A CONTEXT ADAPTIVE PREDICTOR OF SENSOR PATTERN NOISE FOR CAMERA SOURCE IDENTIFICATION

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ABSTRACT

Sensor pattern noise (SPN) is a noise-like spread-spectrum signal inherently cast onto every digital image by each imaging device and has been recognised as a reliable device fingerprint for camera source identification (CSI) and image origin verification. It can be estimated as the noise residual between the image content and its denoised version. However, the SPN extracted from a single image can be contaminated largely by image scene because image edge noise is usually much stronger than the SPN. So the identification performance is heavily dependent upon the purity of the estimated SPN, especially for small size images because they have less and weaker SPN. Although there are some existing works dedicated to improving the performance of source camera identification, an effective method to eliminate the contamination of image scene and extract an accurate SPN is currently lacking. In this paper, we will propose an edge adaptive SPN predictor based on context adaptive interpolation (PCAI) to exclude the contamination of image scene. Different from most of the existing methods extracting SPN from wavelet high frequency coefficients, we extract SPN directly from the spatial domain with a pixel-wise adaptive Wiener filter, based on the assumption that the SPN is a white signal. Extensive experiments show that our proposed PCAI method achieves the best receiver operating characteristic (ROC) performance among all of the state-of-the-art CSI schemes on different sizes of images, and has the best performance in resisting JPEG compression (e.g. with a quality factor of 90%) simultaneously.

Index Terms— Sensor pattern noise, source camera identification, edge adaptive predictor, context adaptive interpolation.

1. INTRODUCTION

Digital images are easy to modify and edit via image editing software. Image content becomes unreliable. Using this kind of forged image should be avoided as evidence in a court of law, as news items, as part of a medical record or as financial documents. There are some works focused on image component forensics in recent years [1] ~ [13]. Lukas *et al.* [3] first proposed using the imaging sensor pattern noise (SPN) for solving the camera source identification (CSI) problem. They extract SPN from wavelet high frequency coefficients with a wavelet-based denoising filter [4]. A camera reference SPN is built by averaging residual noises from multiple images taken by a camera. We call it the basic SPN CSI method in the rest of this paper. Cortiana *et al.* [5] [12] applied an innovative and recently introduced denoising filter, namely a sparse 3D transform-domain collaborative filtering (BM3D in short) proposed by Dabov *et al*. in [6], to extract the SPN. This filter is based on an enhanced sparse representation in a transform domain. Chen *et al.* [7] proposed a maximum likelihood method to estimate the camera reference SPN. We call it the MLE SPN CSI method in this paper. Goljan *et al.* [8] proposed using peak to correlation energy (*PCE*) to suppress periodic noise contamination and enhance the CSI performance. Fridrich *et al.* [9] proposed a forgery detection method using sensor noise as a kind of watermark for image. The experimental results show that this method can recognise a forgery operation. Li [10] demonstrates that the SPN extracted from a single image can be contaminated by image scene details and proposes that the strong signal component in an SPN should be attenuated. However, attenuating the interference from scene details may also attenuate the useful SPN component [11]. Based on the assumption that the extracted SPN is a white noise [4] and the proposed white correlation theorem [11], Kang *et al.* [11] proposed a detection statistic *CCN* (correlation over circular correlation norm) to lower the false positive rate to be half of that with *PCE* [8] and a white camera reference SPN to enhance the ROC performance. The noise residues extracted from the original images are whitened first and averaged to generate the white camera phase reference SPN. We call this "phase SPN" CSI method.

Although there have been prior studies dedicated to improving the performance of CSI based on SPN in recent years, an effective method to eliminate the contamination of the image scene details (e.g. texture, periodic structure) and extract an accurate SPN from images is currently lacking. For image forgery detection based on SPN, the final performance is largely dependent on the detection rate on small image block. Small images usually have less SPN information and are more vulnerable to the impact of image scene edge, so the identification performance for small images needs to be improved further. In this paper, an edge adaptive SPN predictor based on context adaptive interpolation (CAI) [14] and pixel-wise adaptive Wiener filter is proposed. Thanks to its adaptability to image edge and context, the predicted SPN has less scene noise from an image. Extensive experiments have shown that our proposed PCAI method achieves the best ROC performance among all of the state-of-the-art CSI schemes on different sizes of images, and has the best performance in resisting mild JPEG compression simultaneously.

The rest of this paper is organised as follows. In section 2 we will introduce CAI and propose a SPN predictor based on

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CAI to improve the CSI performance. Section 3 will show the experimental results compared with some other camera identification methods to examine the ROC performance. The conclusion is set out in section 4.

2. PROPOSED PCAI SPN EXTRACTION METHOD

2.1 Context adaptive interpolator

The context adaptive interpolator (CAI) [14] is an adaptive algorithm employing edge directed interpolation. The local region is classified into four types: smooth, horizontally-edged, vertically-edged and other. In the smooth region, a mean filter is used to estimate the centre pixel value; in edged regions, the interpolation is undertaken along the edge; in other regions a median filter is applied. Taking p to be a centre pixel value to be interpolated, and $\mathbf{t} = [n, s, e, w]^T$ to be a vector of its four-neighboring pixels as Fig. 1, the CAI predicted pixel value $\hat{p}$ can be formulated as

$$\hat{p} = \begin{cases} mean(\mathbf{t}) & (\max(\mathbf{t}) - \min(\mathbf{t}) \le 20) \\ (n+s)/2 & (|e-w| - |n-s| > 20) \\ (e+w)/2 & (|n-s| - |e-w| > 20) \\ median(\mathbf{t}) & (otherwise) \end{cases} \tag{1}$$

In (1), a smooth region will never be estimated as the edged region and the interpolation prediction in edged regions are adapted from the gradient adaptive predictor (GAP) [15], with an ad hoc threshold.

	n	
w	p	e
	s	

Fig. 1 Neighborhood pixels in CAI

2.2 SPN predictor based on CAI

The SPN can be estimated as the noise residual between the image content and its denoised version. But besides SPN, the noise residual also includes image scene noise, especially in edge regions. The CAI can predict a centre pixel value more accurately than some other nonadaptive interpolation algorithms because it is adaptive to image local context. So the difference between the predicted value and actual value can suppress the impact of image edge noise while, at the same time, keeping the SPN component. We may take this difference $\mathbf{D}$ as an approximate SPN.

$$\mathbf{D} = \mathbf{I} - \mathrm{CAI}(\mathbf{I}) \tag{2}$$

where $\mathrm{CAI}(\mathbf{I})$ expresses a pixel-wise CAI prediction of an image $\mathbf{I}$.

In order to further eliminate the impact of the scene noise and extract a more accurate camera reference SPN, we then perform a pixel-wise adaptive Wiener filtering, based on statistics estimated from the neighborhood of each pixel, assuming the SPN is a white Gaussian signal corrupted by the image content. It is noted that, different from most of the existing methods extracting SPN from wavelet high frequency coefficients, we extract SPN from a spatial domain based on the assumption that the SPN is a white Gaussian signal [8]. For every pixel, the optimal predictor (in the mean square error sense) for the final residual noise (*i.e.* estimated SPN) is

$$\mathbf{N}(i,j) = \mathbf{D}(i,j)\frac{\sigma_0^2}{\hat{\sigma}^2(i,j) + \sigma_0^2} \tag{3}$$

where $\hat{\sigma}^2$ is the estimated local variance for the original noise-free image and σ_0^2 is the overall variance of the AWGN signal, *i.e.* the SPN here. To a large extent, the performance of the predictor is dependent on the accuracy of the estimated local variance. We use the Maximum A-Posteriori Probability (MAP) estimation to estimate the local variance as following

$$\hat{\sigma}^2(i,j) = \max\left(0, \frac{1}{m^2}\sum_{(p,q)\in N_m} \mathbf{D}^2(p,q) - \sigma_0^2\right) \tag{4}$$

where m is the size of a neighbourhood N_m for each pixel. Here we take $m = 3$. The overall variance of the SPN σ_0^2 is also unknown, but our experiments show that the impact of σ_0^2 is relatively low for the predictor. Similar conclusion is also made in wavelet domain [3]. The dependence of the correlations between the reference pattern and the noise residual on the overall variance is relatively flat. So we use $\sigma_0^2 = 9$ in all experiments to make sure that the predictor extracts relatively consistent level of the SPN.

Finally, the estimated camera reference SPN is obtained by averaging all the residual noise $\mathbf{N}$ extracted from the same camera.

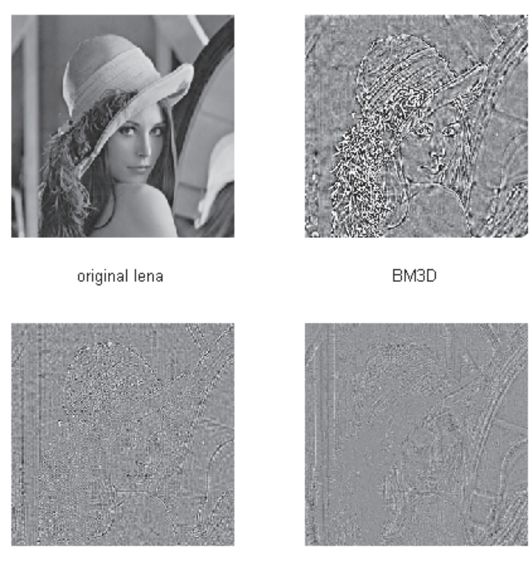

Fig. 2 Noise residue extracted by different filters

Our proposed SPN predictor based on CAI (PCAI) is adaptive to image edge and local variance, so the predicted SPN ***N*** has less scene noise from the original image than other denoising filters. Fig. 2 shows the noise residual ***N*** using the proposed PCAI compared with Mihcak's wavelet filter [4] and BM3D filter [6]. It is observed that the proposed method can suppress the effect of image scene content very well.

3. THE EXPERIMENTAL RESULTS

In this section, we will examine the CSI performance of the proposed PCAI method. For fair comparison, we choose the newly developed detection statistic *CCN* [11] to measure the similarity between the image noise residue and a camera's reference SPN for all methods. Table 1 shows the image format, native resolution and imaging sensor property of the cameras used in the experiments (PS is short for PowerShot). We have two sub-image datasets for each camera: the test image dataset and original image dataset. All images are in JPEG format with the highest JPEG quality factor provided by the cameras, except in raw data format for the Nikon D40 and Minolta A2. A camera identification experiment is performed on the luminance component with different image block sizes. All image blocks are cropped from the centres of the full size images.

Table 1. Cameras used in the experiments

Camera Brand	Sensor	Resolution	Format
Canon PS A3000 IS	1/2.3'' CCD	3648x2736	JPEG
Canon PS A610	1/1.8'' CCD	2592x1944	JPEG
Canon PS A620	1/1.8'' CCD	3072x2304	JPEG
Panasonic Lumix DMC-FZ30	1/1.8'' CCD	3264x2448	JPEG
Nikon D300	23.6×15.8mm CMOS	4288x2848	JPEG
Nikon D40	23.7×15.6 mm CCD	3040x2012	NEF
Minolta A2	2/3'' CCD	3272x2454	MRW

We know that the camera type and image database used for CSI experiments could more or less influence the experiment results. So we will draw together the ROC curve of all the cameras, called the *overall ROC curve* [2], instead of ROC curve for each camera. We first extract the camera reference SPN using all images from the original image dataset (at least 100 images and most of them are blue sky images) for each camera. Then we select 200 test images taken by each camera randomly as positive samples and 1200 test images taken by the other six cameras (each camera is responsible for 200) as negative samples. So we will obtain 200 positive and 1200 negative sample correlation values for each camera in order to draw the *overall ROC curve*.

Figs. 3–5 show the *overall ROC curves* performance of our proposed PCAI compared with other SPN CSI methods. All the test images are of three sizes(*i.e.* 128x128, 256x256 and 512x512 pixels) cropped from the centres of the 1400 photos in the test image dataset. In order to show the detail of the ROC curves with low FPR (false positive rate), the horizontal axis of the ROC curve is in logarithmic scale. For the method "PCAI Phase SPN", the noise residuals extracted by PCAI are whitened first and then averaged to generate the final camera reference SPN. "BM3D SPN" denotes the SPN extraction method with a BM3D denoising filter.

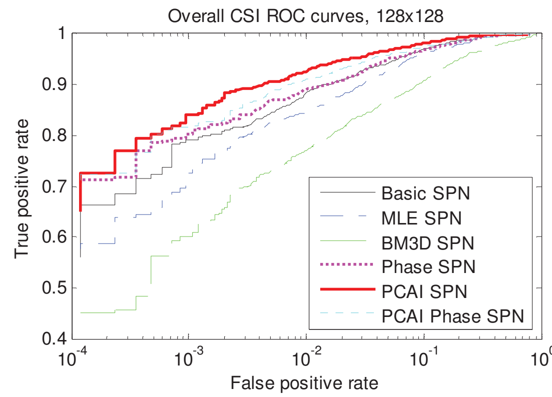

Fig. 3 The *overall ROC curves* for image size 128x128 pixels

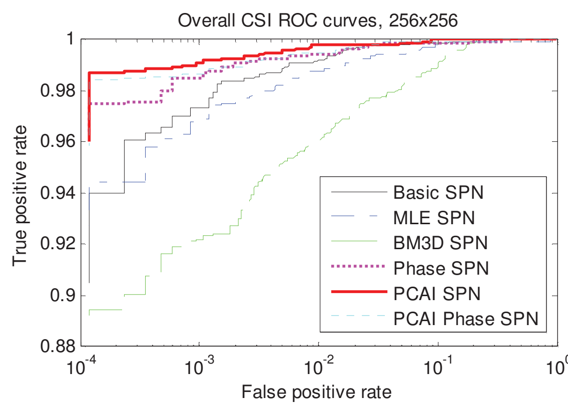

Fig. 4 The *overall ROC curves* for image size 256x256 pixels

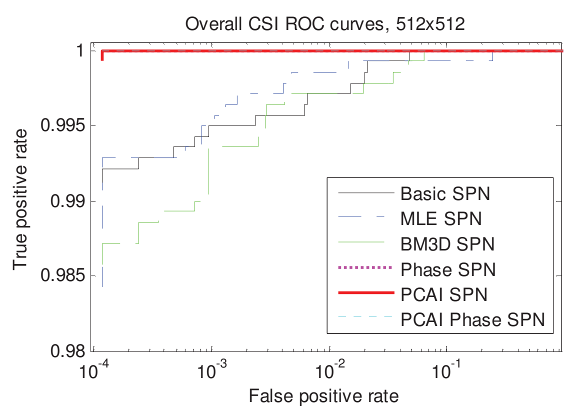

Fig. 5 The *overall ROC curves* for image size 512x512 pixels

The experimental results show that the proposed PCAI method outperforms the others and enhances the ROC performance of CSI, especially for small size images, *e.g.*

128x128 and 256x256 pixels. Both the "PCAI SPN" and "Phase SPN" methods can achieve a 100% TPR (true positive rate) at experimental zero FPR on an image block of 512x512 pixels. As the SPN extracted by PCAI has less scene noise, the whiten process of "PCAI Phase SPN" method can not further enhance the ROC performance, so its performance is similar to "PCAI SPN" method.

Table 2 shows the TPR of different CSI methods at experimental zero FPR. The TPR of the proposed PCAI method is always the largest regardless of the image size is. The experimental results show that the proposed method can increase the TPR prominently in the case of trustworthy identification which is with a low FPR. The "BM3D SPN" performance for images of small size is not as well as that for full size images mentioned in [5] mainly because the BM3D filter needs more pixels information to perform a sparse 3D transformation.

Table 2. The TPR of six methods at experimental zero FPR

Method	Image size (pixels)		
	128x128	256x256	512x512
PCAI SPN	**0.727**	**0.987**	**1**
PCAI Phase SPN	0.724	0.984	1
Phase SPN	0.713	0.975	1
Basic SPN	0.664	0.940	0.992
MLE SPN	0.587	0.944	0.993
BM3D SPN	0.451	0.894	0.987

The SPN becomes weak if the image is JPEG compressed. Figure 6 shows the *overall ROC curve*s performance on a JPEG compressed image of 512x512 pixels with quality factor (QF) being 90%. Results with other size are similar. Experimental results show that the proposed method also has the best performance in resisting mild JPEG compression.

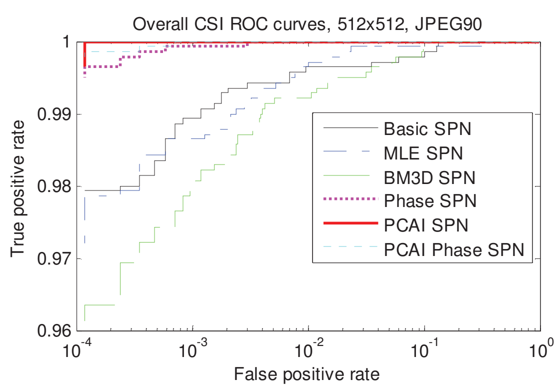

Fig. 6 The *overall ROC curve*s with JPEG QF being 90%

4. CONCLUSION

In this paper, we propose a context adaptive SPN predictor used for SPN extraction and apply it to enhance the ROC performance of CSI. The proposed PCAI SPN method can suppress the effect of image content better because it is adaptive to image edge and local variance. Different from most of the existing methods of extracting SPN from wavelet high frequency coefficients, we extract SPN directly from the spatial domain with a pixel-wise adaptive Wiener filter, based on the assumption that the SPN is a white signal. Extensive experiments show that the ROC performance of the proposed method outperforms the existing state-of-the-art methods on different sizes of images and has the best performance in resisting mild JPEG compression.

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