A Novel Image Based on Harris Point Detect us Features

Shanmugasundari M
ME computer science and Engineering, Infant Jesus College of Engineering and Technology
shanmugasundari91@gmail.com
Mr. M.Varghese,M.Tech,(Ph.D)
Professor, Dept of computer science and Engineering,
Infant Jesus College of Engineering and Technology

***Abstract*—The designs an efficient image hashing with a ring partition and a non-negative matrix factorization (NMF), which is with both the rotation robustness and good discriminative capability. The key contribution is a novel construction of rotation-invariant secondary image, which is used for the first time in image hashing and helps to make image hash resistant to rotation. In addition, NMF coefficients are approximately linearly changed by content-preserving manipulations, so as to measure hash similarity with correlation coefficient. We conduct experiments for illustrating the efficiency with 346 images. Our experiments show that the proposed hashing is robust against content-preserving operations, such as image rotation, JPEG compression, watermark embedding, Gaussian low-pass filtering, gamma correction, brightness adjustment, contrast adjustment and image scaling. Receiver operating characteristics (ROC) curve comparisons are also conducted with the state of-the-art algorithms, and demonstrate that the proposed hashing is much better than all these algorithms in classification performances with respect to robustness and discrimination.**

***Index Terms*—Image hashing, multimedia security, non-negative matrix factorization, ring partition.**

I. INTRODUCTION

The Internet and multimedia devices, such as digital cameras, scanners and smart cell phones, have made us easier and faster to capture, store, share and convey hundreds of thousands of images, songs and videos. While we are enjoying our life increasingly with multimedia products, there are still many challenging problems faced by academia and industries. For example, there may be multiple copies for an image in a PC, where the copies can be in different digital representations with visual contents the same with the original one. It is clearly an actual yet challenging issue to efficiently search for all similar versions (including the original one and its copies) of the image from large-scale multimedia data [1, 2]. In particular, while powerful multimedia tools make digital operations, such as editing and tampering, much easier than ever before, assurance of multimedia content security has been an important concern to multimedia community [3]. These real demands lead to an emerging multimedia technology, known as image hashing. We study a new yet robust image hashing in this paper.

Image hashing not only allows us to quickly find image copies in large databases, but also can ensure content security of digital images. Image hashing maps an input image to a short string, called image hash, and has been widely used in image retrieval [1], image authentication [4], digital watermarking [5], image copy detection [6], tamper detection [7], image indexing [8], multimedia forensics [9], and reduced-reference image quality assessment [10].There are some classical cryptographic hash functions, e.g., SHA-1 and MD5, which can message into a fixed size string. However, they are sensitive to bit-level changes and cannot be suitable for image hashing. This is because digital images often undergo normal digital processing, such as JPEG compression and image enhancement in real applications, This is the first one of two basic properties of image hash function, known as perceptual robustness, i.e., a hash function should be robust against content-preserving operations, such as geometric transform, format conversion and JPEG compression. In other words, hashes of an image and its processed versions are expected to be the same or very similar. Hash will be expected to be significantly changed only when visual content is altered by malicious operations, such as object deletion and object insertion. Another basic property is the discriminative capability, This means that hash distance between different images should be large enough. Moreover, image hash function should satisfy additional properties when it is applied to some applications. For example, image hash must be dependent on one or several keys for application in digital forensics.

Consequently, there are many image hashing algorithms successfully designed in last decade. From an applied context, there are still some limitations in image hashing. For example, image rotation is a useful operation. In the post-processing of photographs, image rotation has frequently been exploited to correct those photographs with imperfect ground level. However, most of them are sensitive to rotation, mainly including, such as [4], [11], [12], [13], [14] and [15]. This means that they will falsely identify those corrected photographs as different images.

Some methods are robust against rotation, but their discriminative capabilities are not good enough, such as [16], [17],[18], [19], [20] and [21]. It is a challenging task to simultaneously satisfy both the requirements of rotation robustness and good discriminative capability in developing high performance hashing algorithms. In this paper, we propose an efficient robust image hashing to meet both rotation robustness and good discriminative capability. This algorithm is based on a ring partition and a nonnegative matrix factorization (NMF). The key technique is a novel construction of secondary image achieved by the ring partition. The secondary image is invariant to image rotation and then makes our algorithm resistant to rotation. In addition, the use of NMF provides the proposed algorithm good discriminative capability. This is because NMF is an efficient technique for learning parts-based representation, and the more information about local image content an image hash contains, the more discriminative the image hash.

We conduct experiments for illustrating the efficiency with 346 images, including 146 images in the USC-SIPI Image Database [22], and 200 different color images, where 100 images are taken from the Ground Truth Database [23], 67 images are downloaded from the Internet, and 33 images are captured by digital cameras. Our experiments demonstrate that the proposed algorithm reaches a desirable tradeoff between the rotation robustness and the discriminative capability.

2. LITERATURE SURVEY

Recent development of perceptual image hashing Assume the availability of such an intermediate hash vector that has been extracted from the image and a model on its distribution. the present a solution to the second step by developing such a clustering algorithm based on the distribution of intermediate hash vectors. the first step extracts visually significant features from an image to produce an intermediate hash. A variety of feature detectors may be applied. The second step clusters perceptually identical inputs while minimizing the likelihood of collision for perceptually distinct inputs to compress the intermediate hash to a final hash.

3. OVERVIEW

3.1. EXISTING SYSTEM

In existing Different kind of algorithms are implemented such as DWT (Discrete Wavelet Transform), PCA(Principle component Analysis), Vector Quantization(VQ).And also Rash method, SVD-SVD method, RT-DFD method are used.

DEMERITS:

Existing System does not efficient to set of action such as Jpeg compression, watermarking, image rotation, Gamma correction, Brightness and Contrast adjustment, Gaussian low-pass filtering, image Scaling. Performance of the existing systems poor.

3.2. PROPOSED SYSTEM

The propose a new framework to hash the image process in function such as Jpeg compression, watermarking, image rotation, Gamma correction, Brightness and Contrast adjustment, Gaussian low-pass filtering, image Scaling. Rotation manipulation takes image center as origin of coordinates. The ring partition can be done by calculating the circle radii and the distance between each pixel and the image center. NMF distinguished from other methods by its non-negativity constraint This allows a parts-based representation because only addition is additive combinations are all other. Finally from the hash value the identify the original and the reference images. After Hashing the analyze about our classification. Then the find accuracy of our result.

4. RELATED WORK

The earliest work of image hashing is introduced by Schneider and Chang [24] at the 3rd International Conference on Image Processing (ICIP). At the 7th ICIP, Venkatesan et al. [11] published their famous paper entitled 'Robust image hashing'. From then on, many researchers have devoted themselves to developing image hashing algorithms. In terms of the underlying techniques, the existing hashing algorithms can be roughly classified into five categories as follows.

The first class includes hashing algorithms based on discrete wavelet transform (DWT) [4, 11, 25, 26]. Venkatesan et al. [11] used statistics of wavelet coefficients to construct image hashes. This method is resilient to JPEG compression, median filtering and rotation within 2°, but fragile to gamma correction and contrast adjustment. Monga and Evans [25] exploited the end-stopped wavelet transform to detect visually significant feature points. To make a short hash, Monga et al. [26] proposed a heuristic clustering algorithm with a polynomial time for feature point compression. Ahmed et al. [4] gave a secure image hashing scheme for authentication by using DWT and SHA-1. It can be applied to tamper detection, but fragile to some normal digital processing, such as brightness adjustment and contrast adjustment.

The second class is the use of discrete cosine transform (DCT) [12, 13]. Fridrich and Goljan [12] found that DCT coefficients can indicate image content and then proposed a robust hashing based on this observation for application in digital watermarking. This hashing is robust against normal processing, but sensitive to image rotation. Lin and Chang [13] designed an image authentication system using robust hashing, which is based on invariant relations between DCT coefficients at the same position in separate blocks. The hashing method can distinguish JPEG compression from malicious attacks and is also fragile to rotation.

The third class advocates the Radon transform (RT) [16,18, 27]. Lefebvre et al. [16] are the first of exploiting RT to construct robust hashes. Seo et al. [27] used autocorrelation of each projection in the RT domain to design image hashing. Motivated by RT, Roover et al. [18] designed a scheme called RASH method by dividing an image into a set of radial projections of image pixels, extracting RAdial Variance (RAV) vector from these radial projections, and compressing the RAV vector by DCT. The RASH method is resilient to image rotation and rescaling, but its discriminative capability needs to be improved.

The fourth class develops image hashing techniques with discrete Fourier transform (DFT) [14, 19, 21]. Swaminathan et al. [19] used the DFT coefficients to produce image hashes. This algorithm is resilient to several content- preserving modifications, such as moderate geometric transforms and filtering. Wu et al. [14] exploited RT combining with DWT and DFT to develop image hashing. Their algorithm is robust against print-scan attack and small angle rotation. Recently, Lei et al. [21] extracted moment features from RT domain and used significant DFT coefficients of the moments to produce hashes. The RT-DFT hashing is better than the methods [19, 27] in classification performances between the perceptual robustness and the discriminative capability.

The last class proposes to employ the matrix factorization [7, 17, 20]. Kozat et al. [17] viewed images and attacks as a sequence of linear operators, and proposed to calculate hashes using singular value decompositions (SVDs). This method, called SVD-SVD hashing, is robust against geometric attacks, e.g., rotation, at the cost of significantly increasing misclassification. Monga and Mihcak [20] pioneered the use of NMF to derive image hashing. They applied NMF to some sub-images, used the combination coefficients in the matrix factorization to construct a secondary image, obtained its low-rank matrix approximation by using NMF again, and concatenated the matrix entries to form an NMF-NMF vector.

To make a short hash, they calculated the inner product between the NMF-NMF vector and a set of weight vectors which have i.i.d. Gaussian components of zero mean and unit variance. The NMF-NMF-SQ hashing is resilient to geometric attacks, but it cannot resist some normal manipulations, e.g., watermark embedding.

5. MODULES

The Modules are

- NMF
- Ring Partition
- Illustration of our image hashing.

A. NMF

NMF is an efficient technique of dimensionality reduction, which has shown better performance than principal components analysis (PCA) and vector quantization (VQ) in learning parts-based representation [37]. In fact, NMF has been successfully used in face recognition [38], image representation [39], and image analysis [40], signal separation [41], data clustering [42], and so on. The matrices **B** and **C** are called the base matrix and the coefficient matrix (or encoding matrix), respectively. They can be used to approximately represent **V** such that:

$$\mathbf{V} \approx \mathbf{BC} \tag{1}$$

In literature, various algorithms [43, 44] have been proposed to achieve NMF. In this paper, we employ the multiplicative update rules [43] to find **B** and **C** as follows.

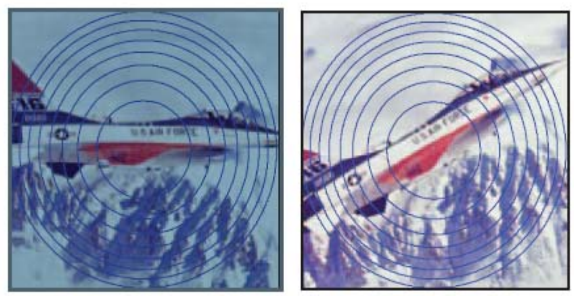
$$\begin{cases} B_{i,k} \leftarrow B_{i,k} \dfrac{\sum_{j=1}^{N} C_{k,j} V_{i,j} / (\mathbf{BC})_{i,j}}{\sum_{j=1}^{N} C_{k,j}} \\ C_{k,j} \leftarrow C_{k,j} \dfrac{\sum_{i=1}^{M} B_{i,k} V_{i,j} / (\mathbf{BC})_{i,j}}{\sum_{i=1}^{M} B_{i,k}} \end{cases}$$
$$i = 1,\ldots,M;\ j = 1,\ldots,N;\ k = 1,\ldots,K \tag{2}$$

The above rules correspond to minimizing the generalized Kullback-Leibler (KL) divergence as follows.

$$F = \sum_{i=1}^{M} \sum_{j=1}^{N} \left[V_{i,j} \log \frac{V_{i,j}}{(\mathbf{BC})_{i,j}} - V_{i,j} + (\mathbf{BC})_{i,j} \right] \tag{3}$$

B. Ring Partition

In general, rotation manipulation takes image center as origin of coordinates. Fig. 2 (a) is a central part of Airplane, and (b) is the corresponding part of the rotated Airplane. Obviously, visual contents in the corresponding rings of Figs. 2 (a) and (b) are kept unchanged after image rotation. Thus, to make image hash resilient to rotation, we can divide an image into different rings and use them to form a secondary image invariant to rotation. Fig. 3 is a schematic diagram of secondary image construction, where (a) is a square image divided into 7 rings and (b) is the secondary image formed by these rings. Detailed scheme of secondary image construction is as follows.



(a) Central part of Airplane (b) Rotated by 30°
Fig. 2. Ring partition of an image and its rotated version.

Let the size of square image be m m, n be the total number of rings and Rk be a set of those pixel values in the k-th ring (k=1, 2, …, n). In inscribed circle of the square image and divide the inscribed circle into rings with equal area. This is because each ring is expected to be a column of the secondary image. The ring partition can be done by calculating the circle radii and the distance between each pixel and the image center. As shown in Fig. 3 (a), the pixels of each ring can be determined by two neighbor radii except those of the innermost ring. Suppose that rk is the k-th radius (k=1, 2, …, n), which is labeled from small value to big value.

Thus, $r1$ and rn are the radii of the innermost and outmost circles, respectively. Clearly, rn= $m/2$ for the $m \times m$ images, other radii, the area of the inscribed circle A and the average area of each ring A are firstly calculated as follows.

$$A=\pi r_n^2$$
$$\mu_A=\lfloor A/n \rfloor \quad (4)$$

$$r_1=\sqrt{\frac{\mu_A}{\pi}} \quad (5)$$

Thus, other radii rk (k=2, 3, …, n-1) can be obtained by the following equation.

$$r_k=\sqrt{\frac{\mu_A+\pi r_{k-1}^2}{\pi}} \quad (6)$$

Let $p(x, y)$ be the value of the pixel in the y-th row and the x-th column of the image (x, y m). Suppose that (xc, yc) are the coordinates of the image center. Thus, xc=m/2+0.5 and yc=m/2+0.5 if m is an even number. Otherwise, xc=(m+1)/2 and yc=(m+1)/2. So the distance between $p(x, y)$ and the image center (xc, yc) can be measured by the Euclidean distance as follows.

$$d_{x,y}=\sqrt{(x-x_c)^2+(y-y_c)^2} \quad (7)$$

$$\mathbf{R}_1=\{p(x,y) \mid d_{x,y}\le r_1\} \quad (8)$$

C. Illustrating our approach

Below our image hashing is illustrated with an example step by step as follows.

(1) *Preprocessing*. The input image is firstly mapped to a normalized size m m by bilinear interpolation. This ensures that our hashing is resilient to scaling operation and hashes of different size images have the same length. For an RGB color image, we convert it into YCbCr color space by the following equation.

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112 \\ 112 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \quad (9)$$

where R, G and B represent the red, green and blue components of a pixel, and Y, Cb, and Cr are the luminance, blue-difference chroma and red-difference chroma, respectively. After color space conversion, we take the luminance component **Y** for representation.

(2) *Ring partition.* Divide **Y** into n rings and exploit them to produce a secondary image **V** by using the scheme described in the Subsection 3.2. The aim of this step is to construct a rotation-invariant matrix for dimensionality reduction.

(3) *NMF*. Apply NMF to **V** and then the coefficient matrix **C** is available. Concatenate the matrix entries and obtain a compact image hash. Thus, the hash length is L=nK, where n is the number of rings and K is the rank for NMF.

To measure similarity between two image hashes, we take correlation coefficient as the metric. Let **h**(1)=[h1(1), h2(1), …, hL(1)] and **h**(2)=[h1(2), h2(2), …, hL(2)] be two image hashes. Thus, the correlation coefficient is defined as,

$$S=\frac{\sum_{i=1}^{L}[h_i^{(1)}-\mu_1][h_i^{(2)}-\mu_2]}{\sqrt{\sum_{i=1}^{L}[h_i^{(1)}-\mu_1]^2}\sqrt{\sum_{i=1}^{L}[h_i^{(2)}-\mu_2]^2}+\varepsilon} \quad (10)$$

The more similar the input images, the bigger the S value. If S is bigger than a pre-defined threshold T, the images are viewed as visually identical images. Otherwise, they are different images or one is a tampered