PhD inInformation Technology and Electrical Engineering

Università degli Studi di Napoli Federico II

PhD Student: Francesco Marra

XXX Cycle

Training and Research Activities Report – Third Year

Tutor: Carlo Sasone – co-Tutor: Luisa Verdoliva

1. Information

PhD Student : Francesco Marra

MS title: Computer Engineering – University of Naples Federico II

PhD cycle: XXX – ITEE University of Naples Federico II

Fellowship type: PhD student grant

Tutor: Carlo Sansone – **co-Tutor:** Luisa Verdoliva

I received my MS degree (cum laude) in Computer Engineering from the Univesità degli Studi di Napoli Federico II.

I have been Research Fellow at University of Cagliari from October 2013 to October 2014, in collaboration with SIVA and GRIP group of University of Naples. In this period I published the following conference paper:

F. Marra, F. Roli, D. Cozzolino, C. Sansone, L. Verdoliva, "Attacking the triangle test in sensor-based camera identification," in Image Processing (ICIP), 2014 IEEE International Conference on , vol., no., pp.5307-5311, 27-30 Oct. 2014

During the first and second years of the PhD course, I have published two conference paper and two journal paper:

F. Marra, G. Poggi, C. Sansone, L. Verdoliva "Correlation Clustering for PRNU-based Blind Image Source Identification" - WIFS Workshop on Information Forensics and Security, 2016

F. Marra, G. Poggi, C. Sansone, L. Verdoliva - "A study of co-occurrence based local features for camera model identification" at Multimedia Tools and Applications, 2017

F. Marra, G. Poggi, F. Roli, C. Sansone, L. Verdoliva "Counter-forensics in machine learning based forgery detection" - SPIE Media Watermarking, Security and Forensics, 2016

F. Marra, G. Poggi, C. Sansone, L. Verdoliva - "Evaluation of Residual-Based Local Features for Camera Model Identification" at BioFor - New Trends in Image Analysis and Processing -- ICIAP 2015 Workshops

2. Study and Training activities

Courses

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Seminars

1. MINIX3: a reliable and secure operating system – Prof. Andrew S. Tanenbaum – 30/11/2016 (0.4 CFU)

2. Workshop on Deep Learning for Visual Computing - Prof. Simone Bianco - 21/11/16 (1 CFU)

External courses and Summer School

(1) PhD Summer School: IEEE SPS Winter School on Security and Privacy Issues in Biometrics – 8-12 Jan 2017 – Abu Dhabi (3 CFU)

(2) PhD Summer School: IEEE-EURASIP Summer School on Signal Processing – Signal Processing meets Deep Learning –4-8 Sept 2017 Capri (4 CFU)

Periods spent abroad

Research aboard at "WaveLab" – University of Salzburg (tutor: Prof. Andreas Uhl) 20 March - 20 July 2017

	Credits year 1		Credits year 2		Credits year 3									
						1	2	3	4	5	6			
	Estimated	Summary	Estimated	Summary	Estimated	bimonth	Bimonth	bimonth	bimonth	bimonth	bimonth	Summary	Total	Check
	20	16	10	12	6						4	4	32	30-70
	5	5,2	5	5,6	3,4	0,4	3				0	3,4	14,2	10-30
	35	35	45	45	52	10	6	10	10	10	8	54	134	80-140
	60	56,2	60	62,6	61,4	10,4	9	10	10	10	12	61,4	180,2	180

1. Research activity

The wide diffusion of powerful image editing tools has made image manipulation very easy.
This impacts on many fields of life, and is especially dangerous in the forensic field, where images may be used as crucial evidence in court. Therefore, in the last decade, digital image forensics has grown tremendously, and new methodologies have been developed to track an image source and determine its integrity. In particular, the interest has focused on passive techniques, which detect traces of manipulations from the analysis of the image itself, with no need of collaboration on the part of the user.
Some of the most successful camera-based methods rely on the PRNU. Its use was first proposed in \cite{Lukas2006}, both for source identification and forgery localization. In my research activity I focus on PRNU-based methods for forgery detection and localization.
Several improvements have been proposed with respect to the basic method of \cite{Lukas2006}.

in \cite{Chen2008} a predictor is estimated which adapts the statistical decision test locally to take into account image features, such as texture, flatness and intensity, thus reducing the probability of false alarms. In \cite{Chierchia2014}, instead, the problem is recast in terms of Bayesian estimation, using a Markov random field (MRF) prior to model the strong spatial dependencies and take decisions jointly rather than individually for each pixel.

In \cite{Chierchia2011} and \cite{Chierchia2014b} the problem of small forgery detection is addressed, resorting to image segmentation and guided filtering to improve the decision statistics.

Further improvements have been recently proposed by considering the use of discriminative random fields \cite{Chakraborty2017} or by introducing multiscale analysis \cite{Korus2017}. All these methods rely on the assumption that a large number of images are available, which are known to come from the camera of interest. However, such an hypothesis is not reasonable in a real-world scenario. Therefore, in this paper we propose and analyze a framework for image forgery localization in a blind scenario \cite{Cozzolino2014_phase2}. We only assume to have a certain number of images, whose origin, however, is unknown. Then we estimate one or more PRNU's by means of a blind source clustering algorithm and use them to establish the integrity of the image under test. In the following Section we describe the PRNU-based framework for blind forgery localization, while in Section 3 present experimental results of \cite{Cozzolino2017} with reference to various clustering approaches \cite{Bloy2008, Amerini2014, Marra2016}.

In both camera identification and forgery localization tasks, the PRNU of the camera of interest is given in advance, or is accurately estimated from a large number of images coming from the camera. However, in many forensic scenarios, and especially in investigation, no information is available on the origin of the images under analysis, neither the probe nor the dataset. Often, however, it is reasonable to assume that the images in the dataset come from just a few different devices. With this assumption, we can pursue PRNU-based forgery localization in a blind scenario, following the framework shown in Fig.\ref{fig:Framework1} and already outlined in \cite{Cozzolino2014_phase2}.

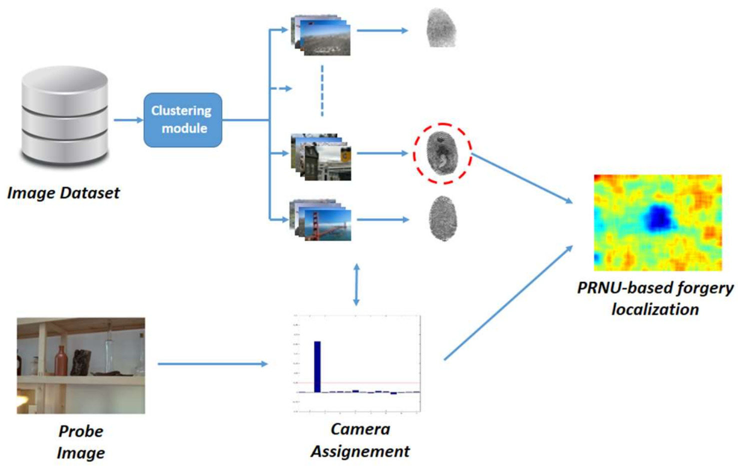

Fig. 1- A framework for PRNU-based forgery localization in a blind

The proposed framework consists of four steps

1. Residual-based image clustering;
2. Cluster PRNU estimation;
3. Camera assignment;
4. Forgery localization.

The first two steps allow us to group together images coming from the same camera and to estimate their PRNU. Then, in step 3, the test image is associated with one of the clusters (or possibly none) by a PRNU-based correlation test. Finally, the tampered area of the test image is localized by detecting the absence of the selected PRNU.

Experiments on the popular Dresden dataset prove the proposed algorithm to consistently outperform the state of the art, often quite significantly.The performance gain is even larger when images are drawn from social networks, testifying of a good robustness to the processing chain routinely performed on such popular media. Moreover, the proposed algorithm is totally blind, as it does not require the user to set critical parameters, such as the number of clusters, or some thresholds on data similarity. Last but not least, the computational complexity remains fully affordable even in the most challenging experiments.

References

[1] R. Kaur, A. Kaur : Digital Forensics In International Journal of Computer Applications V.50 – No.5, 2012

[2] M. Kirchner and T. Gloe, “Forensic camera model identification,” in Handbook of Digital Forensics of Multimedia Data and Devices, T. Ho and S. Li, Eds. Wiley-IEEE Press, 2015.

[3] J. Luk`aˇs, J. Fridrich, and M. Goljan, "Digital camera identification from sensor pattern noise," IEEE Transactions on Information Forensics and Security, vol. 1, no. 2, pp. 205–214, june 2006.

[4] M. Chen, J. Fridrich, M. Goljan, and J. Luk´as, "Determining image origin and integrity using sensor noise," IEEE Transactions on Information Forensics and Security, vol. 3, no. 1, pp. 74–90, March 2008.

[5] Y. Huang, J. Zhang, and H. Huang, "Camera model identification with unknown models," IEEE Transactions on Information Forensics and Security, vol. 10, no. 12, pp. 2692–2704, 2015.

[6] F. Costa, E. Silva, M. Eckmann, W. Scheirer, and A. Rocha, "Open set source camera attribution and device linking," Pattern Recognition Letters, vol. 39, pp. 92–101, 2014.

[7] G. Chierchia, G. Poggi, C. Sansone, and L. Verdoliva, "A Bayesian-MRF approach for PRNU-based image forgery detection," IEEE Transactions on Information Forensics and Security, vol. 9, no. 4, pp. 554–567, April 2014.

[8] G. Chierchia, D. Cozzolino, G. Poggi, C. Sansone, and L. Verdoliva, "Guided filtering for PRNU-based localization of small-size image forgeries," in IEEE 2014 International Conference on Acoustics, Speech and Signal Processing, 2014, pp. 6231–6235.

[9] G. Chierchia, S. Parrilli, G. Poggi, C. Sansone, and L. Verdoliva, "On the influence of denoising in PRNU based forgery detection," in 2nd ACM workshop on Multimedia in Forensics, Security and Intelligence, 2010, pp. 117–122.

[10] C. Li, "Source camera identification using enhanced sensor pattern noise," IEEE Transactions on Information Forensics and Security, vol. 5, no. 2, pp. 280–287, June 2010.

[11] G. J. Bloy, "Blind camera fingerprinting and image clustering," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 30, no. 3, pp. 532–534, March 2008.

[12] D. Cozzolino, D. Gragnaniello, and L.Verdoliva, "Image forgery localization through the fusion of camera-based, feature-based and pixelbased techniques," in IEEE Conference on Image Processing (ICIP),

October 2014, pp. 5237–5241.

[13] R. Caldelli, I. Amerini, F. Picchioni, and M. Innocenti, "Fast image clustering of unknown source images," in IEEE International Workshop on Information Forensics and Security, Dec 2010, pp. 1–5.

[14] O. Fahmy, "An efficient clustering technique for cameras identification using sensor pattern noise," in International Conference on Systems, Signals and Image Processing, 2015, pp. 249–252.

[15] I. Amerini, R. Caldelli, P. Crescenzi, A. D. Mastio, and A. Marino, "Blind image clustering based on the normalized cuts criterion for camera identification," Signal Processing: Image Communication, vol. 29, no. 8, pp. 831 – 843, 2014.

[16] J. Shi and J. Malik, "Normalized cuts and image segmentation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 8, pp. 888–905, Aug. 2000.

[17] F. Marra, G. Poggi, C. Sansone, L. Verdoliva - "Camera model identification through SPAM features" at Multimedia Tools and Applications, 2016

[18] N. Bansal, A. Blum, and S. Chawla, "Correlation clustering," in Foundations of Computer Science, 2002. Proceedings. The 43rd Annual IEEE Symposium on, 2002, pp. 238–247.

[19] S. Bagon and M. Galun, "Large scale correlation clustering optimization," CoRR, vol. abs/1112.2903, 2011.

[20] C. Rother, V. Kolmogorov, V. Lempitsky, and M. Szummer, "Optimizing binary MRFs via extended roof duality," in Computer Vision and Pattern Recognition, 2007. CVPR '07. IEEE Conference on, June 2007, pp. 1–8.

[21] D. Huang and J.-H. Lai and C.-D. Wang, "Combining multiple clusterings via crowd agreement estimation and multi-granularity link analysis ", Neurocomputing, 2015

2. Products

Conference papers

D. Cozzolino, F. Marra, G. Poggi, C. Sansone, L. Verdoliva - "PRNU-Based Forgery Localization in a Blind Scenario" at International Conference on Image Analysis and Processing, ICIAP 2017

Journal papers

F. Marra, G. Poggi, C. Sansone, L. Verdoliva - "A deep learning approach for iris sensor model identification" at Pattern Recognition Letters, 2017

F. Marra, G. Poggi, C. Sansone, L. Verdoliva - "Blind Image Source Clustering by consensus clustering" at IEEE Transactions on Information Forensics and Security, 2017