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Robust Image Hashing with Visual Map and SVD

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Abstract **– Image hashing is a short and compact sequence, which can represent image itself. It is an important technology in the field of multimedia information security. At present, image hashing has been widely used in image authentication, image indexing, copy detection, image quality assessment and image watermarking. In this paper, we propose a novel image hashing with visual map and SVD (singular value decomposition). A contribution is feature extraction from image visual map. Since visual attention model can well retain visual region information, desirable discrimination of hashing algorithm is achieved. In addition, hash generation via SVD from visual map ensures good classification performance between robustness and discrimination. The effectiveness of hashing algorithm is validated by two open databases.**

Keywords **– Image Hashing, Visual Attention Model, SVD, Image Feature.**

I. Introduction

It is universally acknowledged that people access most information of the outside world through images. With the rapid development of technology, many people share information on the Internet. However, some software can fast and easy tamper image information, which makes efficient distinguishing between similar and tamper image is a hot topic. Image hashing [1, 2] is an important technology for multimedia security. Its properties enable effective identification of tampered images.

The property of recognizing similar images is called robustness, and the property of distinguishing different tampered images is called uniqueness [3]. The two are mutually constraining. A good performance of hashing is to reach a balance between robustness and uniqueness.

II. Designed Hashing Algorithm

A. *Preprocessing*

Interpolation and Gaussian low-pass filtering are used to preprocess input images. The input image is converted to the $N \times N$ gray image by bi-cubic interpolation. Then, Gaussian low-pass filtering is adopted to remove noise.

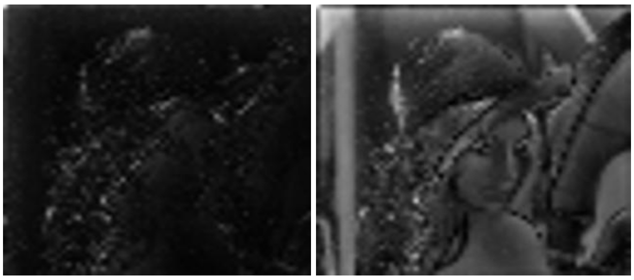
B. *Visual Map Generation*

Visual attention model is a computational scheme for detecting visually significant region. Here, we adopt a developed visual attention model, called ITTI [4]. It is able to better distinguish and identify salient regions of an image. ITTI combines luminance visual map, color visual map and orientation visual map to obtain the final visual map. Figure 1 shows these saliency map. Thus, it can be obtained by

$$\mathrm{M} = \frac{1}{3}(\mathrm{L} + \mathrm{F} + \mathrm{O}) \tag{1}$$

in which L, F and O represent luminance, color and orientation visual map, respectively. The size of M is $N \times N$.

(a) Luminance visual map. (b) Color visual map.



(c) Orientation visual map. (d) Visual map.

Fig. 1. ITTI visual map.

C. *Feature Extraction via SVD*

Feature extraction is a key part of perceptual hashing algorithms. We utilize SVD [5] to extract robust feature for hash construction. SVD is an efficient tool in data compression. It can be obtained by.

$$\mathrm{U} = \mathrm{USV}^{\mathrm{T}} \tag{2}$$

in which S is singular value matrix. The first singular value S_1 and the second singular value S_2 retain the most information of an image. We divide M into $b \times b$ non-overlapping blocks B_i ($P^2 \geq i \geq 1$), and there is a total of $P^2 = (M / b)^2$ image blocks. SVD is applied to every image block, and obtain a block feature (S_{1i}, S_{2i}). Then, let the mean of the first singular value in all image blocks be μ_{S1} and the mean of the second singular value in all image blocks be μ_{S2}. The compression feature distance between the point of the i-th block (S_{1i}, S_{2i}) and the reference point (μ_{S1}, μ_{S2}) by the below equation.

$$D_i = \sqrt{(S_{1i} - \mu_{S1})^2 + (S_{2i} - \mu_{S2})^2} \tag{3}$$

Finally, image hash **D** is consisted by concatenating all blocks feature distance D_i. Therefore, the length of **D** is P^2.

In addition, the similarity of two image hashes can be measured by L_2 norm.

III. Experiment

The input image size and the block size are 512×512 and 64×64, respectively, i.e., N=512 and b=64. The length of our hash is 64. Since robustness and uniqueness are two basic properties in image hashing, we verify the performance of hashing algorithm in terms of robustness and uniqueness, respectively. And the overall performance is shown in last part.

A. *Robustness*

Kodak Lossless True Color Image Suite [6] is a popular database, consist 24 color images. Figure 2 shows some typical images in the Kodak Lossless database. We adopt 10 types of robust operations with different parameters, including contrast adjustment and brightness adjustment are provided by Photoshop. Pepper & salt noise, speckle noise, 3×3 Gaussian low-pass filtering and gamma correction are provided by MATLAB. Image scaling, JPEG compression, watermark embedding and the combinational operations of rotation, cropping and scaling are provided by StirMark. More different parameters details of robust operations can be referred to [7]. Total of 74 robustness attacks. Therefore, 24×74 = 1776 pairs of similar images are generated for robustness experiment.

Fig. 2. Some typical images of Kodak image dataset.

The L_2 norm between images and its post-attack versions is measured and Table 1 lists the minimum, maximum, mean and standard deviation under different operations. The maximum similarity distances under RCR operations are 680.79, and the maximum similarity distances of other operations is less than 360, and the average of the similarity distances of all operations is less than 410. These all indicate that the algorithm have good perceptual robustness.

Table 1. Mean of L_2 norms with robustness dataset.

Operation	**Max**	**Min**	**Mean**	**Standard Deviation**
BA	186.43	21.77	84.42	43.52
CA	191.36	14.76	45.54	30.93
GC	240.09	24.55	105.05	53.92
3×3 GF	211.53	1.41	56.32	47.31
SN	186.56	13.89	64.83	30.87
SPN	357.44	16.94	74.63	39.68
JG	194.40	51.63	104.80	27.60
WE	326.47	64.76	113.81	41.50
IS	223.08	12.88	78.41	44.89
RCR	680.79	154.36	401.26	101.15

B. *Uniqueness*

Uncompressed Color Image Database (UCID) [8] are adopted to valid uniqueness for our image algorithm. UCID includes 1338 color images, which are different image. We calculate the L_2 norm as the similarity between different images. The total of 594453 similarity distances. The results are illustrated in Figure 3. It is shown that the maximum L_2 norm is 1141.17, the minimum L_2 norm is 302.72, the average of all L_2 norm is

711.36, and the standard deviation is 92.01. It can be showed that the mean of similarity distances between identical images is much larger than the mean of similarity distances between different images, which proves the good discrimination of the proposed hashing algorithm.

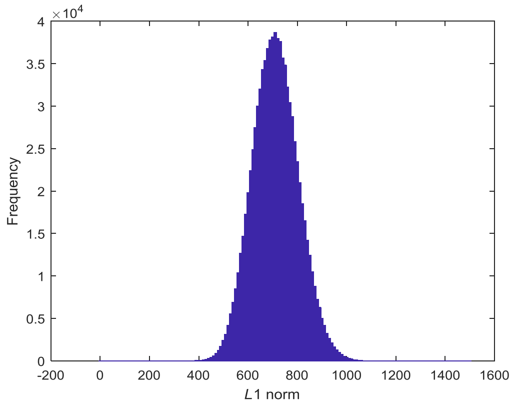


Fig. 3. Distribution of 594453 similarity distances.

IV. Performance Comparisons

We verify the overall performance of image hashing algorithm through ROC method [9]. In ROC graph, the x-axis is uniqueness and the y-axis is robustness. In ROC graph, the closer curve to the top left corner shows the better classification performances. Three compared algorithm respective similarity metrics remain, i.e., SVD-CVA scheme and SVD-CVA scheme use the L_2 norm, GF-LVQ scheme uses the normalized Hamming distances. Three popular image hashing algorithms are used to compare, SVD-CSLBP [10], CVA-DWT [11], GF-LVQ [12]. Figure 4 shows the ROC with five hashing algorithms. It is proved that our hashing has better the overall performance between robustness and uniqueness.

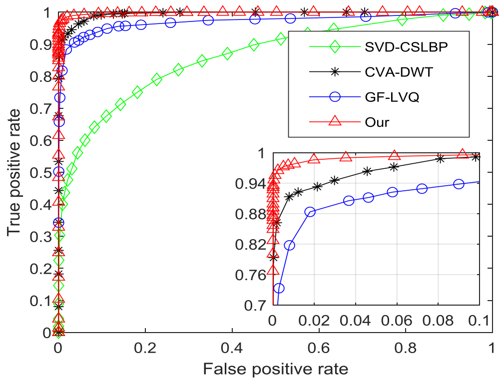


Fig. 4. Four algorithms compared for the overall performance.

V. Conclusion

In this paper, we have designed a hashing algorithm via visual map and SVD. The innovation of combine them to generate compact image hashes. We generate visual map to retain image interesting information, which helps to improve robustness. In addition, we extract useful features from visual map for hash construction. This step can achieve good uniqueness. Experimental results have demonstrated that hashing algorithm is robust against operations and good uniqueness. The ROC has shown that the overall performance of hashing algorithm is better than other four algorithms.

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