Survey on Recapture Detection Algorithms

Mr. Vinayak K. Shingote[1], Prof. Ashish Kumar[2]

Department of Computer Engineering, G.H.Raisoni College of Engineering and Management, Ahmednagar[1,2]

Abstract: With the development of multimedia technology and digital devices, it is very easier to recapture image of high quality from LCD screens and the use of such recapture image in authentication can be harmful. An attacker may choose to recapture a forged image in order to hide imperfections and to increase its authenticity. To do forensic analysis of such images for evidence is very important. So detection of recapture images from set of images is very important in this case. In this paper we did survey of various recapture image detection algorithms with their pros and cons. Also we studied various features like aliasing, blurriness etc. of recaptured images, which can differentiate recapture image from original one.

Index Terms: Multimedia Technology, LCD, Image Forensic, Recapture Detection, Aliasing, Blurriness.

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 it was asingle capture of a natural scene.

II. FEATURES OF RECAPTURED IMAGES

In this section we provide an overview of some of the more common features found in images that have been recaptured from LCD monitors.

2.1 Aliasing:

Aliasing is sometimes introduced in digital camera images when the scene is insufficiently band-limited or contains detail with very high spatial frequencies [20]. In cameras that are equipped with a Color Filter Array (CFA) [21] the color channels are normally sampled at frequencies that are lower than the native frequency of the image sensor.
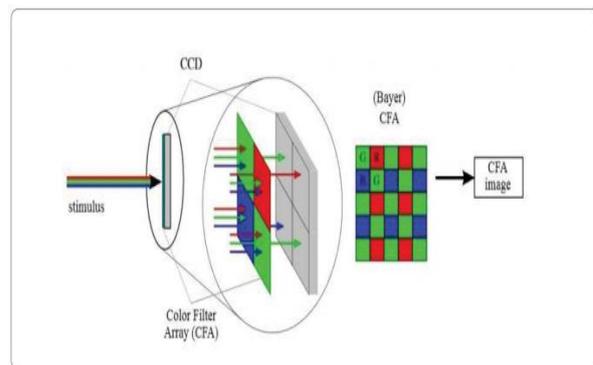

Fig.1. Bayes Color Filter Array

The recapture of an image displayed on the screen of an LCD monitor is, therefore, highly likely to introduce aliasing due to the high frequency periodic pattern of the monitor pixel grid structure. Indeed, casually recaptured still images or videos of LCDs are often characterized by the presence of aliasing artifacts, also referred to as color moiré, over the visible region of the display. These artifacts are very difficult to eliminate through post-processing. Therefore, aliasing can be used as a feature for detecting recaptures. When aliasing artifacts are present in the recaptured image, the 2D DFT of the noise residual is likely to exhibit peaks in the 2D spectrum. Detection of these peaks allows the identification of recaptured images [2], [15].

2.2 Blurriness:

There are three possible scenarios that blurriness can arise in a recaptured image. First, the first capture device or the printing device could be of low resolution. Second, the attack image may be small and the display medium may have to be placed outside of the focus range due to a

specific recaptured setting. One way of characterizing the blur is with the point spread function (PSF) of the capture device. In practice measuring the PSF of a device is not easily achieved and the line spread function (LSF) is used instead. By definition, a line spread function is a 1-D function corresponding to the first derivative of the edge spread function(ESF) [19].

2.3 Noise:
The two main sources of noise associated with images captured with a digital camera at normal and high levels of scène illumination are temporal noise, comprising mainly of shot noise, and fixed pattern noise which is dominated by Photo Response Non-Uniformity (PRNU) noise. The distribution of image noise in the recaptured image will be predominantly influenced by the noise characteristics of the recapture camera, the brightness setting of the LCD monitor, the capture distance and the scene content.

2.4 Contrast, Color and Illumination Non-Uniformity:
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.Color balance errors in a recaptured image can be minimized by calibrating the display monitor and by presetting the white point of the recapture camera to the LCD monitor white point before recapture.

A luminance gradient may be noticeable in recaptured images containing large regions that are low in texture or detail. Identification of the luminance gradient would enable recaptured images to be detected.
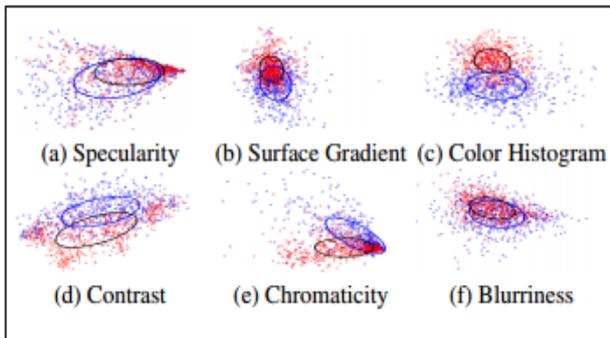

Fig.2. 2D projection of the physical feature distribution for the real-scene image sets (red) and the recaptured image sets (blue).

2.5 Surface Gradient:
If we consider image recapturing as an image rendering process, it would have a different non-linear response compared to that of a camera. In fig 2, we can see the different features, which can be considered in detection of recaptured images.

III. EXISTING SYSTEM

In [1] the edge blurriness and distortion introduced by the recapture process as a feature to detect if a given image has been captured from an LCD monitor. They show that the edges found in single and recaptured images can be fully

characterized by their line spread function (LSF). They then describe how sets of elementary atoms that provide a sparse representation of LSFs can be learned using the K-SVD dictionary learning method. Specifically, a single-capture dictionary is created from a training set of single captured images and a second one from recaptured images. They also compute an edge spread width from the line spread function of the image and combine this feature with the dictionary approximation errors to train an SVM classifier. They classify a query image as single or recaptured depending on its location relative to the SVM hyper plane. The problem of detecting recaptured images from printed material, such as photographic paper or magazines, has been addressed in the literature [4], [5]. The methods identify are captured print from its specularity or from the dithering patterns applied by the printer. The specularity of a recaptured photo are modulated by the mesostructure of the photo surface, and its spatial distribution can be used for differentiating recaptured photos from the original photos. In photographic copying, an image is firstly printed on glossy inkjet photo paper, thus dithering that results from printing disturbs the natural statistics of images to some extent. By comparing recaptured images with their corresponding real-scene images, we find the difference between them. The details of recaptured images are more blurry, which indicates that the correlations among the pixels in recaptured images are weaker. The color of recaptured images and their corresponding rela-scene images are little different. Markov transition probabilities extracted from DCT coefficients array.

Several researchers have considered the recapture detection of images both from prints and from LCD monitors [6], [7]. They develop detectors based on several features associated with recaptured images including the non-linearity of the tone response curve, the spatial distribution of the secularity in the image, image contrast, color, chromaticity and sharpness. They have shown that recaptured images can be visually distinguishable from the original ones reliably by inspecting the spatial distribution of their secular component. They used the two parameters σ and β of the generalized Rayleigh histogram model as features. Propose a general physical model for the image recapturing process, which provides a physical insight into the recaptured image detection. The features inspired by the general model achieve significantly better classification performance on the low resolution (VGA or QVGA) images as compared to the wavelet statistical features.

The Detectionof recaptured images from LCD monitors has been equally addressed in the literature, for example by Cao and Kot [8], where a detector for recaptured detection based on some features of recaptured images is proposed. The fine texture pattern sometimes present in recaptured images is detected by computing Local Binary Pattern (LBP) features at multiple scales. The loss of detail in the recaptured image, due to the relatively low display resolution of the monitor compared to the camera's image sensor, is detected by computing amulti-scale wavelet decomposition where the mean and standard deviation of the absolute wavelet coefficients are used as features.

Papers	Features	Advantages	Disadvantages
Recaptured Photo Detection Using Specularity Distribution [4]	Specularity Distribution	• Method worked on surface planner property. • Method works on physical property of images which never changed.	• Specular component of a recaptured image is related to mesostructure of a planar surface only. • Algorithm works only for planner surface images
Markov-based image forensics for photographic copying from printed picture [5]	Dithering Effects	• Gives very accurate results for printed pictures almost 99% accurate result.	• Fewer images are used to train classifier. • Need to set appropriate threshold for DCT coefficient only on that threshold result gets vary.
Is Physics-based Liveness Detection Truly Possible with a Single Image? [6]	The non-linearity of the tone response curve The spatial distribution of the secularity in the image. Image Contrast Colour chromaticity and sharpness.	• System work for both i.e for printed images and recapture from LCD monitors • Consider physical liveness of face shapes like lips, eye brows shapes etc. which gives more precise result for face recognisation system.	• The input image needs to be reasonably sharp in order to resolve the image specularity which generally has narrow spatial support. • If the image is out of focus or motion blur is present, the micro textures will not be faithfully captured in the image.
Single-view recaptured image detection based on physics-based features [7]		• System consider multiple physical features of images • System works for low resolution too. • System work for smart phone camera recaptured images.	• Dataset is that the scale of the recaptured images is smaller than the corresponding real images. • Another characteristics of the dataset is the white border in the attack image which is purposefully preserved in order to mimic a practical attack situation.
Identification of recaptured photographs on LCD screens [8]	Local Binary Pattern (LBP) features, Multi-Scale Wavelet Statistics (MSWS), Color Features (CF)	• Performs better than wavelet statistics features • Probabilistic support vector machine (PSVM) classifier performs better.	• Need proper setup for recapturing images. • System does not work for high quality printed images. •
Digital image forensics for photographic copying [10]	the noise and the traces of double JPEG compression	• Algorithm works for double compressed images. • Noise parameter make differ in results • Worked on compression and decompression technique.	• Need to have understanding of compression and decompression • For training, needs to divide images in random groups, which want more memory consumption.
Image recapture detection using multiple features [11]	blurriness, texture, noise and colour features	• An image recaptures detection method using a richer descriptor set. • System uses multiple features which gives more accurate result.	• Time complexity is more. • For training, needs to divide images in random groups, which want more memory consumption.
An Image Recapture Detection Algorithm Based on Learning Dictionaries of Edge Profiles [1]	Aliasing effect and edge blurriness	• Use of trained dictionaries gives more accurate result. • Large Dataset has been used for training purpose.	• To remove aliasing effect need human intervention. • Need sharp edges for detection. • System work only for their dataset. • Need proper train set for SVM.
Screenshot identification using combing artifact from interlaced video [16]	Unique characteristic of interlaced video, combing artifact.	• System also works for recaptured images too.	• More robust combing artifact needs to features in the motionless interlaced video clip to achieve higher identification accuracy. • Also, need additional image, video formats and encoding
Video recapture detection based on ghosting artifact Analysis [17]	Ghosting Artifacts	• System work on very basic theory of synchronization between video frame and tripod. • System also works for recaptured images too.	• Need human intervention for video recapturing. • No classifier used for classification. • Works only on high quality videos.
Video jitter analysis for automatic bootleg detection [18]	Jitter effect	• Automatic segmentation of video • Motion based detection so gives, more accuracy.	• Need high quality video. • Not handle multiple sequences in videos. • No classifier used for classification.

The apparent increase in saturation in colors of the recaptured image is detected using 21 different color features. Finally, the output of the individual detectors is fed into a trained probabilistic SVM classifier.

Yin and Fang [9] detect images recaptured from an LCD monitor by analyzing noise features and by detecting traces of double peg compression using the MBFDF algorithm [10].To estimate the noise features the image was denoised using three different discrete wavelet transforms and statistical features such as mean, variance, skewness and kurtosis were computed from the histogram of the extracted noise residual. Their experimental results suggest that the proposed features perform well for detecting photographic copying from LCD monitors.

Ke et al. [11] train a support vector machine to classify recaptured images from LCD monitors with a 136 dimension feature set. Their descriptors are based on blurriness, texture, noise and colour features. They apply their method to a dataset of recaptured images taken with smart-phone cameras and claim a detection rate of 97.2% when the features are combined.

The images used in their dataset [12] are low in resolution and quality, however, due to the smart-phone cameras used to perform their capture. 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, and 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.

Recently there have been efforts to detect recapture of videos [16]–[18]. These methods use features which are unique to video systems. 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 interlaced video screenshot from sub-bands on discrete wavelet transform (DWT) and vertical and horizontal differential histograms. The detector is based on the analysis of a characteristic ghosting artifact left by the recapture process.

The first step consists in estimating the motion vectors. For each frame Yi a set of key-points is extracted using multi-scale approach. Verify patch for matching frame. In particular, since ghosting can be modeled as the effect of a filtering operation, our novel approach exploits the motion between frames to retrieve information about the ghosting filter (i.e., the shape), and verifies if such a filter may have been used on the frames. If the answer is positive, the frames are considered recaptured. They propose [18] a simple yet effective method to automatically detect recaptured videos. The proposed technique is based on the detection of high-frequency motion uniformity present in the video sequence, introduced by camera jitter during recapture. Since the method is based on characteristics at a higher level of abstraction (i.e. trajectory of image

features), it is robust to anti forensic methods and poor quality input signals. The proposed method is validated with standard video sequences with different input resolutions.

IV. CONCLUSION

In this paper, we study various features which can differentiate original images from recaptured one like aliasing, blurriness, noise, surface gradient etc. Using these features many researchers proposed new algorithms to detect recaptured images or videos. So here we study algorithms of many researchers who used different features for detection of recapture image.

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 on another machine learning algorithms for better result.

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