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Blind image clustering based on the Normalized Cuts criterion for camera identification

I. Amerini [a], R. Caldelli [a,c,*], P. Crescenzi [b], A. Del Mastio [a], A. Marino [d]

[a] MICC - Media Integration and Communication Center, University of Florence, Florence, Italy
[b] DINFO - Department of Information Engineering, University of Florence, Florence, Italy
[c] CNIT - National Interuniversity Consortium for Telecommunications, Parma, Italy
[d] DI - Department of Computer Science, University of Milan, Milan, Italy

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ABSTRACT

Camera identification is a well known problem in image forensics, addressing the issue to identify the camera a digital image has been shot by. In this paper, we pose our attention to the task of clustering images, belonging to a heterogenous set, in groups coming from the same camera and of doing this in a blind manner; this means that side information neither about the sources nor, above all, about the number of expected clusters is requested. A novel methodology based on Normalized Cuts (NC) criterion is presented and evaluated in comparison with other state-of-the-art techniques, such as Multi-Class Spectral Clustering (MCSC) and Hierarchical Agglomerative Clustering (HAC). The proposed method well fits the problem of blind image clustering because it does not a priori require the knowledge of the amount of classes in which the dataset has to be divided but it needs only a stop threshold; such a threshold has been properly defined by means of a ROC curves approach by relying on the goodness of cluster aggregation. Several experimental tests have been carried out in different operative conditions and the proposed methodology globally presents superior performances in terms of clustering accuracy and robustness as well as a reduced computational burden.

1. Introduction

Digital images can be easily manipulated by common users for disparate purposes so that origin and authenticity of the digital content we are looking at is often very difficult to be assessed without uncertainty. Technological instruments which allow to give answers to basic questions regarding image origin and image authenticity are needed [1]. Both these issues are anyway connected and sometimes are investigated together. However, by focusing on the task of assessing image origin, the two main aspects are to be studied: the first one is to understand which kind of device has generated that digital image (e.g. a scanner, a digital camera) [2–5] and the second one is to succeed in determining which is the specific sensor that has acquired such a content (i.e. the specific brand and/or model of a camera) [6–8]. The main idea behind this kind of approaches is that each sensor leaves a sort of unique fingerprint on the digital content it acquires due to some intrinsic imperfections of the acquisition process. Usually this kind of fingerprint is computed by means of the extraction of PRNU (Photo Response Non-Uniformity) noise [9] from an image through

* Corresponding author at: MICC - Media Integration and Communication Center, University of Florence, Florence, Italy.
E-mail addresses: irene.amerini@unifi.it (I. Amerini), roberto.caldelli@unifi.it (R. Caldelli), pierluigi.crescenzi@unifi.it (P. Crescenzi), andrea.delmastio@unifi.it (A. Del Mastio), andrea.marino.it@gmail.com (A. Marino).

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a digital filtering operation. After that, the PRNU of the to-be-checked image is compared with the pre-computed PRNU fingerprints, belonging to a reference set, and then it is assigned to a certain digital camera. Nowadays most of the image source attribution approaches operate in a closed set scenario, where an image is generated by one of n known cameras available during training [9–12].

However, in a realistic situation, images could have been generated by an unknown device not available in the set of cameras under investigation; so it is important to consider the source camera attribution problem in a open set scenario. In particular, it could be the case, for instance, in which the forensic analyst has a set of photographs in hand and he wants to know if those images were taken by the same camera or not. To find an automatic method to solve this kind of problem could have important implication in the case of inspection of big amount of images like photo repository on Internet (e.g. Picasa, Flickr) and on social networks. Usually, in these circumstances, when the number of cameras and images scales up, methods which resort at the adoption of digest-based descriptors are taken into account [13,14] to reduce computational burden but maintaining performances in terms of classification accuracy.

In [15] the image source attribution problem in an open set scenario is faced attesting if a set of images were taken by a specific camera by comparing each of these images to a reference image. The constraint is that the digital camera of the reference image is known even if the analyst does not have physical access to it. Li in [16] proposed a classification system to distinguish among images taken by unknown digital cameras. First of all, PRNU is extracted and enhanced from each image, which is used as the fingerprint of the camera that has taken the image. Secondly, an unsupervised classifier is applied to a training set of PRNUs to cluster them into classes; centroids of previously identified classes are used as the trained classifier to test a new dataset.

Starting from the idea in [16], the paper in [17] presented an improved approach working in a completely open set scenario. The authors proposed to employ a blind classification to group images taken by digital camera by implementing a different enhancer function with respect to [16] to improve PRNU quality and then a HAC clustering procedure is presented. Another blind-classification method to group digital camera images is presented in [18], where the authors formulate the classification task as a graph partitioning problem by using a multiclass spectral clustering. A drawback of this method is the stop criterion, so in [19] the usage of a Silhouette coefficient is proposed to overcome this limitation. Nonetheless, the use of Silhouette coefficient is not able to completely solve the randomness of the multiclass spectral clustering, in fact, the random selection of the starting point in the clustering procedure implies multiple and sometimes very different results in the classification of images.

In this paper, the problem of classifying images without the use of a trained set is faced by overcoming the randomness problem generated by the multi-class spectral clustering. Such an improvement is mainly achieved by resorting at a new and effective clustering procedure, based on *Normalized Cuts criterion* [20], and by introducing a novel and simple method to determine an automatic stop criterion; such a criterion relies on the goodness of cluster aggregation and the estimation of the cut-off threshold is obtained by means of ROC curves [21]. Experimental results are provided to confirm that the proposed technique permits to achieve higher performances both in image grouping (in terms of true/false positive rate – TPR/FPR) and of computational burden with respect to the state-of-the-art methods.

The paper is organized as follows: Section 2 describes the state of the art regarding multi-class spectral clustering method, while Section 3 presents the new proposed one; in Section 4 experimental results are presented and Section 5 concludes the paper. In Appendix A, a detailed description of the evaluation metrics used for the experimental tests is provided.

2. An analysis on multi-class spectral clustering

This section is dedicated to the analysis of the multi-class spectral clustering (MCSC) method, as presented in [18,22] (see Section 2.1). By following this approach, each image is considered as a node in a weighted undirected graph, thus making the clustering task to converge to a graph partitioning problem, where images (nodes) belonging to the same partition are assigned as acquired by the same digital camera. However, such a technique has two main open issues that will be discussed hereafter: firstly, it provides results that strictly depend on the random starting point and, secondly, it needs a stop criterion. In Section 2.2, an in-depth analysis on such issues is presented.

2.1. The MCSC algorithm

Given an image set I of N images (each one indicated as I_i, $i=[1,N]$), a weighted undirected graph G is defined on I such as $G=(V,\varepsilon,W)$, where $V=\{V_i\}$, $i=[1,N]$ is the set of all nodes/images (V_i corresponds to I_i), and ε is the edge set, whose elements are represented by the entries of the affinity matrix $W=\{w_{ij}\}$. The complete structure of the graph can thus be characterized by means of its affinity matrix W. Note that each image is described by its PRNU noise, extracted as previously described in Section 1, and it will be used for the whole clustering process; thus, in the following, when the terms *image* or *noise image* will be adopted, they will state for *PRNU noise extracted from the image*, if not otherwise defined.

Partitioning the graph is accomplished by finding the optimal relaxed solution of the eigensolution matrix of W; the basic steps are presented hereafter:

1. Given the weight matrix W and the number of classes K.
2. Find the optimal eigensolution Z^* and normalize it to $\tilde{X}^*$.
3. Define a new working matrix R^*, having N rows and K columns.
4. Select a random row of the matrix $\tilde{X}^*$ and assign it to the first column of the matrix R^*.