

Video and Image Recapture Detection based on Edge Profiles and Color Moments

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ABSTRACT: High quality images can be recaptured from printed materials, magazines, LCD screens etc. using high fidelity cameras. Recapturing an image is the process of retaking an original natural scene image which is presented on a medium using a camera. In the current scenario, many video and image editing softwares are available. Forger can manipulate a digital image to produce a forged image. Forged images are easy to identify. The authenticity of a forged image or video can be increased by recapturing it. Video recapturing is the process of retaking original scene on media using a second camera. Among different features aliasing, blurriness and color moments are less scene dependent features. This paper aims at providing a detailed overview on how recaptured images and videos can be identified using color moments and dictionary learning of edge profiles.

KEYWORDS: Image forensics, K-SVD, LCD, recapture, recapture detection, single capture, support vector machine.

I. INTRODUCTION

In many fields like journalism, medical, digital forensics, scientific publication etc. digital image plays an important role. Digital images can convey information easily. Traditionally and historically, there has been confidence in the integrity of visual data, such that a picture printed in a newspaper is commonly accepted as a certification of the truthfulness of the news, or in front of a court of law, video surveillance recordings are proposed as probatory material. Current softwares allow creating photo realistic computer graphics. For the viewers these forged images are indistinguishable from photographic images.

Today almost everybody has hand held devices for recording, storing and sharing of large amount of digital images. With the increased use of multimedia, huge amount of videos and images are shared among individuals. Many image editing and video editing softwares are now widely available, which makes it extremely simple to alter the contents of an image, or to create new images. This kind of tampering is no more restricted to experts.

Even if the forger is highly skilled, some imperfections will be present in the forged images or videos. To increase the authenticity of forged images, forger can recapture them from an LCD monitor or from printed materials using high fidelity cameras.

There are two broad categories for recapture video detection: techniques originally developed for images applied frame-wise to videos and algorithms specifically designed for video sequences. Recapture video and recapture image detection is an application of video and image forensics. There are various approaches for recaptured image detection. This paper presents a new recapture detection algorithm using the edge blurriness and color features of the image and video frames.

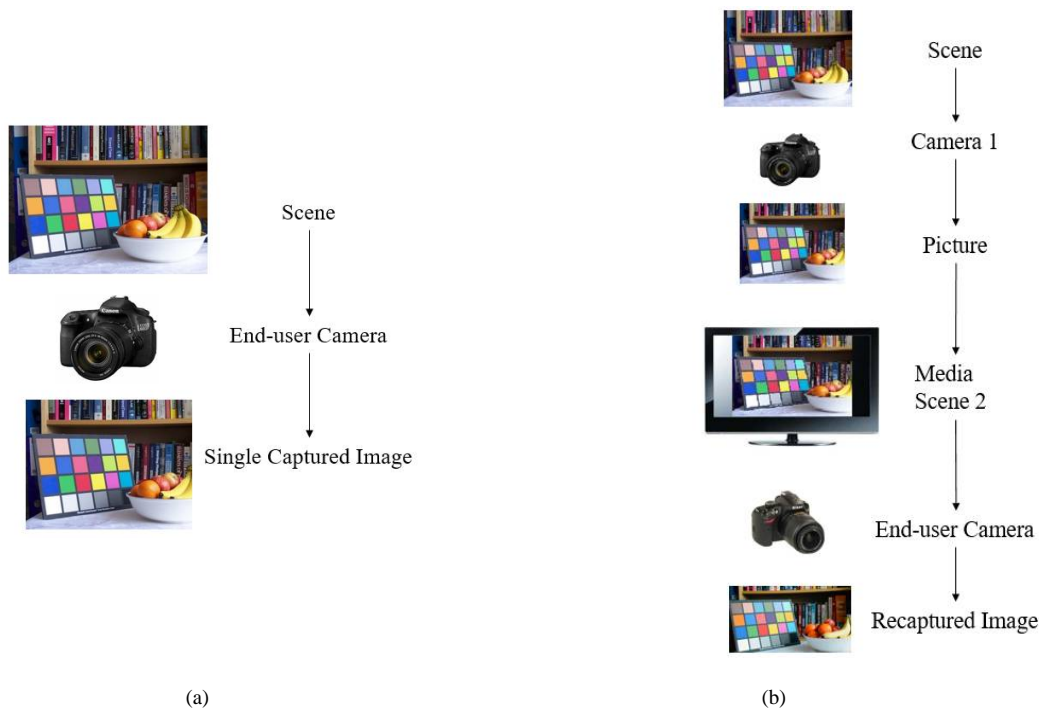


Fig. 1. (a) The process to produce the real scene image (b) The process to produce the recapture image

II. RELATED WORK

H. Yu et al. addressed recapture image detection from printed materials such as magazines or photographic paper in literature [1]. They discovered that the meso structure of photo surface modulates the specularity of recaptured photo.

J. Bai et al. proposed and validated a physics-based method to detect image recaptured from both printed material and LCD screen using only a single image in [2]. A linear SVM classifier is generated based on several features such as the special distribution of the specularity in the image, non-linearity of tone response curve, image color, contrast, sharpness, and chromaticity.

In [3] authors X. Gao et al. presented a physical model for image recapturing and the features derived from the model are used in a recaptured image detector. The system does not explicitly extract the 3D geometry.

Cao and Kot in [4] first constructed high quality recaptured image dataset. They proposed a set of statistical features to prevent the image recapturing attacks which includes Local binary pattern (LBP), Multi-scale wavelet statistics (MSWS) and color features. These features are then used to train a probabilistic support vector machine (PSVM) classifier for identification of the finely recaptured images.

Kose and Dugelay in [5] developed a new face anti-spoofing approach, which is based on analysis of texture and contrast characteristics of recaptured and captured images. In a spoofing attempt, image rotation is quite possible. Therefore, a rotation invariant local binary pattern variance (LBPV) based method is selected to be used in this system.

An image recapture detection method based on multiple feature descriptors is proposed by Ke et al. in [6]. The method uses combinations of low-level features including sensor pattern noise features, difference histogram, color information and texture features to identify the recaptured images from original images.

Liu and Wang presented an approach for identifying recaptured image based on DCT coefficients in [7]. The low frequency of an image mainly reflects such information as texture and profile details.

Ni, Zhao and Zhai proposed an effective recaptured image forensics algorithm through color moments and DCT coefficients features in [8]. Because of the differences of light and environments, recaptured images exhibit the color diversity. Recapture images suffer from double JPEG compression due to second camera shooting and it in turn changes the DCT coefficients.

Yu et al. presented a fast and cooperation free solution to the image recapture detection problem in literature [9] which is based on HSV color space. To extract specified features in each partitioned layer they constructed a color space pyramid. Their features can have both local and global properties in the pyramid.

Thongkamwitoon et al. [10] presented a framework for the identification of an image acquisition chain using dictionaries of edge profiles in the literature. In [11] they said the fact that the edge profiles of single and recaptured images are markedly different and trained two alternative dictionaries using the KSVD approach [12]. They provided a comprehensive overview of the traces found in recaptured images in [13], and argued that aliasing and blurriness are

the least scene dependent features. They then showed how aliasing can be eliminated by setting the capture parameters to predetermined values. Driven by this finding, proposed a recapture detection algorithm based on learned edge blurriness. Two sets of dictionaries are trained using the K-singular value decomposition approach from the line spread profiles of selected edges from single captured and recaptured images. A support vector machine classifier is then built using dictionary approximation errors and the mean edge spread width from the training images.

In [14] M. Visentini-Scarzanella and P. L. Dragotti presented a technique for the automatic detection of recaptured videos, which is an application to video forensics. In the proposed method scene jitter is used as the cue for classification.

Bestagini et al. presented a video recapture detection technique in [15]. They first characterized the video recapture model. A digital camcorder is used to focus on the common scenario of recaptured from LCD monitor. And a recapture detector is proposed based on analysis of characteristics ghosting artifact left by the recapture process. The characteristic ghosting artifact is generated as consequence of lack of synchronization between camera and the monitor, which is used to detect whether a sequence is recaptured or not.

III. PROPOSED SYSTEM

In this section we propose a new approach for recapture detection of both video and images. The method is based on the edge blurriness and color moments. These are least scene dependent features. The method in paper [13] is used to extract the edge blurriness features. The edge blurriness is characterized by the line spread profile of the edges in the images instead of edge spread profile. The differences between the line spread profiles of the single captured and recaptured images and videos are characterized using two parameters related to edges: a sparse representation error E_d and an average line spread width $\bar{\lambda}$. Sparse representation error E_d , represents the difference in errors, E_{SC} and E_{RC} . Color moments are discussed in [8].

The proposed method contains a training stage and a classification stage. In the training stage, a support vector machine (SVM) is trained using the features extracted from known images. In the classification stage, an unknown image is given to the trained model for detection.

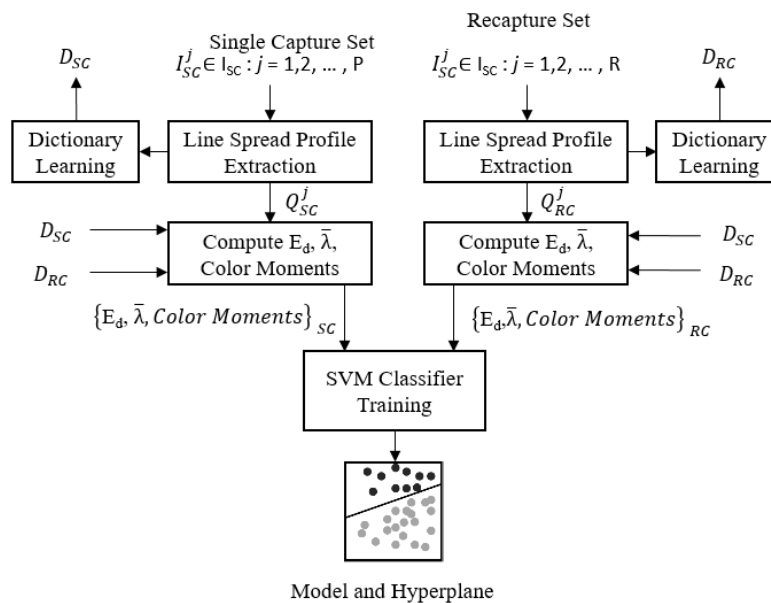


Fig. 2. Schematic diagram of training process

Fig 2 depicts the training process which is as follows

1. Two sets of video frames and images are used for training process, a single capture set I_{SC} and a recapture set I_{RC} .
2. Line spread profile matrices Q_{SC}^j and Q_{RC}^j are extracted from the single captured and recaptured images respectively.
3. The feature matrices S_{SC} and S_{RC} are created from the line spread profiles matrices Q_{SC}^j and Q_{RC}^j .
4. Dictionaries D_{SC} and D_{RC} are trained using feature matrices S_{SC} and S_{RC} . K-SVD approach in [12] is used to train Dictionaries D_{SC} and D_{RC} .
5. Compute the training features $E_d, \bar{\lambda}$ (using D_{SC} and D_{RC}) and color moments.
6. Train an SVM classifier with the extracted features and obtain the hyperplane.

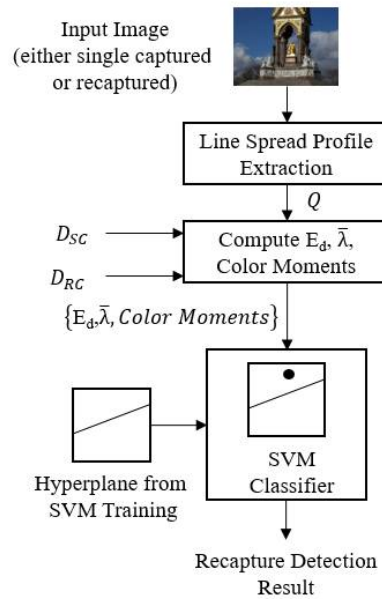


Fig. 3. Diagram showing overview of classification process

Classification process is shown in Fig 3. Steps in classification process are as follows.

1. Give a query image is to the system.
2. Extract the line spread profile Q of the query image.
3. Compute the features $E_d, \bar{\lambda}$ and color moments.
4. Use the SVM hyperplane to get the classification result

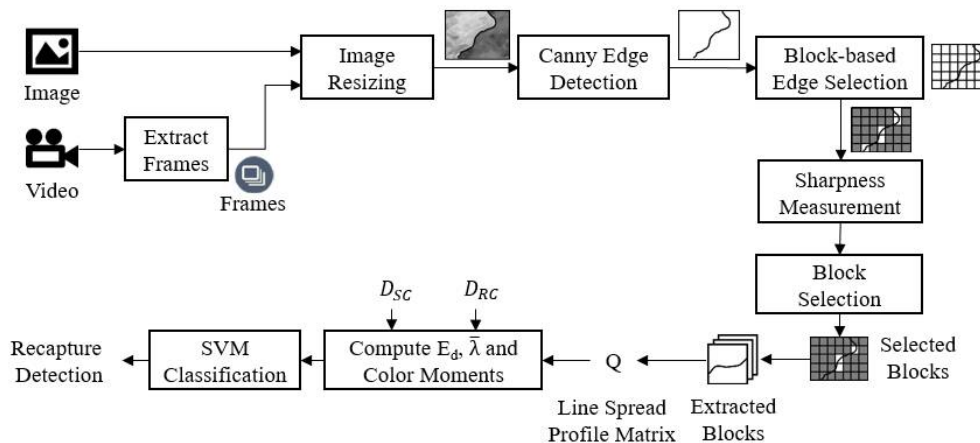


Fig. 4. Working diagram of the proposed method

A. EDGE DETECTION AND LINE SPREAD PROFILE EXTRACTION

Fig 4 shows the overall working of the proposed system. Edge detection and line spread profile extraction are as follows.

1. There are two sets of inputs, images and videos. Extract key frames from the video.
2. In the image resizing stage, the images and video frames are resized to a standard size.
3. Edge detection is done using Canny Edge Detector [16]. The edge profiles are extracted locally.
4. The query image is divided into a number of non-overlapping square blocks. Size of each block is 16×16 pixels.
5. Detect blocks with sharp single edge.
6. Detected blocks are then ranked according to their sharpness measurement. Thus blocks with prominent edge features are selected.
7. The extracted blocks forms the line spread profile of the image.

B. DICTIONARY LEARNING ALGORITHM

Two overcomplete dictionaries D_{SC} and D_{RC} are created using the K-SVD approach. D_{RC} and D_{SC} provides an optimal sparse representation of the line spread profiles from recaptured and single captured images and video frames respectively. The dictionary learning can be used as a tool to train the characteristics of the distortion patterns present in the edges found in naturally occurring images. The recapture process introduces sharpness degradation to the recaptured image or video.

Feature matrices S_{SC} and S_{RC} are generated by concatenating the line spread profile matrices Q_{SC}^j and Q_{RC}^j horizontally over all the training images in each respective set. Using the K-SVD approach dictionaries D_{SC} and D_{RC} are generated from S_{SC} and S_{RC} respectively.

C. FEATURE EXTRACTION

In the proposed method eight features are selected for SVM training and classification. They are the difference of approximation error E_d , average line spread profile width $\bar{\lambda}$ and six color features. The six color features includes mean and standard deviation of three color channels red, green and blue. The first two parameters E_d and $\bar{\lambda}$ are extracted from the line spread profile matrix Q . The color features are extracted directly from the image.

The abilities of the two dictionaries D_{SC} and D_{RC} to provide a sparse representation of the line spread profiles from a query image is given by the first parameter E_d . For an unknown image we need to find the line spread profile matrix Q . Two approximation errors E_{SC} and E_{RC} are calculated using the dictionaries and Q .

Approximation error E_{SC} using dictionary D_{SC} trained from single captured images [13]:

$$E_{SC} = \|Q - D_{SC}X_1\|_F^2 \quad (1)$$

Approximation error E_{RC} using dictionary D_{RC} trained from recaptured images is [13]:

$$E_{RC} = \|Q - D_{RC}X_1\|_F^2 \quad (2)$$

X_1 is the coefficients matrix computed using the orthogonal matching pursuit algorithm [17] with dictionary D_{SC} . Similarly X_2 is computed from dictionary D_{RC} .

How well each dictionary fits the line spread profile matrix Q is described by the approximation errors E_{SC} and E_{RC} .

Difference of approximation error E_d is the difference of E_{SC} and E_{RC} [13].

$$E_d = E_{SC} - E_{RC} \quad (3)$$

From the evaluation it is found that the value of E_d is negative for most of the single captured images. And E_d is positive for most of the recaptured images.

Value of λ is defined as the distance that allows 95% of spectral energy of the spread function to be captured. Compute the spread width λ_i of all the line spread profiles. Taking the average of all λ_i gives the average line spread profile width $\bar{\lambda}$. Since the recaptured images are distorted by the recapturing process, value of $\bar{\lambda}$ for recaptured images is greater than that for single captured images.

Color is one of the widely used feature for image representation. Mean and standard deviation of the three color channels forms the six color features for the proposed method.

IV. EXPERIMENTAL RESULTS

A. EXPERIMENTAL DESIGN

Thongkamwitoon et al. developed a database [18] of images recaptured from an LCD monitor for the purpose of testing and evaluating recapture detection algorithm. The database contains 1035 single captured images and 2520 recaptured images. 12 different cameras are used to create the database.

The algorithm is trained using 144 single captured images and 144 recaptured images from [18]. The training set is created using 16 images from 9 different single capture set and 20-21 images from 7 different recapture set.

B. PERFORMANCE EVALUATION

The proposed algorithm is tested using 900 single captured images and 1260 recaptured images. The testing results are shown in Table I. First half of the table shows the test results with the single capture image set and the bottom half shows the results for recapture image set. The proposed method is compared with two other methods. The first method [13] consider only two features, difference in approximation error E_d and average line spread width $\bar{\lambda}$. The second method uses the six color features.

Using the existing method [13], out of 900 single capture images, 843 images correctly classified giving a true negative rate (TN) 93.67%. For the recapture image set, the existing method classified 1209 images correctly giving true positive rate (TP) of 95.95%.

Using only the six color moments for training the SVM the results are poor. For the single capture set only 592 images correctly classified, TN is only 65.78%. In case of recapture image set, only 895 images correctly classified, TP is 71.03%.

In the proposed method eight features of the existing methods are combined. Which gives better results than the existing methods. In case of single capture detection, proposed method detected 865 images correctly giving a TN of 96.11%. In recapture detection, 1226 images detected correctly giving TP of 97.30%.

Table I: Recapture detection Result

Camera Model	No. of images	No. of images misclassified		
		Existing Method ($E_d, \bar{\lambda}$)	Using color moments	Proposed Method ($E_d, \bar{\lambda}, \text{color moments}$)
Single Capture Database				
V550 (Silver)	100	17	40	12
V550 (Black)	100	13	43	8
V610	100	6	43	6
D40	100	3	23	3
D70s	100	12	23	2
TZ7	100	2	38	2
EOS 600D	100	2	41	2
E-PM2	100	2	22	0
RX100	100	0	35	0
Total	900	57	308	35
Recapture Database				
TZ10	180	0	23	0
D3200	180	0	148	8
EOS 60D	180	0	1	0
D70	180	3	128	12
EOS 600D	180	1	3	0
E-PM2	180	47	6	12
RX100	180	0	56	2
Total	1260	51	365	34

V. CONCLUSION

The problem of detecting recaptured images and videos from LCD screens has been addressed in this paper. Out of many features aliasing, blurriness and color moments are found to be less scene dependent features. To characterize the edge blurriness features, two dictionaries are trained using K-SVD algorithm. Six color features are also used to classify the recaptured images and videos. SVM classifier is used to classify the single captured and recaptured images and videos. When comparing with the existing methods our method gives a performance of 97.30% for recapture detection and 96.11% for single capture detection.

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