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Image Recapture Detection Using Multiple Features

Yongzhen Ke[1], Qingqing Shan[1], Fan Qin[2*] and Weidong Min[1]

[1]*School of Computer Science and Software Engineering, Tianjin Polytechnic University, China*

[2]*Department of Logistics Management, Nankai University, China*

keyongzhen@tjpu.edu.cn, fannq@163.com

Abstract

With advances in image display technology, recapturing good-quality images from high-fidelity artificial scenery on a LCD screen becomes possible. Forgers can recapture the artificially generated scenery and use the recaptured image to fool image forensic system. Image recapture detection is to distinguish real-scene images from the recaptured ones. An image recapture detection method based on multiple feature descriptors is proposed in this paper, which uses combinations of low-level features including texture, noise, difference histogram and color information. One hundred and thirty-six dimensions of features are extracted to train a support vector machine classifier with RBF kernel. Experimental results show that the proposed method is efficient with good detection rate of distinguishing real-scene images from the recaptured ones. It also possesses low dimensional features and low time complexity.

Keywords: *Image Forensics, Image Recapture Detection, Color, Texture, Noise, SVM*

1. Introduction

With the advancement in graphics rendering techniques and image reproduction devices, distinguishing photorealistic computer graphics and re-photographed images from true photographs is challenging. A 3D scene can be first captured as an image and reproduced on a physical surface such as a printing paper or an LCD display before it is recaptured again under a different illumination. In general, the re-photographing process is pure image-based and involves no graphics models or rendering, unless the original image is computer graphics. Recaptured images are also different from the common photographs in that what being captured is an image reproduction surface instead of a general scene. Image recapture detection (IRD) technology distinguishes images of real scenes from the recaptured images, i.e., images of media that display real-scene images such as printed pictures or LCD display.

One of the important applications of IRD is in face authentication system. IRD is also useful for general object recognition to differentiate the objects on a poster from the real ones, which improves the intelligence of robot vision. Another important application for IRD is in composite image detection. One way to cover compositions in a composite image is to recapture it. This kind of image compositions can be detected through IRD. It should be noted that during the image recapturing process, the tampering anomalies, *e.g.*, splicing discontinuity and resampling artifacts, are automatically removed and the intrinsic image regularities which are originally disturbed due to the tampering operations are automatically restored. Identification of the recaptured images is an important task to facilitate the current image forensic system. Recaptured images from LCD screen are largely perceptually

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indistinguishable to humans because recapturing can turn a doctored image into a quintessential photograph. However, there are fine differences between LCD screen recaptured images and non-recaptured ones. IRD can detect such fine differences and makes it harder for doctored images to escape detection through recapturing.

In this paper, we study the problem of distinguishing two image classes, i.e., images of true natural scenes and the recaptured natural-scene images on a computer. Although computer graphics and recaptured images can be as perceptually photorealistic as real photographs, their underlying image formation processes have distinctive characteristics. Such differences, though subtle, can be used for distinguishing these images. Based on our analysis, we further propose several sets of image features, including texture features, sensor pattern noise features, difference histogram and color features to identify the recaptured images from natural images.

This paper is organized as follows. Previous work is reviewed in Section 2. In Section 3, the proposed image recapture detection method and several types of image features for automatic identification of recaptured images are described in detail. Section 4 describes the experimental results and discussion. Finally, Section 5 concludes this paper and discusses the future extension.

2. Related Work

More and more researches have been done to detect recaptured images from real ones. Jiangwei Li *et al.*, [1] explored the high frequency component using Fourier Spectra and found that high frequency component of photographs is less than that of live face image because recaptured photographs are smaller in size and produce less high frequency components than real live image. This technique is applicable for less sampled or low resolution photographic images but will not produce expected results for high resolution (quality) photographic image. To distinguish the image of live face from still photograph of same person, Tanzeem Choudhury *et al.*, [2] presented depth information evaluation from both real person and his or her photograph. There is another technique available to estimate the depth information for the classification of live face image or recaptured photograph because depth map is constant in the case of photograph and live face yields various depth values but it is not easy to estimate depth information when head of the person is in stationary position. Hany Faridy and Siwei Lyu [3] performed an experiment on classifying photographic images and scanned images using wavelet statistical features which captured the deviation from the normal image statistics resulted from the image printing and scanning process. Hang Yu *et al.*, [4] studied the ambient light reflected off the paper as recaptured by a high resolution camera. Part of the light is reflected as specularity. Such reflectance carries a spatial pattern similar to the fine texture of a paper which is more pronounced in the specular component of the recaptured image. The fine texture is a characteristic of recaptured images from paper printouts. Hang Yu *et al.*, proposed a way to extract the micro-texture on the A4-size printing paper from the specularity component of a recaptured image. Later, Jiamin Bai *et al.*, [5] extended the work in [4] to model this texture pattern with a histogram of gradient magnitude on specularity components. The shape of the histogram after being normalized to a unity area is modeled by a generalized Rayleigh distribution with two parameters a and b. The parameters can be used as features for distinguishing recaptured images from non-recaptured 3D scene images. The authors proposed a method to detect spooling attacks using printed photos by analyzing the micro-textures presented on the paper using a linear SVM classifier. The major drawback of this method is that it required high-resolution input images in order to discriminate the fine micro-texture of the used spoofing medium. Tian-Tsong Ng *et al.*, [6] devised a set of physics-motivated geometry features to classify photographic images and photorealistic computer graphic images. They showed that the geometry features have the capability of distinguishing computer graphics recaptured from an LCD display when the recaptured images have a resolution high enough to resolve the grid structure of the display. Xinting Gao *et al.*, [7] proposed a general physical model for the recaptured process. A set of physical features is inspired by the model such as the contextual background information, the spatial distribution of specularity that is related to the surface geometry, the image gradient that captures the non-linearity in the recaptured image rendering process, the color information and contrast that is related to the quality of reproduction rendering, and a blurriness measure that is related to the recapturing process. The physical features are used to classify the recaptured images from the real ones. The study of Hong Cao and Alex C. Kot [8] showed that recaptured images from LCD screen are largely perceptually indistinguishable to humans, but meanwhile there are fine differences between LCD screen recaptured images and non-recaptured ones. A recapture detection algorithm that uses a combination of color and resolution features and a Support Vector Machine (SVM) classifier was presented in [8]. Neslihan Kose and Jean-Luc Dugelay [9] proposed a new face anti-spoofing approach based on analysis of contrast and texture characteristics of captured and recaptured images.

3. The Proposed Image Recaptured Detection Method

In [7], Xinting Gao *et al.*, proposed a general image recapturing model, which gives us clues for detecting the recaptured image from the real-scene image. The clues include the difference in the radiometric non-linearity arising from the various response functions, the possible backlight and patches of highlight for a recaptured image, the contextual information from the background scene of a recaptured image, the distinct properties of the display medium for a recaptured image, chromatic properties of the printing devices, and so on. Previous studies [10] have shown that significant improvement can be achieved using different types (or combinations) of low-level features. A strong set of features provides high discriminatory power. To take advantage of the rich information provided by multiple feature descriptors, an image recapture detection method integrates feature descriptors based on texture features, sensor pattern noise features, difference histogram and color features with SVM. The training and testing procedures are illustrated in Figure 1 and discussed in more details in the next paragraphs.

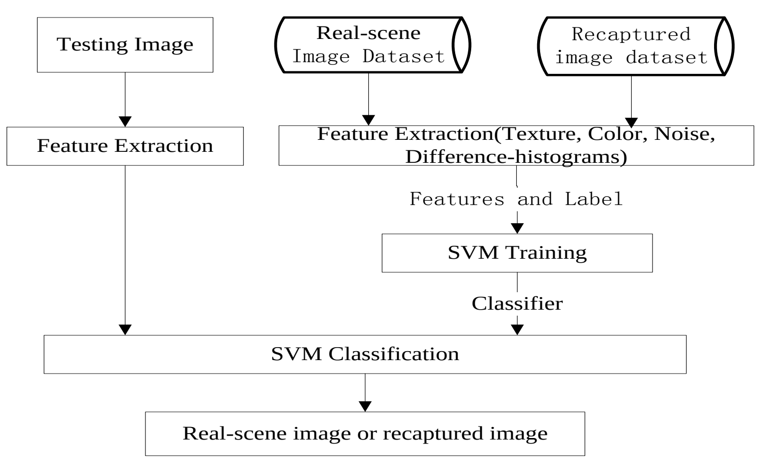

Figure 1. The proposed framework of image recaptured detection

The steps performed in our detection method are as the following. For each image in real-scene image datasets and recaptured image datasets, features including texture, color, difference histogram and noise are extracted. Then, features and label are used to train a SVM classifier. For a testing image, extracted features are fed into SVM classifier, which classifies those features as the features of either a real-scene image or recaptured image.

3.1. Low-Level Feature Extraction

The feature descriptors considered in this paper include information related to blurring (difference histograms), color (color moment and contrast), and texture (Local Binary Patterns). A summary of these descriptors is presented as follows.

3.1.1. Difference-histograms: Because the first capture device or the printing device could be of low resolution, or the display medium may not be in the focus range of the camera in a specific recaptured setting, blurriness can arise in a recaptured image. Besides, the brightness of the LCD screen affects the recaptured image in a way that the high-frequency regions (borders) become susceptible to a "blurring" effect due to the pixels with higher values brightening their neighborhood. The blur effect is caused by a loss of the high frequency content. Therefore recaptured image contains less high frequency components. In this paper, we explore such information as a distinguishing feature in order to detect whether an image is a spoof or not by using difference histograms. Difference-histograms have been used to identify computer generated graphics from real photograph [11].

For a given image I , its first order difference image is defined as I_i , where i denotes four directions (horizontal, vertical, diagonal, anti-diagonal) of difference images. So the first order difference images can be computed as follow:

$$I_i = I * f_i \ , \ i \in \{h, v, d, a\} \tag{1}$$

where f_i are convolution kernels in four directions.

$$f_h = (1,-1),\ f_v = \begin{pmatrix} 1 \\ -1 \end{pmatrix},\ f_d = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix},\ f_a = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}. \tag{2}$$

A similar process can be done for second-order difference images:

$$I_{i,j} = I * f_i * f_j \ , \quad i, j \in \{h, v, d, a\} \ . \tag{3}$$

Notice that $I_{i,j} = I_{j,i}$, so we can get 14 difference images in total. Then we compute the normalized histogram H_i :

$$H_i(n) = \frac{\#\{(x,y) : I_i(x,y) = n\}}{N}, \quad -255 \le n \le 255 \ . \tag{4}$$

where N is the total number of pixels in difference image I_i, and # denotes the cardinal number of a set. For each difference images, we can get the following features:

$$H(0), \frac{H(1)+H(-1)}{2}, \ldots, \frac{H(k)+H(-k)}{2} \tag{5}$$

Thus we can get 14(1+k) histogram features.

3.1.2. Texture feature: Because a human face is a complex non-rigid 3D object whereas a photograph can be seen as a planar rigid object, the surface properties of real faces and prints, for example, pigments, are also different for face spoofing detection. These two distinctive properties may cause characteristic specular reflections and shades. In addition, face prints often contain printing artifacts, such as jitter and banding, which can be detected with texture [12]. Texture patterns are often easily observable on a poor-quality recaptured image, and are not obvious in finely recaptured image. However, complete elimination of the textures is very difficult [8]. To capture texture, we extract features from Local Binary Patterns (LBP), a method widely used for texture analysis.

The basic version of the LBP operator considers only the eight neighbors of a pixel and produces rather long histograms (256). In literature [13], Heikkilä introduced the CS-LBP operator for region description which is more efficient than LBP.

The scheme functions of LBP and CS-LBP are given as follows:

$$S_{LBP}\left(p_i, p_c\right) = \begin{cases} 1, p_i > p_c \\ 0, otherwise \end{cases} \tag{6}$$

$$S_{CS-LBP}\left(p_i, p_{i+(p/2)}\right) = \begin{cases} 1, p_i - p_{i+(p/2)} > T \\ 0, otherwise \end{cases} \tag{7}$$

where $p_i, p_{i+(p/2)}$ and p_c correspond to the gray-level of center-symmetric pairs of pixels and the center pixel on a circle of radius R, T is the threshold for the CS-LBP descriptor. The binary pattern of LBP and CS-LBP are calculated as

$$LBP_{P,R}(x, y) = \sum_{i=0}^{P-1} S_{LBP}\left(p_i, p_c\right) \times 2^i \tag{8}$$

$$CS-LBP_{P,R,T}(x, y) = \sum_{i=0}^{(P/2)-1} S_{CS-LBP}\left(p_i, p_{i+(p/2)}\right) \times 2^i \tag{9}$$

where (x,y) denotes the coordinates of a pixel.

It is clear that the LBP produces 256 (28) different binary patterns, whereas the CS-LBP produces only 16 (24) different binary pattern for 8 neighbors.

3.1.3. Sensor Pattern Noise: Sensor Pattern Noise has been used to scanner identification [14]. As described in [15], the model of extracting the sensor pattern noise from an image is:

$$Noise = I - F\left(I\right) \tag{10}$$

where F is a denoising function. In order to improve denoising performance, we employ a novel sophisticated denoising filter, namely a sparse 3D transform domain collaborative filtering proposed by Kostadin Dabov *et al.*, [16]. This denoising strategy is based on an enhanced sparse representation in transform domain. The main algorithm is realized using three steps:

1) A 3D transformation is applied by grouping similar 2D image blocks into 3D data arrays.

2) The transformation spectrum is then shrinked.

3) Inverse 3D transformation is applied.

This denoising strategy not only reveals details shared by grouped blocks, but also retains the essential unique characteristics of each individual blocks. After the residual images is processed using the denoising filter, the four first order statistical features from each color channel are computed. So 12 dimension features are extracted from all three color channels of each residual image.

3.1.4. Color Features: Because the light transmitted from the back can significantly reduce the contrast and saturation of a recaptured image, the color of finely recaptured images still looks different from their original images. Contrast and color moments for an image can be computed as a distinguishing feature. To extract color moments, the first moment (mean), the second moment (variance) and the third moment (skewness) for each cannel of HSV color space and RGB space are taken as features in this paper. To capture these color anomalies, we compose a set of 19 dimension color features including 1 dimension contrast and 18 dimension color moments.

3.2. Classification

After feature extraction, we train a support vector machine (SVM) classifier with RBF kernel using the LSSVM tools. We used the “grid-search” method to find the optimal parameters σ and γ of RBF kernel. To train the LSSVM classifier, we randomly selected half of the images in [17] as training sets, and the rest of the images are used as testing sets.

4. Results and Discussion

In the following results of experiments are described to evaluate several aspects of our proposed approach. First, we compare the performance of different features used in this paper. Second, we compare the proposed method on several datasets. Last, we made comparisons with previous works. In the experiment, we used smart phone recaptured image database [17], in which the real images were obtained by end-user camera of smart phone. Three popular brands of smart phones are used, which are Acer M900, Nokia N95, and HP iPAQ hw6960. For the recaptured images, three categories of recaptured datasets are obtained due to the post processing, which are recaptured images with real environment background (Recaptured Dataset A), recaptured images without real environment background (Recaptured Dataset B), and the image pairs through homography transformation and cropping (Recaptured Dataset C).

4.1. Feature Evaluation

Firstly, we compare the detection performance of different features on recaptured dataset B. Table 1 shows the results of different features on different smart phone in recaptured dataset B. It is observed that difference-histograms and CS-LBP are the most effective features for recaptured dataset B.

Table 1. Detection results with different features on recaptured datasets B

Features	Feature Dimension	Accuracy on AcerB	Accuracy on HPB	Accuracy on NokiaB	Average accuracy on dataset B
Difference-histograms Feature(DH)	98	98.5%	96.0%	99.0%	97.8%
CS-LBP feature	16	91.5%	82.0%	97.5%	90.3%
Sensor Pattern Noise Feature(SPN)	12	87.0%	83.5%	93.5%	88.0%
Color Moments of HSV Color Space(HSV)	9	80.0%	87.5%	86.5%	84.7%
Color Moments of RGB Color Space(RGB)	9	80.5%	89.5%	79.0%	83.0%
Contrast	1	84.5%	81.5%	90.0%	85.3%

Secondly, we compare the detection performance combining with different features, as shown in Table 2. The results show that significant improvement can be achieved when two features are combined, especially for HSV+CSLBP, HSV+DH, CSLBP+DH, CLSBP+RGB, DH+SPN, DH +RGB, DH +contrast.

Last, detection accuracy combined with all the features including difference histogram features, color moment of HSV, contract, CSLBP texture features and Pattern Noise Features will reach 97.2%.

Table 2. Detection results combining different features on recaptured datasets B

Features	Dimension	Accuracy on Acer	Accuracy on HPB	Accuracy on Nokia	Average accuracy on dataset B
HSV+ CSLBP	25	96.0%	88.5%	97.0%	93.8%
HSV+ DH	107	99.5%	95.5%	99.0%	98.0%
HSV+ SPN	21	93.5%	86.0%	93.5%	91.0%
HSV+ Contrast	10	92.5%	93.0%	94.5%	93.3%
CSLBP+DH	114	98.5%	91.0%	99.0%	96.2%
CSLBP +SPN	28	94.5%	83.0%	98.5%	92.0%
CLSBP+RGB	25	96.5%	92.5%	97.5%	95.5%
CLSBP+ Contrast	17	97.0%	86.0%	98.5%	93.8%
DH+SPN	110	97.0%	92.0%	99.0%	96.0%
DH+RGB	107	99.0%	93.5%	99.0%	97.2%

DH+ Contrast	99	97.5%	95.0%	99.5%	97.3%
SPN+RGB	21	92.0%	85.5%	90.5%	89.3%
SPN+ Contrast	13	94.5%	85.0%	94.0%	91.2%
RGB+ Contrast	10	90.5%	92.5%	90.5%	91.2%
CSLBP +DH +HSV	123	99.0%	93.0%	99.0%	97.0%
CSLBP+DH +SPN	126	99.0%	89.5%	99.0%	95.8%
CSLBP +DH+RGB	123	99.0%	92.0%	99.5%	96.8%
CSLBP +DH +Contrast	115	96.0%	93.0%	99.0%	96.0%
HSV +LBP +DH+SPN +Contrast	136	99.0%	93.5%	99.0%	97.2%

4.2. Datasets Evaluation

In this section we evaluate the detection performance of the proposed method on different datasets. From the Table 1 and Table 2, we can find that our proposed method is more effective for Acer M900, Nokia N95 than HP iPAQ hw6960. We also compare the detection performance on Recaptured Dataset A, Recaptured Dataset B and Recaptured Dataset C. The experimental results in Table 3 show that our proposed method is more effective for dataset B than dataset A and dataset C. From the Table 3, we also find that the detection accuracy is getting higher with increasing dimension.

Table 3. Detection results with different features on different datasets

Features	Dimension	Accuracy on Dataset A	Accuracy on Dataset B	Accuracy on Dataset C	Average accuracy
Contrast	1	68.0%	85.3%	54.1%	69.1%
RGB	9	72.0%	83.0%	49.5%	68.2%
HSV	9	73.5%	84.7%	52.8%	70.3%
SPN	12	75.0%	88.0%	59.6%	74.2%
SPN+ Contrast	13	75.5%	91.2%	56.9%	74.5%
CS-LBP	16	73.5%	90.3%	76.1%	80.0%
HSV+ SPN	21	81.0%	91.0%	56.0%	76.0%
HSV+ CSLBP	25	81.5%	93.8%	72.0%	82.4%
CSLBP +SPN	28	79.5%	92%	75.7%	82.4%
DH	98	78.0%	97.8%	79.4%	85.1%

DH+ Contrast	99	75.0%	97.3%	81.6%	84.6%
HSV+ DH	107	81.5%	98.0%	80.0%	86.5%
CSLBP+DH	114	78.5%	96.2%	83.0%	85.9%
CSLBP+DH + SPN	126	81.0%	95.8%	82.6%	86.5%
HSV +CSLBP +DH +SPN +C ontrast	136	85.5%	97.2%	83.0%	88.6%

4.3. Comparisons with Previous Works

We also compare the proposed method to state-of-the-art methods. The results are shown in Table 4, where some results refereed from Table 5 in [17]. The results demonstrate that our proposed method combining with difference histogram features, color moment of HSV, contract, CSLBP texture features and sensor pattern noise features outperforms the other methods although our proposed method have lower feature dimensions. However, our proposed method on Dataset A achieves accuracy of 85.6%, which is lower than 91.3% accuracy of the method using physics feature [7]. The reason is that the background contextual information has been considered in [7] for recaptured dataset A, which is recaptured images with real environment background.

Table 4. Dimensions of features and performance on datasets

Features	Dimension	Accuracy on Dataset A	Accuracy on Dataset B	Accuracy on Dataset C	Average accuracy
Proposed method	136	85.5%	97.2%	83%	88.57%
Wavelets statistics[3]	216	80.76%	80.93%	73.78	78.49%
Markov statistics	486	81.35%	77.3%	65.85	74.84%
Geometry based[6]	192	86.31%	89.33%	80.12%	85.26%
Physics[7]	166	91.3%	86.66%	74.88%	84.28%

5. Conclusions

In this paper, we proposed an image recapture detection method using a richer descriptor set introduced in the image recapturing process including sensor pattern noise feature, texture feature and color information. The proposed method obtained a significant improvement in results. We have tested our approach on a number of varied datasets. The experimental results demonstrate that our method works excellently in identification of the recaptured photos. The future work is to extract more other features in terms of color, texture and noise, and so on, and then design more efficient detection method using best combinations of all the features through intelligent searching algorithm to further achieve better detection accuracy while maintaining optimal time complexity.

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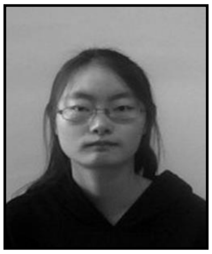
Authors

Yongzhen Ke obtained his BE of computer application at Tianjin Polytechnic University in China in 1997, and received his ME and PhD of computer application at Tianjin University in China in 2000 and 2008, respectively, on the research subjects of information security, image processing and data visualization. From 1997 to the present he worked in Tianjin Polytechnic University, China. Now he is an associate professor at School of Computer Science & Software Engineering, Tianjin Polytechnic University, China. His current research interests include image processing, digital image forensic, network security and application of IoT.



Qingqing Shan obtained her BE of computer application at Tianjin Polytechnic University in China in 2012, and she is a postgraduate at Tianjin University in China now, on the research subjects of image processing and digital image forensic.

Fan Qin obtained her bachelor degree of economics at Nankai University in China in 2000, and received his master degree and PhD of management at Nankai University in China in 2005 and 2009, respectively, on the research subjects of information management, data mining. From 2009 to the present she worked in Nankai University, China. Now she is a lecture at department of logistics management, Nankai University, China. His current research interests include information system management, image recognition, e-commerce and logistics management.

Weidong Min obtained his BE, ME and PhD of computer application at Tsinghua University in China in 1989, 1991 and 1995, respectively, on the research subjects of computer graphics, image processing and computer aided geometric design. He was an assistant professor of Tsinghua University from 1994 to 1995. From 1995 to 1997 he was a postdoctoral researcher at University of Alberta, Canada. From 1998 to 2011 he worked as a senior research project manager at Corel, March Networks and other companies in Canada. Now he is an associate professor at School of Computer Science & Software Engineering, Tianjin Polytechnic University, China. His current research interests include computer graphics, image and video processing, software engineering, distributed system, network resources management.