IDENTIFICATION OF ALIASING-BASED PATTERNS IN RE-CAPTURED LCD SCREENS

Babak Mahdian, Adam Novozámský, Stanislav Saic

Institute of Information Theory Automation of the Czech Academy of Sciences
Prague, Czech Republic

ABSTRACT

In this paper we address the problem of identification of pictures and videos re-captured from LCD screens. We show that they often exhibit detectable periodic patterns that are caused by regular sampling grid of LCD screen and aliasing. We develop a method capable of detecting these patterns by using the theory of cyclostationarity. The term cyclostationarity refers to a special class of signals which exhibit periodicity in their statistics. Such signals have a frequency spectrum correlated with a shifted version of itself. Experimental results quantifying the performance of the developed method are also shown.

***Index Terms*—** Image and Video Recapturing, Cyclostationary, Aliasing, Spectral analysis, CFA, Image forensics

1. INTRODUCTION

In this paper we will deal with automatic recognition of pictures ad videos that have been recaptured from LCD screens. Recent advances in digital camera technology have caused that high resolution images can easily be obtained at a relatively low cost by using digital camera and smart-phones. Moreover, a widespread availability of high quality soft-copy display mediums, such as LCD monitors have made it possible to reproduce digital images with ease by recapturing the photo or the video from a display using a digital camera.

The motivation of detecting re-captured images and videos can be several. For example, automatic distribution of illegally captures movies from LCD screens. Recapturing is an easy tool to eliminate copy-right related invisible watermarks hidden in images and videos. Another area that needs to be capable of detecting recaptured videos and images is the authentication area. Access systems using face recognition techniques are often vulnerable to spoofing attacks. In a spoofing attempt, a person tries to masquerade as another person to gain an access to the system.

Our motivation does come from the digital forensics point of view. A large portion of digital forensics methods are bases on searching for inconsistencies among pixels [1, 2, 3, 4, 5, 6, 7, 8]. This, they can easily be overcome by recapturing a digitally manipulated image or video. The re-captured image would not contain traces of digital manipulation and inconsistencies among pixels. In other words, it would act as an original image. In other words, the forger can display fake images on LCD display and recapture the manipulated digital image to overcome image forensic systems. Consequently, detecting recapturing can signify tampering.

This paper will introduce a method capable of detecting recaptured images and videos by using single images (or single frames). Hence, from now on, we will only consider digital images. In case of videos, the method can easily be applied on individual frames separately.

Recaptured images from the LCD screen are often perceptually indistinguishable to humans. However, there are fine differences between LCD screen recaptured images and non-recaptured ones caused, for example, by regular monitor pixel grid projected into the recaptured image and aliasing. We will use these differences to develop the method presented in this paper. Specifically, we will detect periodic properties present in the LCD recaptured images by using theory and methods of cyclostationarity. The term cyclostationarity refers to a special class of signals which exhibit periodicity in their statistics. Our methods will be based on the fact that a cyclostationary signal has a frequency spectrum correlated with a shifted version of itself.

2. RELATED WORK

The problem of detecting and identifying recaptured images from LCD monitors has received interest from researchers in recent years and we have been observing a growing number of publications in this area.

Ke Yongzhen et al. have used combinations of low-level features including texture, noise, difference histogram, and color information to train a support vector machine classifier capable of detecting recaptured images. Hani Muammar and Pier Luigi Dragotti [9] have searched for the presence of aliasing due to sampling of the monitor pixel grid to identify recaptured images. To validate their approach, an investigation into the aliasing introduced in a digitally recaptured image has been conducted. Xinting Gao et al. [10] have introduced a recaptured image database captured by smart phone cameras. Huacheng Liu and Rangding Wang have proposed

This work has been supported by the Czech Science Foundation under Project no. GACR 13-28462S.

to identify recaptured images using DCT coefficients. They have noticed that the low frequency of an image mainly reflects such information as texture and profile details. So, they described the difference between real images and recaptured images by using the low frequency of DCT coefficients. Thirapiroon Thongkamwitoon et al. [11] have used the fact that edge profiles of single and recaptured images are different in order to detect recaptured images. They have trained two alternative dictionaries using the K-SVD approach to achieve their goal. Neslihan Kose and Jean-Luc Dugelay [12] have proposed an anti-spoofing approach, which is based on analysis of contrast and texture characteristics of captured and recaptured images. A method based on a rotation invariant local binary pattern variance has been used. Xinting Gao et al. [13] have presented a physical model for image recapturing. Their motivation was to make robot vision more intelligent and make a single-image-based counter-measure for re-broadcast attack on a face authentication system feasible. M. Visentini-Scarzanella, P. L. Dragotti [14] have derived a curve model for straight lines deformed after single capture under a radial distortion model and recapturing. P. Bestagini et al. [15] have proposed a detector based on the analysis of a characteristic ghosting artifact left by the recapture process. Xiaoyang Tan et al. have used the Lambertian model to propose strategies to extract the information about different surface properties of a live human face or a photograph. Jiangwei Li et al. [16] have used structure and movement information of live face to propose a live face detection based on the analysis of Fourier spectra. Hong Cao and A.C. Kot [17] have proposed to use a set of statistical features to capture the common anomalies introduced in the camera recapturing process on LCD screens. Jiamin Bai et al. [18] have focused on paper recapturing and used micro-textures present in printed paper to detect images recaptured from printed materials.

3. DETECTING PERIODIC PATTERNS OF RE-CAPTURED LCD SCREEN

In this section, we will develop a method based on the theory of cyclostationarity. The method will use the periodic patterns and artifacts that are present in the recaptured images of LCD screens.

Recapturing a LCD screen by using a CCD or CMOS sensor is a discrete sampling of a regular grid structure of the LCD display. The original image is first shown on the LCD screen and its regular grid and subsequently a camera is used to make a picture of it.

A visual inspection of recaptured pictures and frames of LCD display makes it possible to observe that the there often are present specific periodic patterns and artifacts such as moiré patterns [19, 20]. They are caused by capturing the periodic sampling grid of the LCD monitor or associated aliasing. The exact appearance and intensity of the artifacts is related to several factors such as the sampling rate of the recapturing process or Color Filter Array (CFA) used in the camera [21].

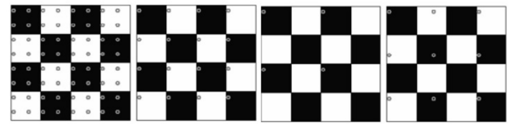

Fig. 1. Shown are various types of sampling of the LCD grid. Please note that in the last two images, a loss of information occur because of an insufficient sampling rate.

According to Nyquist frequency, the sampling rate of the recapturing process must be greater than twice the highest frequency encountered. Sampling at a lower rate results in aliasing. Fig. 1 shows various types of sampling of the LCD grid. Here, the last two images show a sampling process that brings a loss of information because of an insufficient sampling rate.

As pointed out in [9], CFA also plays important role in appearance and intensity of periodic patterns occurred in recaptured images. Many digital cameras are equipped with a single charge coupled device (CCD) or complementary metal oxide semiconductor (CMOS) sensor [21]. At each pixel location, only a single color sample is captured. The color images are typically obtained in conjunction with CFA. The most commonly used CFA is called Bayer CFA after the name of its inventor B.E. Bayer from Eastman Kodak. It consists of alternating red and green pixels on odd lines and green and blue pixels on even lines. Missing colors are computed by an interpolating process, called CFA interpolation. There are many CFA interpolation algorithms that bear into the image's different levels of spatial correlations and lead to different appearances of aliasing artifacts (bilinear, bicubic, medianbased, gradientbased, SHT, adaptive, directional filtering, etc.).

3.1. Periodic Patterns

We will use the following simple, linear and stochastic model describing the recapturing process:

$$f(x) = (u * h)(x) + n(x) \tag{1}$$

where f, u, h, $*$, and n are the measured LCD screen, original LCD screen, system PSF, convolution operator, and a random variable representing the influence of noise sources that are statistically independent from the signal part of the image.

In the last half a century, a lot of work has been done in the field of cylcostationarity [22]. Much of the initial work introducing and examining the use of cyclostationary models in the signal analysis was carried out by W. A. Gardner et al. [23, 24, 25].

A zero–mean signal $f(x)$ is defined to be second order cyclostationary if its second order statistics are periodic. The autocorrelation function of $f(x)$ can be defined as $R_f(x,\delta) = E\{f(x)f^*(x+\delta)\}$. Because of periodicity in x, we easily can represent $f(x)$ in the form of a Fourier series expansion:

$$R_f(x,\delta) = \sum_{\alpha} R_f^{\alpha}(\delta) e^{j2\pi\alpha x}, \tag{2}$$

where α is the cyclic frequency. The parameter R_f^{α} is called Cyclic Autocorrelation Function (CAF) and it is a fundamental parameter of cyclostationarity.

An appropriate way of analyzing cyclostationary properties is by applying the Fourier Transform (FT) to R_f^{α}. The result is called Spectral Correlation Function (SCF).

The discrete version of CAF is defined as:

$$R_f^{\alpha}(l) = \lim_{N\to\infty} \frac{1}{N} \sum_{m=0}^{N-1} f[m] f^*[m+l] e^{-j2\pi\alpha m\Delta m}, \tag{3}$$

where N and Δm denote the number of samples of the signal and sampling interval, respectively. Equivalently, the discrete SCF can be obtained by:

$$S_f^{\alpha}(u) = \sum_{l=-\infty}^{\infty} R_f^{\alpha}(l) e^{-j2\pi u l\Delta l} \tag{4}$$

CAF and SCF are analogous to the autocorrelation function and the power spectral density function for stationary signals. When $\alpha = 0$, the SCF can also be interpreted as the power spectral density of the signal. For other values of α, SCF is the cross–spectral density between the signal and the signal shifted in frequency by α. So, if the signal being analyzed exhibits cyclostationarity, the SCF will be non–zero for some $\alpha \neq 0$. Otherwise, only for $\alpha = 0$, we will have non–zero values.

A cyclostationary signal has a frequency spectrum that is correlated with a shifted version of itself [24]. Based on this, in our method, we focus on detecting the traces of cyclostationarity by estimating the spectral correlation function. To estimate the SCF, we can simply use equation (4). But, due to its computational complexity, we use a more computationally effective SCF estimation method based on Fast Fourier Transform (FFT). FFT algorithm has computational complexity $\mathrm{O}(\mathrm{n}\log_2\mathrm{n})$. Let's say $f(x,y)$ is the image being analyzed and $F(n,u)$ is a matrix containing FFT of image's rows (i.e., $F(1,u)$ contains the one–dimensional FFT of the first row of $f(x,y)$). The SCF can be estimated in the following way:

$$S_f^{\alpha}(u) = \frac{1}{N} \sum_{n=0}^{N-1} F(n,u) \cdot F(n,u+\alpha)^*, \tag{5}$$

where $*$ denotes a complex conjugate and N is the number of image's rows.

Data obtained can be combined together to create the resulting correlation map:

$$\rho_f(\alpha) = \sum_{u} |S_f^{\alpha}(u)|^2 \tag{6}$$

3.2. Derivative filter

Periodic patterns of LCD recaptured images are often weak and not strong enough to be easily detectable using the basic cylcostationarity methods. We overcome this passing the analyzed image through a band–pass filter. Specifically a derivative filter of order two is used.

For an example of results obtained by Eq. 6, see Fig. 2. Here, three digital images and obtained results are shown. Red boxes highlight the analyzed area. The image on the left (Fig. 2 (a)) is a natural and non-recaptured image. Pictures shown in middle and on right (Fig. 2 (b)(c)) are obtained by re-capturing of an LCD screen. Distinctive peaks for pictures in middle and on right are characteristics and signifying the recapturing process. We remind that when $\alpha = 0$, the SCF can be interpreted as the power spectral density of the signal. For other values of α, SCF is the cross–spectral density between the signal and the signal shifted in frequency by α. If the picture being analyzed exhibits cyclostationarity, the SCF will exhibit non–zero values for some $\alpha \neq 0$. If traces of recapturing from an LCD screen is not found, only $\alpha = 0$ have non–zero values and no string and distinctive peak is generated.

3.3. Local Blocks

Periodic patterns of recapturing have typically different intensities in various parts of the image. Thus, to successfully find traces of recapturing, we divide the image into non-overlapping blocks of $R \times R$ pixels. We denote these blocks by $b(x,y)$. The developed method is always separately applied on each individual block.

3.4. Directional analysis

Periodic patterns corresponding to recapturing an LCD screen often are rotated and have complex spatial distributions that are caused by the rotation angle of the LCD monitor in respect to the camera that has been used to make the recapturing as well as sampling rate. To this end, we estimate the SCF and the correlation map in various directions, θ. Specifically, we apply Eq. 5 and 6 systematically at angles θ from 0 to $179°$, in $1°$ increments.

This results in 180 vectors ρ_θ. If the investigated region has been recaptured from an LCD screen, typically, some of ρ_θ contain a specific strong peak corresponding to the cyclostationarity.

4. EXPERIMENTS

To validate theoretical assumptions and to measure the performance of the developed method, we used a derivative filter of order 2 , $\rho_{\mathbf{D^2}}(\alpha)$:

$$\rho_{\mathbf{D^2}}(\alpha) = \sum_{u} |S_{\mathbf{D^2}}^{\alpha}(u)|^2 \tag{7}$$

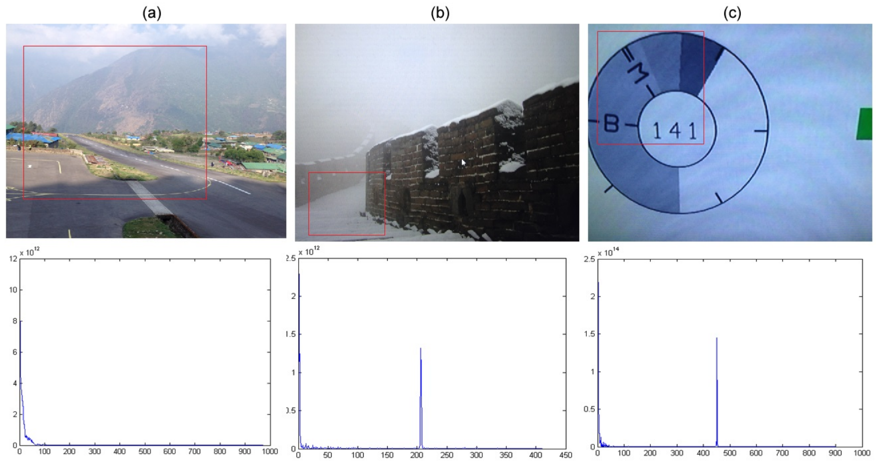

Fig. 2. The image on the left is a natural and non-recaptured image. Pictures shown in middle and on right are re-captured from an LCD screen and exhibit visible traces of aliasing. Corresponding correlation maps generated by Eq. 6 are shown either ($\theta = 0$). Distinctive peaks for the pictures shown in middle and on right are characteristics and signifying the recapturing. Red boxes highlight the analyzed area.

Eq. 7 was applied to green channels of 800 tested images (usually having resolutions higher than 1920×1080 pixels). Images were stored in JPEG files (typically, with JPEG quality factors higher than 85 percent). Size of non-overlapping blocks $b(x, y)$ was set to 420×420 pixels. To automatically detect peaks corresponding to periodic artifacts of LCD recapturing, we used an automatic peak detector (PD) searching for local maximum at positions $\alpha \neq 0$. The PD detects the strongest peak that is significantly larger than the local average. If the size of the found peak lies within a particular threshold, the image is classified that contains patterns of LCD re-capturing, otherwise we say no traces of re-capturing have been found.

Specifically, we used a hypothesis testing approach. By assuming that the observations in maps generated by Eq. 7 are normally distributed, we formulated the null and the alternate hypothesis as follows:
H_o : The peak does not correspond to recapturing
H_a : The peak corresponds to a recaptured image.

Hypothesis testing was carried out in conjunction with t-statistic and a one percent significance level. Not rejecting H_o, signifies that the peak is not a recaptured image. Type I error indicates that in one percent of the cases, we claim that an image is recaptured when it is not. In other words, we are creating a 99 percent confidence interval for the peak size to be a recaptured image.

The hypothesis testing was applied on 400 recaptured and 400 non-recaptured pictures. Results obtained have shown type I error of 3.92 percent and type II error of 8.44 percent.

5. CONCLUSIONS

Detecting the presence of cyclostationarity might signify the presence of LCD recapturing. The proposed method analyzes if the frequency spectrum of the obtained signal is correlated with a shifted version of itself to detect traces of cyclostationarity. Empirical analysis done signifies that the quality and content of tested images play an important role in detecting recaptured LCD screens. For instance, detecting recaptured pictures of dark (e.g., almost black) content has been shown to be very challenging. Moreover, it should be noticed that there are a large number of possible settings of cameras, LCD screens, surrounding lighting, etc. that have an impact on properties of recaptured pictures. For example, by using specific settings of resolution, brightness, shutter speed, capturing mode, etc., it is possible to minimize the impact of aliasing and periodic structure of the monitor grid and produce such re-captured pictures that differ only slightly from original and natural digital images.

6. REFERENCES

[1] B. Mahdian and S. Saic, "A bibliography on blind methods for identifying image forgery," *Image Commun.*, vol. 25, no. 6, pp. 389–399, 2010.

[2] A. Popescu and H. Farid, "Exposing digital forgeries in color filter array interpolated images," *IEEE Transactions on Signal Processing*, vol. 53, no. 10, pp. 3948–3959, 2005. [Online]. Available: www.cs.dartmouth.edu/farid/publications/sp05a.html

[3] G. Sankar, V. Zhao, and Y.-H. Yang, "Feature based

classification of computer graphics and real images," in *ICASSP '09: Proceedings of the 2009 IEEE International Conference on Acoustics, Speech and Signal Processing*. Washington, DC, USA: IEEE Computer Society, 2009, pp. 1513–1516.

[4] Y. Q. Shi, W. Chen, and G. Xuan, "Identifying computer graphics using hsv color model and statistical moments of characteristic functions," in *ICME*, 2007, pp. 1123–1126.

[5] Z. Lin, J. He, X. Tang, and C.-K. Tang, "Fast, automatic and fine-grained tampered jpeg image detection via dct coefficient analysis," *Pattern Recogn.*, vol. 42, no. 11, pp. 2492–2501, 2009.

[6] H. Huang, W. Guo, and Y. Zhang, "Detection of copy-move forgery in digital images using sift algorithm," in *PACIIA '08: Proceedings of the 2008 IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application*. Washington, DC, USA: IEEE Computer Society, 2008, pp. 272–276.

[7] B. Mahdian and S. Saic, "Blind authentication using periodic properties of interpolation," *IEEE Transactions on Information Forensics and Security*, vol. 3, no. 3, pp. 529–538, September 2008.

[8] S. Prasad and K. R. Ramakrishnan, "On resampling detection and its application to image tampering," in *Proceedings of the IEEE International Conference on Multimedia and Exposition*, Toronto, Canada, 2006, pp. 1325–1328.

[9] H. Muammar and P. L. Dragotti, "An investigation into aliasing in images recaptured from an lcd monitor using a digital camera." in *ICASSP*. IEEE, 2013, pp. 2242–2246.

[10] X. Gao, B. Qiu, J. Shen, T.-T. Ng, and Y. Q. Shi, "A smart phone image database for single image recapture detection," in *Proceedings of the 9th International Conference on Digital Watermarking*, ser. IWDW'10. Berlin, Heidelberg: Springer-Verlag, 2011, pp. 90–104.

[11] T. Thongkamwitoon, H. Muammar, and P. L. Dragotti, "Robust image recapture detection using a k-svd learning approach to train dictionaries of edge profiles," *In Proceeding, IEEE International Conference on Image Processing (ICIP)*, 2014.

[12] N. Kose and J.-L. Dugelay, "Classification of captured and recaptured images to detect photograph spoofing," in *ICIEV 2012, IEEE/IAPR International Conference on Informatics, Electronics and Vision, 18-19 May 2012, Dhaka, Bangladesh*, Dhaka, BANGLADESH, 05 2012.

[13] X. Gao, T.-T. Ng, B. Qiu, and S.-F. Chang, "Single-view recaptured image detection based on physics-based features." in *ICME*. IEEE, 2010, pp. 1469–1474.

[14] M. V. Scarzanella and P. L. Dragotti, "Modelling radial distortion chains for video recapture detection." in *MMSP*. IEEE, 2013, pp. 412–417.

[15] P. Bestagini, M. Visentini-Scarzanella, M. Tagliasacchi, P. Dragotti, and S. Tubaro, "Video recapture detection based on ghosting artifact analysis," in *2013 IEEE International Conference on Image Processing (ICIP)*, 2013.

[16] J. Li, Y. Wang, T. Tan, and A. K. Jain, "Live face detection based on the analysis of Fourier spectra," in *In Biometric Technology for Human Identification*, 2004, pp. 296–303.

[17] H. Cao and A. C. Kot, "Identification of recaptured photographs on lcd screens." in *ICASSP*. IEEE, 2010, pp. 1790–1793.

[18] J. Bai, T.-T. Ng, X. Gao, and Y.-Q. Shi, "Is physics-based liveness detection truly possible with a single image?" in *ISCAS*. IEEE, 2010, pp. 3425–3428.

[19] J. C. Krumm and S. A. Shafer, "Sampled-grating and crossed-grating models of moire patterns from digital imaging," *Optical Engineering*, vol. 30, no. 2, pp. 195–206, 1991.

[20] C. Farrow, M. M. Shaw, H. Kim, P. Juhas, and S. Billinge, "The nyquist-shannon sampling theorem and the atomic pair distribution function," *Physical Review B*, vol. 84, 2011.

[21] S.-H. Lam and C.-W. Kok, "Demosaic: Color filter array interpolation for digital cameras," in *PCM '01: Proceedings of the Second IEEE Pacific Rim Conference on Multimedia*. London, UK: Springer-Verlag, 2001, pp. 1084–1089.

[22] W. A. Gardner, A. Napolitano, and L. Paura, "Cyclostationarity: Half a century of research," *Signal Processing*, vol. 86, no. 4, pp. 639–697, 2006.

[23] W. A. Gardner, "Spectral correlation of modulated signals: Part i–analog modulation," *IEEE Transactions on Communications*, vol. 35, no. 6, pp. 584–594, June 1987.

[24] ——, "The spectral correlation theory of cyclostationary time-series," *Signal Process.*, vol. 11, no. 1, pp. 13–36, 1986.

[25] ——, "Exploitation of spectral redundancy in cyclostationary signals," *IEEE Signal Processing Magazine*, vol. 8, no. 2, pp. 14–36, April 1991.