PhD inInformation Technology and Electrical Engineering

Università degli Studi di Napoli Federico II

PhD Student: Francesco Marra

XXX Cycle

Training and Research Activities Report – Second 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 year of the PhD course, I have published two conference paper and one journal paper:

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

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

(1) Ad hoc Course, "Scientific Writing", May/Jun-2016 (3 CFU)

(2) Ad hoc Course, "The Entrepreneurial Analysis of Engineering Research Projects", Feb-2016 (3 CFU)

(3) Ad hoc Course, "Game Theory and analysis of competitive dynamics for industrial systems", Jan-2016 (3 CFU)

(4) Ad hoc Course, "Complementi di Analisi Funzionale", Apr/Jun-2016 (da completare) (6 CFU)

Seminars

(1) Perception-based surround sound recording and reproduction - DIETI- Unina - 22 February 2016 (0.2 CFU)

(2) Model Based and Pattern Based GUI Testing – Prof. Ana Paiva - University of Oporto– 23/25 Nov 2015 (0.8 CFU)

(3) Armi autonome, problemi etici e decisioni politiche – Prof. G. Tamburrini – 1/12/2015 (0.2 CFU)

(4) Big Data and Analytics with Azure – Microsoft Big Data & Cloud Team – 26/04/2015 (0.2 CFU)

(5) An overview on image forensics with emphasis on physics-based scene verification - Dr. Christian Riess – 18/5/2016 (0.2 CFU)

External courses and Summer School

(1) PhD Summer School: VISMAC International Summer Schoool, - GIRPR - 13 to 17 June 2016. (4 CFU)

(2) PhD Summer School: ICVSS International Summer Schoool on Computer Vision – “Computer Vision: What Happens Next?” - 17 to 23 July 2016. (3 CFU)

	Credits year 1		Credits year 2								Credits year 3			
	Estimated	Summary	Estimated	bimonth 1	bimonth 2	bimonth 3	bimonth 4	bimonth 5	bimonth 6	Summary	Estimated	Summary	Total	Check
Modules	20	16	10		6		3	3		12	6	6	34	30-70
Seminars	5	5,2	5	1	0,2	0,2	4,2			5,6	3,2	3,2	14	10-30
Research	35	35	45	9	4	9	4	7	12	45	52	52	132	80-140
	60	56,2	60	10	10,2	9,2	11,2	10	12	62,6	61,4	61,2	180	180

1. Research activity

Digital forensics is a branch of forensic science concerned with the use of digital information produced, stored and transmitted by computers as source of evidence in investigations and legal proceedings [1].

Nowadays it is extremely easy to share digital information thanks to the use of social networks. In 2014 more than 1.8 billion images and videos have been published on the net each day. Besides its explicit value, this wealth of visual data represents a precious source of information for investigations. In order to detect illegal activities and combat crime it is important to determine the origin of a visual asset. Likewise, proving that a photo was taken by a given camera may be important before a court of law, and metadata (e.g. EXIF tags) which can be easily falsified, do not help much.

In the research community, there has been intense research activity on camera identification [2] in the last years. Some papers deal with model identification (which camera model/brand was used to take the photo), while others focus on the recognition of the individual device. Model identification relies either on specific traces related to the in-camera processing pipeline, like color interpolation (CFA pattern) or JPEG compression (JPEG quantization tables), or on more general features [2]. Device identification, instead, is typically based on the Photo-Response Non Uniformity (PRNU) noise of the camera [3], [4]. In both cases, a strong prior information is required in order to characterize the model or device of interest. PRNU-based methods, for example, assume that the camera PRNU pattern is known, or else that a large number of images, guaranteed to come from the target camera, are available. These assumptions are often not met in real-world applications, especially if we think of an open set scenario, like a social network. For this reason, several recent papers try to relax or remove this hypothesis, by limiting the number of known models [5], or by developing blind methods [6]. This work follows this latter path, focusing on blind PRNU-based camera identification, where no prior information is available on the camera.

PRNU, also known as camera fingerprint, is an intrinsic and stable characteristic of each individual camera, caused by tiny imperfections in the manufacturing process of sensor. Since each photo taken by a given camera contains traces of its PRNU pattern, it can be used not only for source identification, but also for image forgery detection and localization [4], [7], [8]. The PRNU can be estimated by averaging some image residuals, obtained after removing the semantic content from images taken by the camera. However, the PRNU is a very weak signal in strong noise, which impacts on the estimate quality. Using better residual extraction [9] and removing artifacts [10] is certainly beneficial, but real improvements can only come when the number of available images increases.

In a blind scenario, some forms of clustering is needed to retrieve images acquired by a given camera. PRNU-based clustering relies on the fact that residuals coming from the same camera exhibit a slightly higher correlation than unrelated residuals. Therefore, by using the normalized cross-correlation among residuals as image distance, one can resort to general-purpose clustering algorithms. Towards this end, [11] uses a simplified version of the pairwise nearest neighbor (PNN) algorithm. Distances between all couples of data points are computed, and the closest pair is merged, recursively, until a suitable stopping condition is met. As clustering proceeds, better and better PRNU estimates are computed. This approach was successfully used in [12] for the task of forgery localization in a blind setting. The main problem of this procedure is the high computational complexity which prevents its use for large scale scenarios. A faster solution can be found in [13], where a hierarchical clustering is used, together with a criterion based on a silhouette coefficient, which combines measures of both cohesion (inside clusters) and separation (among clusters). In order to improve the classification performance of this algorithm in [14] a refinement step based on Hu's moment vector is applied. In [15], instead, the spectral clustering Normalized Cuts algorithm [16] is adopted showing a better performance than previous state of the art.

In my research, I perform clustering based on the so called noise-residuals, obtained form the original images through a denoising step. Since they contain traces of the camera PRNU, residuals originated by the same camera will exhibit a slightly larger correlation, on average, than residuals coming from unrelated images.

I leveraging on this property, and propose a new clustering technique based on three major tools:

- correlation clustering;
- consensus clustering.
- ad hoc cluster refinement;

Correlation clustering (CC) is a recently proposed method for data partitioning [18]. Given a suitable measure of data similarity (correlation), the optimal partition is obtained by solving a constrained energy minimization problem. Integer linear programming tools ensure fast computation.[19][20]

Like all clustering algorithms, CC depends critically on the sensible setting of some parameters. In order to overcome this need, I resort to a well-known *consensus clustering* algorithm [21], which extract a unique solution by aggregating a number of base CC clustering. As a result of these steps, I obtain a first conservative partition, characterized by a very low probability of finding unrelated residuals in the same cluster.

Then I proceed with an *ad hoc refinement algorithm* which iteratively merges clusters. As the algorithm proceeds, larger and larger clusters emerge, leading in turn to better estimates of the corresponding PRNUs, and allowing the inclusion of further small clusters and outliers, until a suitable stopping condition is met.

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

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

Journal papers

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

F. Marra, G. Poggi, C. Sansone, L. Verdoliva - "Blind Image Source Clustering by consensus clustering" at IEEE Transactions on Information Forensics and Security, 2016 **(to submit)**