ROBUST IMAGE HASHING SCHEME FOR IMAGE FORGERY DETECTION

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ABSTRACT

Now a day's digital images are manipulated using powerful image processing tools. It may lead to many problems like Copyright infringement, hostile tampering to the image contents. A robust hashing method is developed for detecting image forgery including removal, insertion, and replacement of objects, and abnormal color modification, and for locating the forged area. The global, local and histogram features are used in forming the hash sequence. The global features are found out using Zernike moments. It represents the luminance and chrominance characteristics of the image as a whole. The local features include position and texture information of salient regions in the image. The histogram features includes the number of pixels with the same intensity. Secret keys are introduced in feature extraction and hash construction. While being robust against content-preserving image processing, the hash is sensitive to malicious tampering and, therefore, applicable to image authentication. The hash of a test image is compared with that of a reference image. When the hash distance is greater than a threshold, the received image is judged as a fake. By decomposing the hashes, the type of image forgery and location of forged areas can be determined.

Keywords: Image forgery, Zernike moments, Image hash, Image authentication.

I INTRODUCTION

Image editing software is widely used in many applications. So ensuring the integrity of the image contents has become an important issue. Image hashing is a technique that extracts a short sequence from the image to represent its contents. Therefore image hash can be used for

image authentication. Different images have different hash function. If the image is maliciously modified, the hash must be changed significantly. In cryptography variety of hash functions are used. Among them MD5and SHA-1 are extremely sensitive to slight changes in the input data. The image hash should be resistant against normal image processing. In general, a good image hash should be reasonably short, robust to ordinary image manipulations, and sensitive to tampering. It should also be unique in the sense different images have significantly different hash values. To make the image hash secure secret keys are used. So that it is difficult for a third party to use the image hash. To meet all the requirements simultaneously, especially perceptual robustness and sensitivity to tampering, is a challenging task. Various image hashing methods have been proposed. Mongaet al. [1] developed a two-step process where an intermediate hash is obtained from the features extracted and the intermediate hash is used to form the final hash. Mainly two types of features are extracted .Feature extraction based on global [2]–[5] or local [6]–[11] features. Global features are generally short but insensitive to changes of small areas in the image, while local features can reflect regional modifications but usually produce longer hashes. In [2], Xiang *et al.* propose a method using invariance of the image histogram to geometric deformations. Histogram represents the number of pixels with a particular pixel value. Histogram images are usually resistant against geometric attacks, but the main disadvantage is that images with similar histogram cannot be distinguished. Tang *et* al.[3] used a global method using nonnegative matrix factorization (NMF). Swami Nathan et al.[4]propose an image hash method based on Fourier-Mellin transform and present a new method and solves many security issues of existing image hashing schemes. Their method is robust to geometric distortions, filtering operations, and various content-preserving manipulations. In [5],Lei et al.calculate DFT of the invariant moments of significant Radon transform coefficients, and normalize/quantize the DFT coefficients to form the image hash for content authentication. Khelifi et al. [6] propose a robust and secure hashing scheme based on virtual watermark detection. The method is robust against normal image processing operations and geometric transformation, and can detect content changes in relatively large areas. In another work, Monga et al. [7] apply NMF to pseudo-randomly selected sub images. In analyzing the NMF-NMF method, Fouad et al. [8] point out that, among the three keys it uses, the first one for pseudo-randomly selecting several sub images is crucial. However, it can be accurately estimated based on the observation of image hash pairs when reused several times on different images. A lexicographical image hashing scheme has been proposed [9] in which a number of feature vectors are taken. This feature vectors are called words and they are used to form the dictionary.

IIBRIEF DESCRIPTION OF USEFUL CONCEPTS

A Zernike Moments

Zernike moments are the mappings of an image onto a set of complex Zernike polynomials .Since Zernike polynomials are orthogonal to each other, Zernike moments can

represent the properties of an image with no redundancy or overlap of information between the moments.

Order *n*	Zernike moments	Number of moments
1	$Z_{1,1}$	1
2	$Z_{2,0}$, $Z_{2,2}$	2
3	$Z_{3,1}$, $Z_{3,3}$	2
4	$Z_{4,0}$, $Z_{4,2}$, $Z_{4,4}$	3
5	$Z_{5,1}$, $Z_{5,3}$, $Z_{5,5}$	3

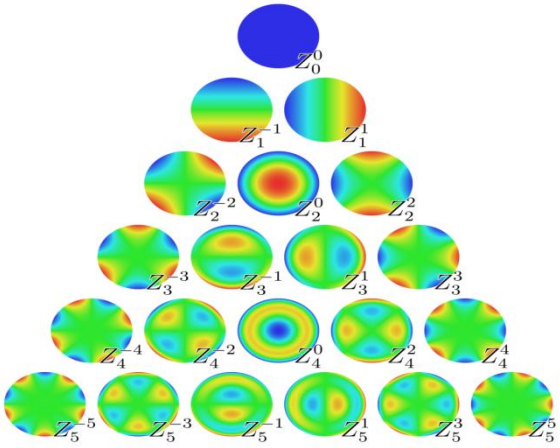

Figure 1: Moments describe numeric quantities at some distance from a reference point or axis.

TheZernike moments are significantly dependent on the scaling and translation of the object in an ROI.Nevertheless, their magnitudes are independent of the rotation angle of the object. Hence, we can utilize them to describe shape characteristics of the objects.

B Salient Region Detection

The region that visually attracts the eye can be called as salient region.Visually salient image regions are useful for manyapplications. It includes object segmentation, adaptive compression, and object recognition. In this paper, we introduce a method for salient region detection that outputs full resolution saliency maps with well-defined boundaries of salient objects. More frequency information is retained in the salient region and thus salient region detection is more accurate than the other techniques. Visual attention results both from fast, pre-attentive, bottom-up visual saliency of the retinal input, as well as from slower, top-down memory and volition based processing that is task-dependent.

C Requirements for a Saliency Map

We set the following requirements for a saliency detector:

- Highlights the largest salient objects.
- The entire salient region should be highlighted.
- A well-defined boundary of the object should be there.
- Noise may create high frequencies and these frequencies should be discarded.
- Efficiently output full resolution saliency maps.

Let lc be the low frequency cut-off value and hc be the high frequency cut-off value. To highlight large salient objects, we need to consider very low frequencies from the original image, i.e. lc has to be low (first criterion). This also helps highlight salient objects uniformly (second criterion).In order to have well defined boundaries, we need to retain high frequencies from the original image, i.e. hc has to be high (third criterion). However, to avoid noise, coding artifacts, and texture patterns, the highest frequencies need to be disregarded (fourth criterion). Since we are interested in a saliency map containing a wide range of frequencies, combining the outputs of several band pass filters with contiguous [lc; hc] pass bands is appropriate.

D DOG Band Pass Filters

In image processing, difference of Gaussians (DOG) is used as an algorithm for feature enhancement that is it removes the unwanted signals and enhances the wanted image. It involves the subtraction of one blurred version of an original image from another, less blurred version of the original. In the simple case of gray scale images, the blurred images are obtained by convolving the original gray scale images with Gaussian kernels having differing standard deviations. Blurring an image using a Gaussiankernel suppresses only high-frequency spatial information. Subtracting one image from the other preserves spatial information that lies between the ranges of frequencies that are preserved in the two blurred images. Thus, the difference of Gaussians is a band-pass filter that discards all but a handful of spatial frequencies that are present in the original gray scale image. Thus difference of Gaussians can be utilized to increase the visibility of edges and other detail present in a digital image. A wide variety of alternative edge sharpening filters are available. But they operate by enhancing high frequency detail. The main problem in enhancing high frequency is that random noise also has a high spatial frequency and many of these sharpening filters tend to enhance noise, which can be an undesirable artifact. By using difference of Gaussians algorithm, high frequency detail that often includes random noise, is removed. So this approach one of the best methods for processing images with a high degree of noise. The disadvantage of applying this algorithm is that the overall contrast of the image is reduced. Thus the image cannot be distinguished that easily from background.

E Computing Saliency

In the proposed method the saliency map S for an image I of width W and height H pixels can thus be formulatedas:

$S(x\ y) = |I_u - I_{whc}(x,y)|$ (1)

Where I_u is the arithmetic mean pixel value of the image.

$I_{whc}(x,y)$ is the Gaussian blurred version of the original image.

To eliminate fine texture details as well as noise and coding artifacts. The norm of the difference is used since we are interested only in the magnitude of the differences. This is computationally quite efficient (fourth criterion). Also, as we operate on the original image without any down sampling,we obtain a full resolution saliency map (last criterion).To extend Eq. to use features of color and luminance, we rewrite it as:

$S(x\ y) = ||I_u - I_{whc}(x,y)||$ (2)

Where I_u is the mean image feature vector,$I_{whc}(x,y)$ is the corresponding image pixel vector value in the Gaussian blurred version of the original image, and || || is the L2 norm. Using the Lab color space, each pixel location is an [L; a; b]T vector, and the L2 norm is the Euclidean distance.

Figure 2:Original Image

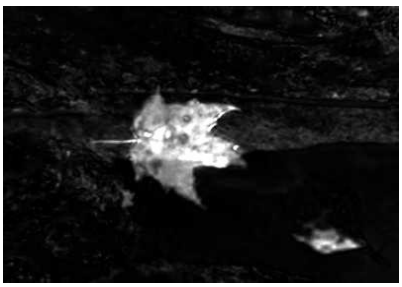

Figure 3:Saliency Map

III PROPOSED HASHING SCHEME

AImage Hash Construction

The image hash generation procedure includes the following

i) Preprocessing:

The image is first rescaled to a fixed size FxFwith bilinear interpolation. In computer vision and image processing, bilinear interpolation is one of the basicresampling techniques. In texture mapping, it is also known as bilinear filtering or bilinear texture mapping, and it can be used to produce a reasonably realistic image. An algorithm is used to map a screen pixel location to a corresponding point on the texture map. A weighted average of the attributes (color, alpha, etc.) of the four surrounding pixels is computed and applied to the screen pixel. This process is repeated for each pixel forming the object being textured. When an image needs to be scaled up, each pixel of the original image needs to be moved in a certain direction based on the scale constant. However, when scaling up an image by a non-integral scale factor, there are pixels (i.e., holes) that are not assigned appropriate pixel values. In this case, those holes should be assigned appropriate RGB or gray scale values so that the output image does not have non-valued pixels.

Bilinear interpolation can be used where perfect image transformation with pixel matching is impossible, so that one can calculate and assign appropriate intensity values to pixels. Unlike other interpolation techniques such as nearest neighbor interpolation and cubic interpolation, bilinear interpolation uses only the 4 nearest pixel values which are located in diagonal directions from a given pixel in order to find the appropriate color intensity values of that pixel. Bilinear interpolation considers the closest 2x2 neighborhood of known pixel values surrounding the unknown pixel's computed location. It then takes a weighted average of these 4 pixels to arrive at its final, interpolated value. After bilinear interpolation the image is converted from RGB to the YCbCr representation. Y and CbCr are used as luminance and chrominance components of the image to generate the hash. The aim of rescaling is to ensure that the generated image hash has a fixed length and the same computation complexity.

Figure 4:Input Image

Figure5: RGB ToYcbcr Conversion

ii) Global Feature Extraction:

Global features are extracted using Zernike moments. Zernike moments of Y and CbCr are calculated. Because shape features can be obtained from a small number of low frequency coefficients, the order does not need to be large. Zernike moments represent the average intensity. Zernike moments are rounded and used to form a global vector, each element in is no more than 255. A secret key is used to randomly generate a row vector with 22random integers in [0, 255]. The encrypted global vector is obtained as

$Z = [(Z'+X1) \bmod 256)$ (3)

iii) Local Feature Extraction:

Largest salient regions are detected from the luminance image Y. The coordinates of top left corner and width/height of each circumscribed rectangle are used to form an element vector, representing the position and size of each salient region.

Figure 6:Salient Region

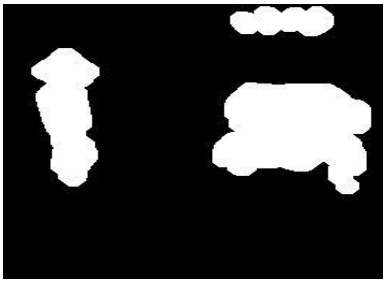

Figure 7:Segmented Region

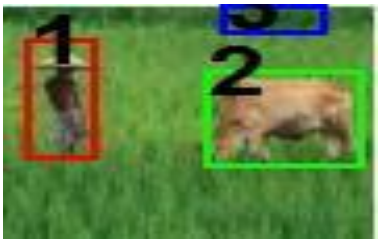

Figure 8: Position

S'= [P T]

In the above equation' P' represents the position and 'T' represents the texture features. Texture features include energy, contrast, and homogeneity. This is found out using gray level co-occurrence matrix. Adaptive segmentation is done to obtain the desired region.

iv) Histogram Features

The insensitivity of the audio histogram shape to time scale modification has been exploited. In this paper, the image histogram shape invariance to geometric distortions is exploited for image hashing. The histogram shape is represented as the relative relations of groups of two different bins. The hash function consists of three broad steps. The input images are filtered with a low-pass Gaussian The histogram is extracted from the preprocessed image by referring to the mean value of the image. Hash Generation: A binary sequence is afterwards computed according to the relative relations in the number of pixels among groups of two different bins. Finally, the key-dependent hash is obtained by randomly permuting the resultant binary sequence. All the three features are combined together to form the final hash.

Image Authentication,

There are two types of hashes. One is the reference hash of the trusted image and the other is the. The hash of a received image. These two hashes are compared to determine whether the test image has the same contents as the trusted one or has been maliciously tampered, or is simply a different image. Here, two images having the same contents (visual appearance) do not need to have identical pixel values. One of them, or both, may have been modified in normal image processing such as contrast enhancement and loss compression. In this case, we say the two images are perceptually the same, or similar

V CONCLUSION

In this paper, an image hashing method is developed using global ,local features and histogram features. The global features are based on Zernike moments representing the luminance and chrominance characteristics of the image as a whole. The local features include

position and texture information of salient regions in the image. Also the histogram features helps to get accurate information about the forgery. Hashes produced with the proposed method are robust against common image processing operations including brightness adjustment, scaling, small angle rotation, JPEG coding and noise contamination.

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