Neurocomputing 204 (2016) 33–40

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

A learning-to-rank approach for image scaling factor estimation

Nan Zhu, Cheng Deng, Xinbo Gao *

Department of Electronic Engineering, Xidian University, Xi'an 710071, China

ARTICLE INFO

Article history:
Received 28 February 2015
Received in revised form
9 June 2015
Accepted 25 June 2015
Available online 13 April 2016

Keywords:
Image forensics
Image resampling
Scaling factor
Learning to rank

ABSTRACT

Over the past years, digital image forensics has become a hot topic in multimedia security field. Among various image forensics technologies, image resampling detection is a standard detection tool. Furthermore, examining parameters of geometric transformations such as scaling factors or rotation angles is very useful for exploring the overall manipulation history of an image. In this paper, we propose a learning-to-rank approach for automatically estimating the scaling factor based on the normalized energy density features and moment features. Specifically, the difference of these features of the ordered image pairs are used for training, then the scaling factor of a new input image can be evaluated from its corresponding rank values. Our proposed method can not only effectively eliminate the long-known ambiguity between upscaling and downscaling in the analysis of resampling but also accurately estimate the factors of downscaling and weak scaling, i.e., the scaling factors near 1. Empirical experiments on extensive images with different scaling factors demonstrate the superiority of our proposed method when compared with the state-of-the-art methods.

1. Introduction

With rapid development of computer technologies, digital image tampering becomes rather convenient and easy. The detection of tampering operations is of great importance since some images are altered and redistributed with malicious purpose. Blind digital image tampering detection techniques which aim at verifying the authenticity and originality of an image without any a prior knowledge is becoming an important research field.

Over the past years, many efforts have been devoted to develop different image forensic technologies [1]. Image forensics uses the fingerprints left behind by image acquisition process and manual manipulations to verify the authenticity of an image. According to the temporal position where the fingerprint is left, the existing fingerprints can be roughly classified into two categories. The first category is in-camera fingerprints such as lateral chromatic aberration (LCA) [2], sensor pattern noise (SPN) [3], color filter array (CFA) interpolation [4], purple fringing aberration (PFA) [5], camera reference function (CRF) [6] and so on. The second category is out-camera fingerprints also called editing-based fingerprints, including image sharpening [7], lighting consistency [8], contrast enhancement [9], double JPEG compression [10] and resampling [11].

Among these forensics technologies, image resampling detection has become a standard detection tool. Furthermore, examining the parameters of geometric transformations such as scaling factors or rotation angles is very useful for exploring an image's overall processing history. Knowing as much as possible about an image's overall processing history can make contribute to resynchronize digital watermarking and identify the source camera [12]. Furthermore, recovering the overall processing history of a tampered image is an important task in the field of image forensics according to the definition of image forensics. However, most of the current resampling detection methods [11,13–17] which related to resampling detection perform unsatisfactory on factor estimation.

In this paper, we propose a learning-to-rank approach for automatically estimating the scaling factor based on the normalized energy density features and moment features. To benefit from the intermediate data, we formulate the scaling factor estimation task as a learning-to-rank problem. Specifically, instead of estimating the scaling factors based on the specific interpolation characteristics or a single feature, a function which can predict the scaling factors in a ranking list is learned. Under this framework, our proposed method can not only effectively eliminate the long-known ambiguity between upscaling and downscaling in the analysis of resampling but also accurately estimate the factors of downscaling and weak scaling, i.e., the scaling factors near 1. Empirical experiments on extensive images with different scaling factors demonstrate the superiority of our proposed method when compared with the state-of-the-art methods.

The rest of this paper is organized as follows. Section 2 summarizes the related work on this topic. Section 3 provides preliminaries and

* Corresponding author.
E-mail address: xbgao@mail.xidian.edu.cn (X. Gao).

http://dx.doi.org/10.1016/j.neucom.2015.06.113
0925-2312/

then we present our proposed method in Section 4. Section 5 evaluates the effectiveness of our method with different image scaling factors on large-scale image dataset. Conclusions and future work are given in Section 6.

2. Background and related work

2.1. Resampling

Oftentimes, the creation of convincing image forgery involves scaling or rotation operations. These resampling procedures make some pixels being a linear combination of its neighbors. These specific periodic correlations among image pixels can be exploited to detect image resampling and estimate the transformation factors. A M/N resampling of a 1-D discrete signal $x[n]$ involves the following steps [13]:

(1) *Upsample*: Create a new signal $x_u[n]$ by inserting $M-1$ zeros after every $x[n]$.
(2) *Interpolate*: Convolve $x_u[n]$ with a low pass filter: $x_i[n]=x_u[n]*h[n]$.
(3) *Decimate*: Collect every Nth sample: $y[n]=x_i[N_n], n=0,1,\ldots$

Resampling in 2-D can be extended in both spatial directions. Different types of resampling algorithms differ in the form of the interpolation filter $h[n]$ in step 2.

2.2. Related work

Several techniques for image forensics based on resampling detection have been reported. However, only a few of them are capable of estimating the scaling factors. These methods can be roughly classified into two categories. The first category is the methods based on the specific interpolation characteristics. As mentioned above, interpolation is an essential step of resampling. This special interpolation periodicities are represented in the form of *p-map* [13,15], second difference [11,14] and cyclic correlation [16]. This kind of methods concentrates on the positions of characteristic resampling peaks. However, the positions of resampling peaks alone cannot reveal the particular resampling factors. Sometimes, images with different resampling factors may have the same periodicity. As shown in Fig. 1, (a) and (e) are scaled down to 75% and up to 150% of the original image, respectively. The corresponding *p-maps* and the spectrum images of the *p-maps* are shown in the second and the third columns. We can find that the characteristic scaling peaks coincide so that the scaling factor cannot be determined by merely using this kind of methods.

The second category is feature-based methods. In [18], Feng et al. proposed a normalized energy density feature for resampling detection which mainly describes the changes of energy density distribution of resampled images in the frequency domain. However, the authors only mentioned that their proposed features can be used to estimate the scaling factors but did not describe how to do. In [19], rather than concentrating on the positions of characteristic resampling peaks, the authors utilized a moment feature to exploit the periodic interpolation characteristics in the frequency domain. In this method, the resampling factor determination is based on a one-versus-one strategy. A series of classifiers are trained between every pair of classes which have different resampling factors. This method is capable of solving the ambiguity in determining the resampled factors. However, these feature based methods cannot exactly estimate the scaling factor, instead, they are very likely only point to an interval of plausible scaling factors.

In [17], a combined method of the two kinds of methods mentioned above is proposed. The authors mentioned that although some scaling factors have the same peak positions in the spectrum of the *p-map*, the distribution of the normalized energy densities are distinguishing. As shown in Fig. 1(d) and (h), while characteristic resampling peaks coincide, the image's normalized energy densities are different. So the authors combined analytical models of periodic interpolation artifacts with the spectral energy distribution of rescaled images to infer exact transformation parameters. They computed the spectrum of *p-map* based on periodic artifacts to find strongest peaks to obtain set S_1 of possible scaling factors. At the same time, they computed the normalized energy density features and feed them into SVM classifier to obtain a range S_2 of the potential factors. Finally, the scaling factor can be estimated from the intersection between S_1 and S_2. This

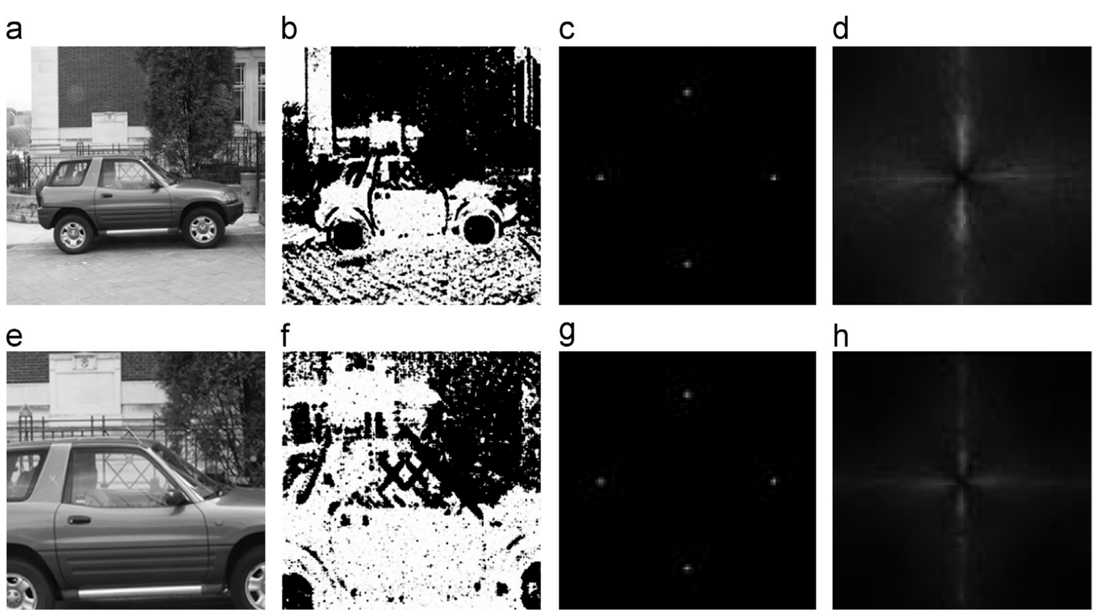

Fig. 1. Resampling detection results for two gray images. (a) Scaled down to 75% of the original image. (b) Corresponding *p-map* of (a). (c) Spectrum map of (b). (d) Normalized energy density distribution of (a). (e) Scaled up to 150% of the original image. (f) Corresponding *p-map* of (e). (g) Spectrum map of (f). (h) Normalized energy density distribution of (e).