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Improved photo response non-uniformity (PRNU) based source camera identification

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ABSTRACT

The concept of using Photo Response Non-Uniformity (PRNU) as a reliable forensic tool to match an image to a source camera is now well established. Traditionally, the PRNU estimation methodologies have centred on a wavelet based de-noising approach. Resultant filtering artefacts in combination with image and JPEG contamination act to reduce the quality of PRNU estimation. In this paper, it is argued that the application calls for a simplified filtering strategy which at its base level may be realised using a combination of adaptive and median filtering applied in the spatial domain. The proposed filtering method is interlinked with a further two stage enhancement strategy where only pixels in the image having high probabilities of significant PRNU bias are retained. This methodology significantly improves the discrimination between matching and non-matching image data sets over that of the common wavelet filtering approach.

1. Introduction

In this paper the focus is on using image sensor pattern noise to match images to the cameras/camera phones that produced those images. A reliable source camera identification technique was developed by Lukas et al. [1,2]. The technique utilises an intrinsic property of all digital imaging sensors known as Photo Response Non-Uniformity (PRNU). PRNU is an almost invisible image artefact that results from the tolerance in the manufacturing processes of all imaging sensors. Uniqueness of manufacturing imperfections and variability of photo-electronic conversion systems produce a small variance in gain between different pixel sensor elements, embedding a weak noise-like pattern into each image that a sensor creates [3]. The underlying mechanism for the production of the noise suggests that the spatial distribution of the pattern is unique and because of this, the pattern is often referred to as the sensor 'fingerprint'. This has been confirmed empirically by many researchers including Goljan et al. [4] who conducted a large scale camera identification test comprising of over 3 million pictures taken with circa 7000 cameras. When a sensor is operated at its base gain, PRNU may be the dominant noise source for a large part of the pixels output range [3]. For higher gain settings (high ISO) this range will be more limited indicating that PRNU extraction is more difficult when images have been produced using lower lighting conditions, shorter exposure times or by the use of higher *f*-numbers. In general PRNU is present at some level in virtually every image and is tolerant to many image processing procedures including gamma correction and lossy compression such as JPEG. It should be noted that PRNU is just one of many types of noise that occur in an image acquisition process and for detailed descriptions, and their influence on PRNU estimation, the reader is referred to [3,5,6].

The technique requires the estimation of the PRNU noise of a camera's imaging sensor, usually established by averaging the extracted noise pattern derived from many images taken by the camera. The 'fingerprint' is then compared to an estimated noise pattern acquired from a questioned image and the magnitude of similarity is provided by the correlation coefficient. Relatively high correlation levels compared to levels expected from known non-matching images indicate that a questioned image was indeed taken by the camera.

The generality of PRNU for all image sensor types and the uniqueness of PRNU noise for individual sensors offer significant opportunities for forensic image analysis. However, PRNU as an embedded signal element is very weak making the extraction task difficult. In this paper a more simplistic but effective filtering strategy than that commonly used for PRNU estimation is described. The method, which is based on filtering in the spatial domain is coupled with further enhancement procedures and shown to result in significantly higher discrimination between matching and non matching images than when compared to the wavelet filtering approach commonly used for this application.

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2. Noise estimation

Much effort is expended in developing signal processing algorithms that reduce noise in images. However, for some forensic applications, as is the case of source camera identification using PRNU, the signal becomes the unwanted element and the noise becomes the wanted element. The aim is then to estimate the noise by effectively removing the signal. Estimating a PRNU fingerprint involves averaging the noise estimates taken from a number of images known to have been produced by the source camera. It is more difficult to obtain good PRNU representation from a single image as the estimate will also contain varying degrees of both the image and temporally related noise contamination.

For image enhancement/restoration applications, it is common to determine a filter's noise reduction performance objectively by use of the mean squared error or peak signal to noise ratio, and subjectively by aesthetic analysis. Wavelet based image noise reduction filters perform well when measured using such criteria and is clearly why wavelet image denoising continues to receive much attention in the literature. Almost universally, wavelet based denoising has been proposed by researchers for PRNU extraction. Wavelet coefficients may be modelled as Gaussian and approximately uncorrelated, forming a good basis for discriminating between image content and additive Gaussian noise. However, it is argued here that a more simplistic spatial domain adaptive filter can produce superior results for PRNU estimation to that of methodologies based in the wavelet domain. The spatial domain filtering strategy reported is shown to be an appropriate first stage in an overall estimation methodology that is designed to retain information from pixels having a high probability of significant PRNU bias.

2.1. Filtering limitations

The effectiveness of PRNU estimation relies on denoising the image using a low pass filtering approach. The filtered response is then subtracted from the original image leaving a residue that ideally contains only the required noise components. However, since the underlying image model and filtering processes are suboptimal the residue signal will also contain components from other noise sources and more significantly from the image itself, reducing the ability to discriminate between matching and non matching data.

As pointed out by Matsushita et al. [7], the wavelet based denoising approach as used for PRNU estimation results in a diffusion of the edges and details of an image, producing a noise residual having many disturbing signals around these areas. This significantly reduces the correlation between the image noise residue and the fingerprint in these regions, producing weakly correlated results. This has prompted a number of researchers to implement a range of diverse additional signal processing strategies to try to overcome this limitation. Chen et al. [6] introduced a correlation predictor to reduce error rates. In other examples Li [8], considers that the higher the noise level the more likely it is to be the result of image detail and suggests various weighting schemes to compensate. Matsushita et al. [7] produce a texture mapping of the image and only use regions of the image that are relatively smooth. Li [9] proposes a colour decoupling process prior to filtering in order to reduce colour interpolation noise which is more prominent around image details. In further PRNU enhancement papers, Liu et al. [10] define and use only data in significant regions based on localised signal to noise ratio measurements, and Hu et al. [11] compare only large components of the extracted noise as does Long et al. [12]. All methods are still based on a wavelet denoising approach. In more recent work, Houten et al. [13] have proposed a non-wavelet based filtering methodology using anisotropic diffusion. This technique reduces processing time by approximately 30% and is shown to marginally improve the performance over the common wavelet (CW) filter used for PRNU estimation [2].

In the work reported in this paper a combination of adaptive spatial domain and median filters, combined with a strategy that seeks to remove data that has a low probability of PRNU bias is used to significantly improve the discrimination between matching and non matching data. The procedures have been implemented using MathWorks Matlab 2012a (http://mathworks.com).

2.2. Modelling

Natural images are likely to contain a combination of smooth regions, textured regions and edges or discontinuities. It may be concluded that images are not globally stationary. However, an image may be considered to have stationarity at a local level [14] and this forms the basis of most image denoising techniques. Smooth regions of an image have low variance and should produce pixels that are dominated by noise and therefore these regions need to be more heavily attenuated. Regions of an image containing sharp transitions and textures have a relatively high variance and, for PRNU estimation (in order to make sure image content doesn't contaminate the noise estimate), these regions should have little or no attenuation applied. This is the principle of the spatial domain filtering strategy proposed.

The physical deviations of the various parameters responsible for PRNU may be modelled overall as a zero mean Gaussian process K. As each pixel will be independent the process may also be considered white. The PRNU fingerprint considered as an averaged process will not contain any image corruption and therefore on a global basis will have a constant variance being modelled as zero mean AWGN. The PRNU contained within a natural image may also be modelled as zero mean WGN on a local scale where the region may be considered smooth and independent of the image. The pixels in smooth areas are considered to be slowly changing and the noise being independently and identically distributed (iid).

As there are wide variances in camera types and camera processing regimes, precise sensor output modelling is difficult to achieve. Chen et al. [6] put forward a simplified generic representation of a sensor output model:

$$I = I_o + I_o \cdot K + \Theta \tag{1}$$

where I is the noisy image, I_o is the noise free image, K is the PRNU and Θ is the sum of all other uncorrelated random noise components. All operators are considered as element-wise. Equation (1) points out the additive-multiplicative relation between the signal without noise and the PRNU noise terms, indicating that the PRNU noise will be higher in regions of higher image intensity. An estimate of the noise free image I_o produced by the sensor is obtained using a denoising filter F:

$$\hat{I}_o = F(I) \tag{2}$$

where the filter output is then subtracted from the noisy image to produce the image noise residual W:

$$W = I - F(I) = I - \hat{I}_o = I_o + I_o \cdot K + \Theta - \hat{I}_o = I_o \cdot K + \Theta + \Xi \tag{3}$$

The term Ξ results from the distortions introduced by the denoising filter, increasing in regions of an image containing edges or textures. After extraction of the noise W from individual images the maximum likelihood (ML) method derived by Chen et al. [6] is used to estimate the PRNU sensor fingerprint R:

$$R = \frac{\sum_{k=1}^{P} W_k I_k}{\sum_{k=1}^{P} (I_k)^2} \tag{4}$$