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An Image and Video Recapture Detection using Acquisition Chains of Edge Profiles

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Abstract: Using smart phone and digital technology it's easy to recapture images and videos from an liquid crystal display (LCD) monitor and from smart phone. Such image and video recapturing activities are a security threat, which allows the forgery images/videos to bypass the current forensic systems. The task of verifying the ownership and history of an image or video is, consequently, more difficult. One approach to detecting an image or video that has been recaptured from an LCD monitor or from smart phone is to search for the presence of aliasing due to the sampling of the monitor or screen pixel grid. In this paper, we show that it is possible to detect recaptured image and video based on feature set of image. By using LCD monitors or smart phone, its add aliasing effect in image, so using features like brightness, contrastness, edge width, blurriness etc., we can identify recaptured image. We find the fact that the edge profiles of single and recaptured images are marked different and we train two alternative dictionaries using the KSVD approach. One dictionary is trained to provide a sparse representation of single captured edges and a second for recaptured edges. Using these two learned dictionaries, we can detect whether a query image has been recaptured with use of Support Vector Machine (SVM). Experiments conducted show that the proposed algorithm is capable of detecting recaptured images and video with a high level of accuracy.

Index Terms: Smart Phone, LCD, Aliasing, Edge Profiles, K-SVD, Sparse Representation, SVM.

I. INTRODUCTION

To restore the trustworthiness of digital images, image forgery detection [10] has been intensively studied in recent years through detection of certain intrinsic image regularities or some common tampering anomalies. Frequently, the tell-tale cues useful for image forensics such as lens distortion, sensor noise pattern and statistics, demosaicing regularity and JPEG characteristics are directly associated with the image creation pipeline, where the light signals are converted into a digital image. Though some forensic methods can efficiently expose the direct tampering made on an image, most existing methods are unable to expose the indirect scenery forgery, where the scenery to be captured is artificially created. Though creating physical scenery in general can be a very difficult and expensive task, with the aid of today's ubiquitous and high-fidelity display technology, generating virtual scenery of reasonable fidelity is still relatively easy and such technology is potentially exploited to defeat the current image forensics systems.

Traditionally, photographs have been associated with a high degree of authenticity and were considered difficult to forge. With the advent of digital photography image tampering is now commonplace and can easily be performed using commercial, widely available, image editing software [3]. In practice, unless an attacker is highly skilled, imperfections in the forged image may be present and the attacker may attempt to conceal them by recapturing the forged image from an LCD monitor. By recapturing the image, an additional level of authenticity, typically associated with a single captured image, is introduced into the forgery making it more difficult to detect. For this reason this paper review various solutions to problem of detecting whether a given image was recaptured with a digital still camera from an image displayed on an LCD monitor or whether its single capture of natural scene.

II. RELATED WORK

Hani Muammar and Pier Luigi Dragotti investigated one approach to detecting an image that has been recaptured from an LCD monitor is to search for the presence of aliasing due to the sampling of the monitor pixel grid. An analysis of aliasing in recaptured images of LCD monitors using digital cameras equipped with a Bayer CFA was presented. The periodic structure of the monitor pixel grid projected on the camera's image sensor was modelled in one dimension by a 2-dimensional square wave. In that paper they show that aliasing can be completely eliminated in a recaptured image by setting the camera to monitor distance to a value determined by the camera lens focal length, the pixel pitch of the LCD monitor and the pixel pitch of the camera's image sensor. A recapture detector should not therefore rely solely on the presence of aliasing, but should make use of other features present in recaptured images such as high scene tonal contrast, changes in color balance and loss in perceived sharpness. Thirapiroon Thongkamwitoon, Hani Muammar, and Pier-Luigi Dragotti proposed algorithm to detect recapture image based on learning dictionaries of edge profiles. They proposed a method for image recapture detection based on the blurriness of edges.

Step 1: Firstly, the query image is converted to greyscale.
Step 2: all edges contained in the image are detected using a Canny Edge Detector [20].

Step 3: Edge profiles are extracted locally
The query image is divided into a number of non-overlapping square blocks B (m, n) of size W × W with W = 16 pixels. Here m and n are the vertical and horizontal indices of the block respectively.
Step 4: For each block, first check whether it contains a horizontal or near horizontal sharp single edge.
Step 5: The block will be detected only when the condition $\eta \geq \beta W$, β=0.6
Step 6: The detected blocks, B (m, n), are then ranked according to their sharpness and edge contrast.
Block sharpness is determined using the technique in which the average width λm,n of line spread profiles of the blocks is estimated.
The contrast of a block is measured by computing the block-based variance, σm,n, of the input image at the detected block.
Step 7: Create Feature matrix:
let Y ∈ IRW×W be a matrix which represents the grey scale values of a block. Each column, yi ; i = 1, 2, · · · ,W, of the matrix Y may, therefore, be considered to represent an edge profile of the image.

This feature matrix is used for training and testing purposes. Here authors used SVM classification algorithm for labelling to images.

Thirapiroon Thongkamwitoon, Hani Muammar, and Pier Luigi Dragotti show that it is possible to detect a recaptured image from the unique nature of the edge profiles present in the image. They leverage the fact that the edge profiles of single and recaptured images are markedly different and they train two alternative dictionaries using the KSVD approach. One dictionary is trained to provide a sparse representation of single captured edges and a second for recaptured edges. Using these two learned dictionaries, they can determine whether a query image has been recaptured. They achieve this by observing the type of dictionary that gives the smallest error in a sparse representation of the edges of the query image.

Step 1: We trained two dictionaries DSC and DRC using features SSC and SRC extracted from the single captured and recaptured images respectively.
Step 2: Each dictionary is considered to provide an optimal representation of the profiles extracted from edges found in each set of training images, respectively.
Step 3: We now assume that a query image containing edges is available (above Algorithm).
Step 4: Given the matrix Q ∈ IRW−1×N which represents all line spread profiles extracted from the detected blocks, the decision for recapture detection can be based on the class of dictionary that gives the smallest representation error.
Step 5: We defineX1 andX2 as the coefficient matrices obtained from the composition of query feature matrix Q using the dictionaries DRC and DSC respectively.
Step 6: The query image is classified into a recapture group if

$$\|\mathbf{Q} - \mathbf{D}_{RC}\mathbf{X}_1\|_F^2 < \|\mathbf{Q} - \mathbf{D}_{SC}\mathbf{X}_2\|_F^2.$$

Otherwise, the query image is classified to the single capture group. Recently there have been efforts to detect recapture of videos [15]–[18]. These methods use features which are unique to video systems.

In [15], A. da Silva Pinto, H. Pedrini, W. Schwartz, and A. Rocha present a solution to video-based face spoofing to biometric systems. Such type of attack is characterized by presenting a video of a real user to the biometric system. To the best of our knowledge, this is the first attempt of dealing with video-based face spoofing based in the analysis of global information that is invariant to video content. Their approach takes advantage of noise signatures generated by the recaptured video to distinguish between fake and valid access. To capture the noise and obtain a compact representation, they use the Fourier spectrum followed by the computation of the visual rhythm and extraction of the graylevel co-occurrence matrices, used as feature descriptors.
In [16], J.-W. Lee, M.-J. Lee, T.-W. Oh, S.-J. Ryu, and H.-K. Lee, propose a screenshot identification scheme using unique characteristic of interlaced video, combing artifact. To do this, several blocks of the input image are selected for the significant combing artifact they have. In each block, eight features that represent the artifact are extracted. These extracted features are applied to train and test support vector machine for identifying whether the input image is a screenshot or not.
In [17], P. Bestagini, M. Visentini-Scarzanella, M. Tagliasacchi, P. L. Dragotti, and S. Tubaro they first characterize the video recapture model, focusing on the common scenario of a sequence recaptured from a LCD monitor using a digital camcorder, then they propose a recapture detector for this case. The detector is based on the analysis of a characteristic ghosting artifact left by the recapture process. The presented algorithm is finally validated by means of tests on original and recaptured sequences.

In [18], M. Visentini-Scarzanella and P. L. Dragotti, paper presents a novel technique for the automatic detection of recaptured videos with applications to video forensics. The proposed technique uses scene jitter as a cue for classification: when recapturing planar surfaces approximately parallel to the imaging plane, any added motion due to jitter will result in approximately uniform high-frequency 2D motion fields. The inter-frame motion trajectories are retrieved with feature tracking techniques, while local and global feature motion are decoupled through 2-level wavelet decomposition. A normalized cross-correlation matrix is then populated with the similarities between the high-frequency components of the tracked features' trajectories. The correlation distribution is then compared with trained models for classification.

III. PROPOSED SYSTEM

In this section we propose a method for image recapture detection based on the blurriness of edges. For this reason, we base our algorithm on the line spread profile of an edge and not the edge spread profile.

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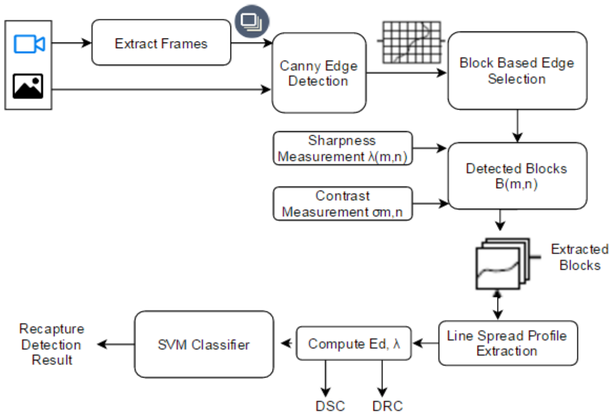

Figure 1: Proposed System Architecture

The proposed algorithm consists of a training stage, in which a support vector machine (SVM) classifier is trained with known images, and a detection stage where the trained classifier is used to classify a given image. A diagram of the classifier training process is shown in Fig. 1.Two sets of known images are used: a set of single capture images, ISC, and a set of recaptured images IRC. The images in each set are indexed with the superscript j and originate from a wide range of known cameras. The number of the images in each set, P and R, may differ. The first step of the classifier stage is to determine a set of edge profiles from each image in each set that represent the sharpest edges found in the image. The first derivative of the edge profiles is then taken to determine a corresponding set of line spread profiles for the image. Thus, for a given image from the set of single capture training images, a matrix QjSC, is generated in which each column of the matrix corresponds to an extracted line spread profile. The equivalent matrix for an image from there captured set is QjRC. Two over-complete dictionaries are constructed by training using the K-SVD approach [19]. The first over-complete dictionary, DSC is trained using the set of single captured images and the second, DRC, using the set of recaptured images. Each dictionary is trained to provide an optimal sparse representation of the line spread profiles extracted from the training set of images.

Key-Frame Extraction for Video:
Determine the number of key-frames; namely, determine the rank of matrix A. We know that the number of singular values is equivalent to the rank of matrix. Video data is a non structured data, and there is not a simple linear relationship between video frames, so the rank of matrix A is usually too big. Therefore, we determine the approximate rank of matrix A by singular value decomposition (SVD).

$$For\ \mathbf{A} \in \mathbf{R}^{m \times n},\ q = \min(m,n),\ if\ k < \mathrm{r} = \mathrm{rank}(\mathbf{A})\ and$$

$$\mathbf{A}_k = \sum_{i=1}^{k} \sigma_i \mathbf{u}_i \mathbf{v}_i^T,$$

$$\min_{\mathrm{rank}(\mathbf{B})=k} \|\mathbf{A}-\mathbf{B}\|_F = \|\mathbf{A}-\mathbf{A}_k\|_F = \sqrt{\sum_{i=k+1}^{q} \sigma_i^2}.$$

Flow of Process:
1. Get Query Image Q
2. Convert Image Q to grayscale Q_q
3. The query image Q is divided into a number of non-overlapping square blocks B (m, n) of size W × W with W = 16 pixels. Here m and n are the vertical and horizontal indices of the block respectively.
4. Canny Edge Detection Algorithm:
The Process of Canny edge detection algorithm can be broken down to 5 different steps:
a. Apply Gaussian filter to smooth the image in order to remove the noise
Find the intensity gradients of the image
b. Apply non-maximum suppression to get rid of spurious response to edge detection
c. Apply double threshold to determine potential edges
d. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

Block based Edge Selection:
1. Check for sharp edge
For each Block {B0……..Bn}
Check horizontal or near horizontal sharp single edge
Rotate block by 90 degree Check for vertical sharp edge
2. Block Selection
Block Bi is detected when
Ŋ ≥ βW
Where Ŋ= No. of columns, β= 0.6
3. The detected blocks, B (m, n) are then ranked according to their sharpness and edge contrast.
4. Calculate line profile matrix Q, λ, E_d.
a. Compute spectral Energy eqi
b. When w=1
Compute spectral Energy ew
c. Compute ratio ew/eqi
If (ew/eqi)> 0.95, Then λ=w else
Goto b
d. $E_d = E_{sc} - E_{RC}$

$$\|\mathbf{Q} - \mathbf{D}_{SC}\mathbf{X}_1\|_F^2 - \|\mathbf{Q} - \mathbf{D}_{RC}\mathbf{X}_2\|_F^2,$$

Where X1 is the corresponding coefficients matrix computed using the orthogonal matching pursuit algorithm with the dictionary DSC.

SVM Classifier
1. For each image, j , in the training set of single and recaptured images, I jSC and IjRC, a pair of parameters, {Ejd , λ j }SC and {Ejd , λ j }RC respectively, are obtained.
2. (λ, E_d) and LBP used to train SVM.

$$K(x,y) = \sum_{i=1}^{n} min(x_i, y_i),$$

Where n is the number of dimensions in the histogram and x and y are the histograms.

IV. PERFORMANCE EVALUATION

A database [20] of images recaptured from an LCD monitor was developed for the purposes of testing and evaluating the performance of the recapture detection algorithm. The

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recapture database comprised 1035 single capture images taken using nine different cameras. Each camera was used to capture 115 images. Out of each set of 115 images, 35 images contained scenes that were common over all nine cameras. Thus, the total number of images containing common scenes was 315. Each image in the set of common single captured images was then recaptured using eight different cameras. This resulted in a total of 2520 recaptured images. As performance analysis we are taking machine learning parameters as result analysis parameters.

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

Table 1: Result Analysis Matrix

	TP	TN	FP	FN
Original Image	If system result is also OI	False	False	If system result is also RCI
Recaptured Image	False	If system result is also OI	If system result is also RCI	False

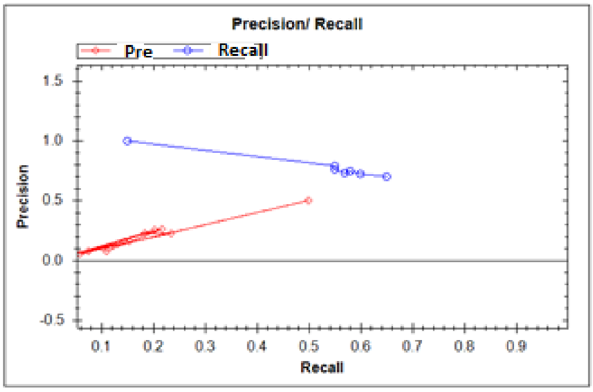

Figure 2: Performance Analysis

V. CONCLUSION

In this paper the problem of detecting images recaptured from LCD monitors has been addressed. A comprehensive overview of the most commonly encountered features in recaptured images concluded that aliasing and blurriness can be extracted most reliably from the image. We then showed how aliasing can be eliminated by properly setting the capture distance, recapture camera lens aperture and focal length. Our approach then focused on a solution for recapture detection based on edge blurriness and distortion. The line spread functions of selected edges were used to train single capture and recapture dictionaries following the K-SVD approach. As proposed work we used LBS- SVM to train the SVM for accurate result. As future work, it will be interesting to analyze more feature of image which can be useful for classification. Also no author works on 3D-images, so this is another interesting direction to proceed this work on 3D images. As per previous work for classification of images many authors used SVM algorithm, so it will another direction for researcher to do more analysis another machine learning algorithm better result.

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