TRAJECTORY OF SINGULAR ENERGIES FOR IMAGE REPLICA DETECTION

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Keywords: Image replica detection, SVD.

Abstract: Image replica detection system can be used by the owners of digital multimedia content to protect their rights against unauthorised use of their material. The paper presents a new approach for content-based image replica detection. A concept of singular energy trajectory is introduced and evaluated. It appears that this trajectory is invariant to many image operations. Moreover, the trajectories of original images and distorted copies are highly correlated. These properties make the proposed method a good tool for image replica detection.

1 INTRODUCTION

Multimedia content producers and providers are substantially interested in protecting their material against unauthorized use and distribution. The easiness of dissemination of such material in digital form makes the copyright protection a big challenge. This is especially true in the case of visual information which can be easy copied, modified and distributed. Designing a reliable tool for automatic detection of replicas of digital content would significantly help to protect the rights of copyright owners.

The system for content-based image replica detection should allow for a fast and reliable identification of original and modified versions of reference images which are subject to copyright protection. The main concept of image replica detection can be characterized as a simple decision system of which the elementary function is to state whether a given 'suspected' image is a copy of a reference image or not. This system should be robust to many popular modifications, such as compression, image editing and enhancement methods available in most image editing applications.

Recently the possibility of designing a visual identifier, which can be used for image replica detection, was also investigated by standardization activities of MPEG group (Bober & Kim, 2006).

In this paper the method for content-based image replica detection using trajectory of features is proposed. The trajectory is constructed by moving rectangular window across the image; in each window position, local features are extracted. Next, the trajectory of local features is used for comparing two images. The chosen local feature is the singular energy of pixel values obtained by performing SVD on image blocks formed by the moving window. As the feature similarity function, the correlation of singular energy coefficients of the trajectory is used.

The outline of the paper is as follows. Section 2 briefly discusses the problem of replica detection including some recent research result. Section 3 introduces the concept of singular energy trajectory for image replica detection. In section 4 experimental results are presented and finally section 5 concludes the paper and proposes further research directions.

2 IMAGE REPLICA DETECTION

Content-based image replica detection system should allow for fast and reliable identification of image replicas, also those which are altered by popular image processing techniques: lossy compression (e.g. JPEG or JPEG 2000), colour conversion, transformations, editing (e.g. cropping). As distinct from the techniques of image copyright protection based on watermarking where additional

Wnukowicz K., Skarbek W. and Galinski G. (2007).
TRAJECTORY OF SINGULAR ENERGIES FOR IMAGE REPLICA DETECTION.
In *Proceedings of the Second International Conference on Signal Processing and Multimedia Applications*, pages 434-439
DOI: 10.5220/0002135904340439

information need to be embedded into images, in such systems image signatures are extracted directly from the visual content of images.

The main application of content-based image replica detection system is detection of copyright infringements. Other possible applications would be detection of illicit content or image forgery, identification of multiple copies of the same image in an image database or identification of specific content (e.g. commercial) in TV programme.

In recent years a number of publications have been addressing the image replica detection problem. Some of them proposed to use the general visual features such as colour, shape or texture to detect image replicas. The results of using that features in detecting replicas were rather poor. Other methods made use of spatial decomposition of an image and the local features were used for comparing images in order to detect replicas. This operation apparently improved detection rate for some types of image modifications. Another method was presented in (Ke *et al.*, 2004). It uses the concept of key or interest points which gives good results in detecting replicas for a wide range of image modifications, but the drawback of this method is high computational cost and the size of image features is relatively large.

The detection of image replicas is usually based on similarity of the features. The decision whether the suspected image is a replica of some reference image can be made by applying simple threshold on the feature's distance function or a more complex classifier can be applied. In (Maret *et al.,* 2006) the method for building classifier for replica detection system is presented. The proposed system uses selected visual features to build classification system which assigns input images into two classes: replicas and non-replicas of a given reference image. The classification system is based on support vector machines and a single classifier is build for each reference image. For each reference image, a test database containing replicas and non-replicas of that image was used for partitioning the feature space into two non-overlapping areas; the parameters of the partitioning were determined during the training stage for the classifiers. In the classification stage the visual features are extracted from each tested image and the images are classified according to parameters obtained in the training stage.

Recently, the problem of image identification was also recognized by MPEG community (Bober & Kim, 2006). Designing a robust image identifier would be beneficial to multimedia applications and image databases. Core experiments were set up for investigating possible technologies and algorithms.

Initial experiments have focused on investigating the possibility of applying the existing descriptors of MPEG-7 standard in replica detection applications. These experiments showed that existing descriptors, which were designed for image similarity retrieval, give poor results in image replica detection tasks. A need for a new 'visual identifier' descriptor, which would be specialized for image identification and replica detection, was suggested and new requirements for core experiments were specified (Bober & Kim, 2006). The idea is to extract a single descriptor per image (image signature), then the decision if an image is a copy of another is made according to similarity of the descriptors. The specification of core experiments includes the set of tested image modifications, definition of image dataset for proposal evaluation, the requirements on success rate of the identification, constraints on the extraction complexity and the descriptor size. One of the evaluated proposals is included in (Brasnett & Bober, 2007). This proposal is based on Trace Transform (Kadyrov & Petrou, 2001) which is derived from Radon Transform. The performance of this descriptor appeared to be quite good, and the work on further evaluation is in progress.

The evaluation method and the dataset used in MPEG experiments on visual identifier were adopted also in our experiments to assess the performance of the proposed replica detection method.

3 IMAGE DESCRIPTION BY TRAJECTORY OF FEATURES

Our method for image replica detection uses local features in an image which is partitioned into fixed number of blocks. The blocks can be overlapped or not. In each block a local feature is computed and the successive blocks form trajectory of features. Then, the correlation of the feature trajectories is used to obtain the similarity of two images.

3.1 Characteristics of the Method

The preliminary assumption of the design of our algorithm is that the possible modifications of image copies are limited to certain class of image editing effects. This class excludes operation such as rotation, changing aspect ratio, and cropping. We believe that for a broad range of images (e.g.

portraits, landscapes), operations, such as rotations or changing aspect ratio, are rarely used as they make images look unnatural. On the other hand image cropping is an example of other class of modifications: sub-image editing, which is not in the focus of this work. Nevertheless, we assume that copies obtained by small rotations, small cropping or small image shifting could be detected by our method. The class of operations on original images which should be supported by the proposed method includes: lossy compression, resizing (preserving aspect ratio), filter effects (blur, adding noise, etc.), colour conversions such as conversion to monochrome, histogram equalisation, changing colour resolution, brightening, contrast changing, gamma correction etc.

3.2 Building Trajectory of Features

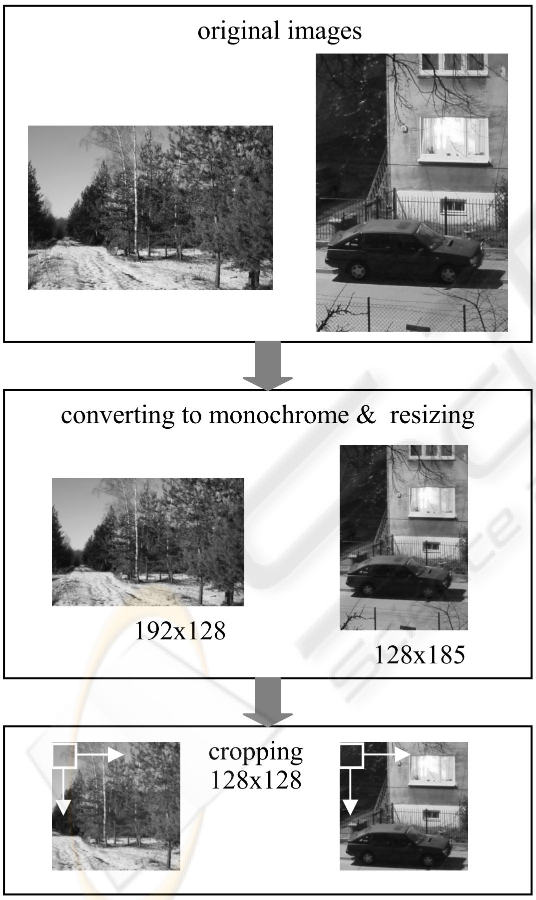

Figure 1: Pre-processing steps for feature trajectory extraction.

Building the image trajectory is preceded by pre-processing step presented in Figure 1. First, the input image is converted to greyscale. This operation is performed in order to obtain invariance to various colour conversions. Next, the greyscale image is resized in such a way that the shorter edge of the image consists of 128 pixels. Finally, the central part of the image is cropped to obtain the image of size 128x128 pixels. This assures the fixed size of images to be used for trajectory extraction.

The image obtained in pre-processing step is used to extract the trajectory of features. The trajectory is computed in image blocks of the size of MxN. The window block is moved across the image and in each window position local features are computed. The image blocks can be ordered for example in raster scan or along the Hilbert curve. In this work we assumed raster scan from left to right with step m, and from top to bottom with step n. Let S denotes input image width and height (S = 128 in the current approach), then the number of trajectory anchor points equals: $((S–M)/m+1)*((S–N)/n+1)$.

3.3 Singular Energy of Image Blocks

In (Skarbek, 2007) a concept of image singular energy trajectory is introduced. Image blocks can be characterised by a local signal energy measured by the sum of squared pixel intensities in the block. The signal energy of a block is not invariant to most image processing operations. However, if we consider the fractional distribution of the energy in singular channels, defined by singular directions of image blocks, the situation becomes much better.

Singular energy is obtained by SVD decomposition. Let f_1, ... f_L be the sequence of pixel blocks drawn from the image f. Performing the singular decomposition of the matrix f_i, we consider only r dominant singular values $\sigma_i(1),\ldots,\sigma_i(r)$.

It is well known that the singular energy of a block f_i is decomposed into the sum of all squared singular values of f_i:

$$\|f_i\|_F^2 = \sum_k \sigma_i^2(k), \sum_k \frac{\sigma_i^2(k)}{\|f_i\|_F^2} = 1 \qquad (1)$$

The image singular energy trajectory of rank r is defined as the sequence of points in r dimensional unit cube $[0,1]^r$:

$$\left(\frac{\sigma_i^2(1)}{\|f_i\|_F^2}, \ldots, \frac{\sigma_i^2(r)}{\|f_i\|_F^2} \right), i = 1, \ldots, L \qquad (2)$$

Figure 2 shows 2-D trajectories of singular energy for images ‘lena’ and ‘baboon’ where the horizontal axis represents the first singular energy, and the vertical axis represents the second singular energy.

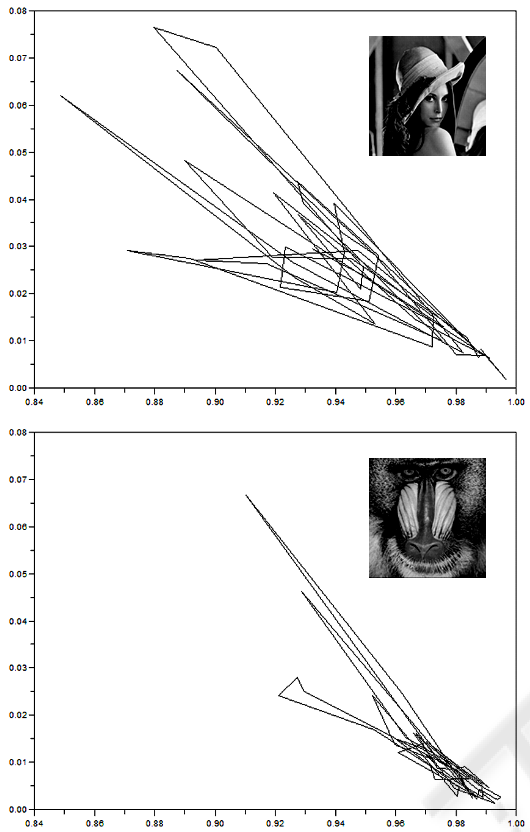

Figure 2: Graphical representations of singular energy trajectories in 2D singular energy space for images: ‘lena’ and ‘baboon’.

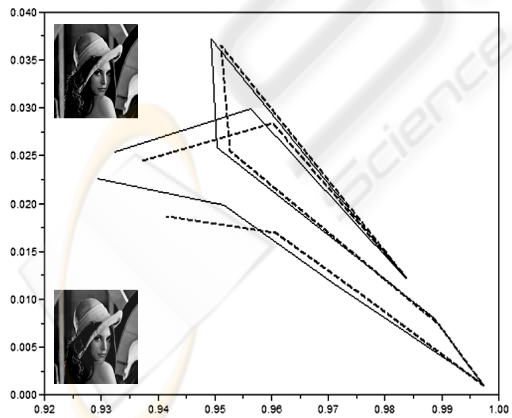

Figure 3: Fragment of singular energy trajectory for original image ‘lena’ (solid line) and corresponding fragment for distorted replica (dashed line).

Figure 3 shows fragments of singular energy trajectories for original image ‘lena’ and its distorted version obtained by blurring. It can be seen that the two trajectories are correlated. Because of the fact that the singular energy trajectories of original images and their modified copies are highly correlated we used correlation as the similarity function. The correlation is computed using Pearson formula, where 1 corresponds to maximum correlation, 0 means no correlation, and -1 corresponds to inverse correlation.

4 EXPERIMENTS AND RESULTS

To assess the performance of replica detection using singular energy trajectories we carried out several experiments. The image dataset and the methodology of experiments were taken from MPEG core experiments for visual identifier (Bober & Kim, 2006). The correlation of 1-D trajectories of singular energies was chosen as the similarity function.

The performance of replica detection algorithm can be characterised by: accuracy of the detection, computational cost, and descriptor size. The accuracy of the system can be measured by two kinds of errors: the number of non-replicas incorrectly detected as replicas, called false positive, and the number of copies not detected as replicas, called false negative. The relation between the false positive and the false negative rates of a detection system can be represented by receiver operating characteristic (ROC) graph which shows inverse proportionality of both variables (because higher false positive rates correspond to lower false negative rates).

According to definition of MPEG experiments, the accuracy of detection is assessed in two steps. In the first step, a large database of unrelated (non-replica) images is used to determine operational conditions corresponding to one per million false positive rate (1ppm). The number of images in the database is N=60551, and all pairs of different images in the database is used for that purpose. The total number of comparison is then N*(N-1)/2 = 1 833 181 525. The operational point of the algorithm for 1 ppm false positive rate should be set in such a way, that the number of image pairs falsely recognized as replicas is not grater than 1833. Figure 4 depicts an example histogram of feature trajectory correlations for non-replica images and the obtained point of 1 ppm false positive rate, determined by the threshold on correlation of trajectories between two compared images.

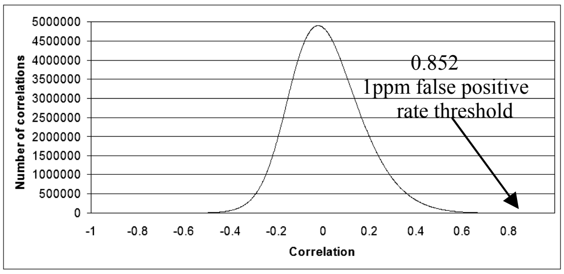

Figure 4: Trajectory correlation histogram for non-replica images. The histogram bin size is set to 0.001.

In the next step, the success rate of the algorithm is determined using the previously obtained operational point for 1ppm false positive rate. For this purpose a database of N=3944 original images and their modified versions is used. The success rate is determined for each modification by performing the detection algorithm to original images and their modified versions. If the number of successfully detected copies is K and the number of all original images is M, the success rate is defined as K/M. The success rate equal 1 means, that all images were successfully detected, 0 means no image was detected. The modified versions of original images were created as specified in MPEG core experiments by applying the following processes: brightening (+5%, +10%, +20%), colour to monochrome conversion, JPEG compression (quality factors 95, 80, 65), colour reduction (to 16 and 8 bits per pixel), Gaussian noise, histogram equalization, blur, scaling (decreasing size by 50%).

We compared the success rates for different block sizes and different number of blocks for 3 most significant singular energies. The block sizes are 16x16 and 32x32. For block 16x16, the block was moved in raster scan order every 8 pixels (overlapped blocks) and every 16 pixels (non-overlapped blocks). For block 32x32, the block was moved every 16 pixels (overlapped blocks).

Tables 1-3 present the results on success rate for 3 most significant singular energy channels. The trajectories for each channel were computed and compared separately. Table 1 shows the results on success rate for block size 16x16 with moving step 8 (horizontally and vertically, which gives 225 trajectory points). The 1ppm false positive thresholds obtained for the singular energy trajectory correlations are: 0.906 for the first channel, 0.852 for the second channel, and 0.885 for the third channel. Table 2 shows the results on success rate for block size 16x16 and the moving step 16 (which gives 64 trajectory points). The 1ppm false positive thresholds are: 0.930, 0.912, and 0.930 respectively. Table 3 shows the results on success rate for block size 32x32 and the moving step 16 (which gives 49 trajectory points). The 1ppm false positive thresholds are: 0.968, 0.944, and 0.957 respectively.

Table 1: Success rates of replica detection corresponding to 1ppm false positive rate for 1-D trajectories of singular energy channels (using block size 16x16, step 8x8).

Singular energy channel	1 (%)	2 (%)	3 (%)
scale to 50%	99.18	99.39	98.88
JPEG, q = 95	100	100	100
JPEG, q = 80	99.87	99.84	99.59
JPEG, q = 65	99.72	99.79	99.26
bright. +5%	99.9	99.92	99.77
bright. +10%	99.77	99.84	99.59
bright. +20%	99.21	99.54	99.06
blur (3)	99.8	99.8	99.59
blur (5)	99.19	99.54	98.7
noise (6)	98.88	99.59	98.85
noise (20)	98.61	99.39	98.55
noise (64)	97.54	98.94	97.46
color 8 bpp	98.05	98.83	98.3
color 16 bpp	96.72	97.21	96.83
grey	99.44	99.59	99.21
hist. equaliz.	75.89	83.54	77.31

Table 2: Success rates of replica detection corresponding to 1ppm false positive rate for 1-D trajectories of singular energy channels (using block size 16x16, step 16x16).

Singular energy channel	1 (%)	2 (%)	3 (%)
scale to 50%	99.11	99.26	98.33
JPEG, q = 95	100	100	100
JPEG, q = 80	99.9	99.87	99.47
JPEG, q = 65	99.67	99.72	98.96
bright. +5%	99.87	99.85	99.62
bright. +10%	99.7	99.72	99.47
bright. +20%	98.96	99.14	98.05
blur (3)	99.65	99.62	99.09
blur (5)	98.2	99.11	94.85
noise (6)	98.68	99.31	98.38
noise (20)	98.33	99.04	98.05
noise (64)	97.03	98.38	96.55
color 8 bpp	97.87	98.53	97.52
color 16 bpp	96.55	96.86	96.12
Grey	99.29	99.34	98.76
hist. equaliz.	71.04	74.39	68.10

Table 3: Success rates of replica detection corresponding to 1ppm false positive rate for 1-D trajectories of singular energy channels (using block size 32x32, step 16x16).

Singular energy channel	1 (%)	2 (%)	3 (%)
scale to 50%	98.15	98.96	98.07
JPEG, q = 95	100	100	100
JPEG, q = 80	99.9	99.94	99.77
JPEG, q = 65	99.72	99.77	99.57
bright. +5%	99.82	99.85	99.7
bright. +10%	99.32	99.59	99.29
bright. +20%	96.93	98.25	96.81
blur (3)	98.43	99.77	98.86
blur (5)	92.69	98.91	94.8
noise (6)	99.21	99.69	99.26
noise (20)	98.91	99.59	98.99
noise (64)	97.9	99.24	98.53
color 8 bpp	97.97	99.06	98.05
color 16 bpp	97.69	98.4	97.79
grey	98.17	98.91	98.45
hist. equaliz.	63.44	70.36	64.9

The best result appeared to be obtained when the second singular energy is used, it is worth to note that in may come from the best (lowest value) correlation threshold obtained from 1 ppm false positive test. The overall best result was achieved for 225-point trajectory with overlapped image blocks of size 16x16 pixels. However, for some distortions better results were obtained when using a smaller number of trajectory points but with a bigger block size 32x32. This was observed for replicas obtained by lossy compression and adding Gaussian noise.

5 CONCLUSIONS

The paper presents the method for replica detection using singular energy trajectory. The results for 3 different trajectory parameters and 3 singular energy channels are presented. The achieved success rate is quite high as it exceeds 98 - 99 % for most of the image modifications and at the same time the false positive rate is very low. The result is apparently better than obtained using the features designed for image similarity retrieval. We plan to extend our method to detect sub-image copies by investigating partial similarity of trajectories.

We observed that the images of which copies are usually missed during the detection have big regions with small pixel variance, which causes that most of the pixel energy is concentrated in the first singular channel. This causes that the correlation of singular energy between original and distorted image is low because the ratio between the signal energy of original image and the noise introduced by distortions becomes low. To achieve better success rate, such cases should be detected and different distance function should be used – possibly using 3-D trajectory of combined energy channels. We expect to improve the detection rate of the method by solving this problem in our future work.

ACKNOWLEDGEMENTS

The work presented was developed within VISNET II, a European Network of Excellence (http://www.visnet-noe.org), funded under the European Commission IST FP6 programme.

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