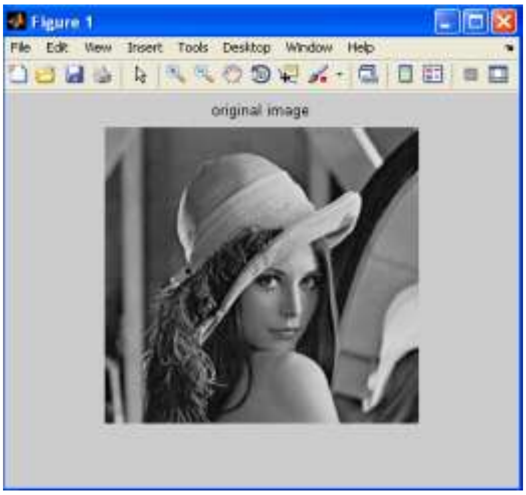

Figure 2 input image

The Figure 3 shows the segmented image of the input image.

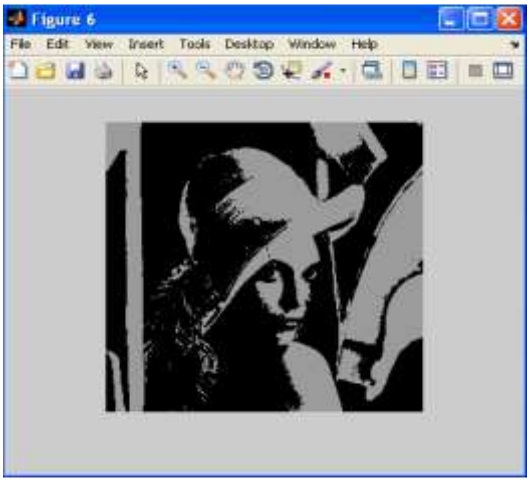

Figure 3. Segmented Image

One of the watermarked image is shown in figure 4 with PSNR value 42.6dB.

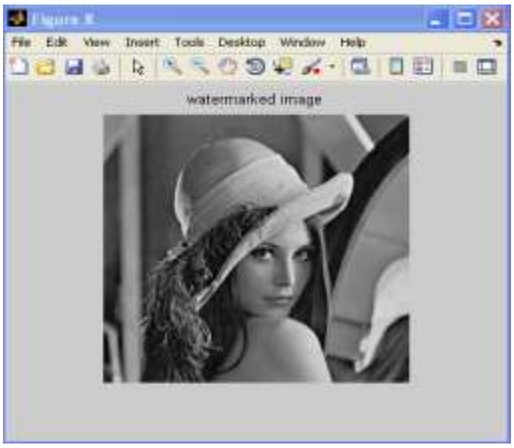

Figure 4. Watermarked image

4. CONCLUSION

The image modeling provides a better guidance to adaptively adjust the watermark embedding strength utilizing NVF. Meanwhile, the image normalization and scale invariant feature SIFT extraction are used to achieve the RST invariance. The spread spectrum and linear correlation are used for watermark embedding and detection. The experimental results show that the proposed algorithm performs well against rotation, scaling, and other attacks such as Gaussian noise pollution and JPEG compression.

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