

# Accurate Detection of Demosaicing Regularity for Digital Image Forensics

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**Abstract**—In this paper, we propose a novel accurate detection framework of demosaicing regularity from different source images. The proposed framework first reversely classify the demosaiced samples into several categories and then estimates the underlying demosaicing formulas for each category based on partial second-order derivative correlation models, which detect both the intra-channel and the cross-channel demosaicing correlation. An expectation-maximization reverse classification scheme is used to iteratively resolve the ambiguous demosaicing axes in order to best reveal the implicit grouping adopted by the underlying demosaicing algorithm. Comparison results based on syntactic images show that our proposed formulation significantly improves the accuracy of the regenerated demosaiced samples from the sensor samples for a large number of diversified demosaicing algorithms. By running sequential forward feature selection, our reduced feature sets used in conjunction with the probabilistic SVM classifier achieve superior performance in identifying 16 demosaicing algorithms in the presence of common camera post-demosaicing processing. When applied to real applications including camera model and RAW-tool identification, our selected features achieve nearly perfect classification performances based on large sets of cropped image blocks.

**Index Terms**—Color filter array, digital still camera, demosaicing, image regularity, RAW tool, source identification

## I. INTRODUCTION

CAMERAS are regarded as trustworthy devices and photos traditionally imply truth. Nowadays, digital photos have been widely used as historical records and as evidences of real happenings in applications from journalist reporting, police investigation, law enforcement, insurance, medical and dental examination, military, museum to consumer photography. While digital photos are conveniently used, their credibility has been severely challenged due to numerous fraudulent cases involving image forgeries, e.g. the fake results on human stem-cell research [1]. The numerous low-cost yet powerful digital tools have enabled easy image creation, modification and distribution, which make fraudulent image forgeries easier than ever. To restore the public trust towards digital photos,

passive image forensics has become a booming research area to mainly address photo-authentication related challenges, such as source identification, tampering discovery and steganalysis. As suggested in [2], forensic software is urgently needed from scientific journal editors to detect signs of deliberate image tweaks. Very often, image forensics needs to detect some common tampering artifacts or inconsistencies of certain image regularities. Since passive image forensics does not rely on information hiding, which usually requires cooperative sources and compatible end-to-end protocols, it has a brighter application prospect than the active forensics.

Recently, passive forensics has been studied for digital images acquired by various digital still cameras (DSC) and scanners. For DSCs, previous works have mainly detected the following intrinsic image regularities:

- *Optical regularities*: illumination, lens distortion [10] and chromatic aberration, etc.;
- *Sensor imperfections*: sensor noise [11, 17, 20], dust pattern [15] and camera response function [16], etc.;
- *Processing regularities*: demosaicing [3-7, 18, 19], white balancing, gamma correction, JPEG compression, etc.;
- *Statistical regularities*: image quality metrics [8], wavelet statistics [12], binary similarity metrics, etc.

The different regularities are associated with different origins and their detections are useful in various forensic tasks. For instance, the work in [11, 17, 20] extracts photo-response non-uniformity (PRNU) sensor noises for individual camera identification and tampering detection. The work in [7, 18, 19] estimates the demosaicing parameters for non-intrusive component forensic analysis on different camera models. Another work in [14] fuses several types of statistical image regularities and applies a feature selection technique to blindly identify cellular camera models from their output low-resolution images. The forensic performances depend on both the image regularity types and the appropriateness of the detection methods. It is also pointed out in [9, 13] that comprehensive forensic analysis should be based on a suite of forensic tools which examine different image properties. In general, forensic system based on one type of regularity may be attacked with ease by a sophisticated attacker while covering up all tampering artifacts and restoring all image regularities into a tampered photo is believed to be very difficult.

In this paper, we consider accurate detection of demosaicing regularity, an important processing regularity associated with

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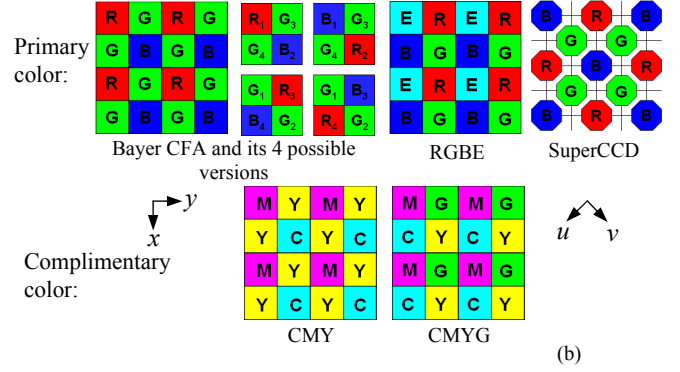
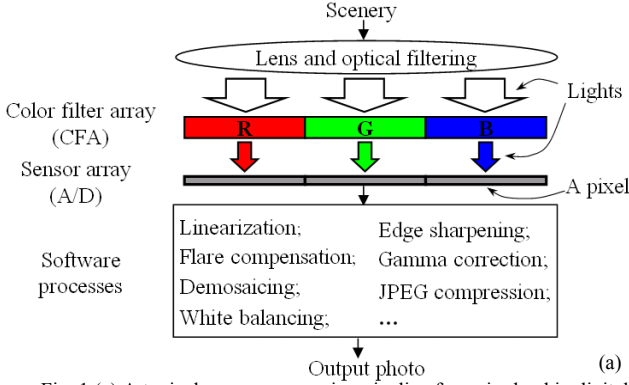


Fig. 1 (a) A typical camera processing pipeline for a single-chip digital still camera [25]; (b) Common color filter array (CFA) patterns

single-chip camera processing in Fig. 1(a). Motivated by the fact that  $2/3$  color samples of a common photo are reconstructed by a demosaicing technique consisting of only a few formulas and this large population of reconstructed samples provides a good basis of reliable statistical characterization of the applied demosaicing technique. In this paper, we aim to accurately estimate the demosaicing formulas for diversified demosaicing algorithms. Our proposed framework employs a partial second-order image derivative correlation model, which detects both the intra-color channel and the cross-channel demosaicing correlation. A reverse classification scheme is incorporated to precisely classify the demosaiced samples into small categories, which best reveal the original demosaicing grouping. Compared with an existing method, our estimated demosaicing formulas regenerate the demosaiced samples from the sensor samples with significantly improved accuracy. Our reduced set of demosaicing features also perform significantly better in identification of 16 demosaicing algorithms in the presence of common camera post-demosaicing processes. For real applications including camera and RAW-tool identification, large-scale tests show that our proposed features achieve nearly perfect identification performances based on the cropped image blocks.

This paper is organized as follows: In Section II, we briefly describe the major differences of existing demosaicing algorithms and discuss the existing detection methods of demosaicing regularity. Section III derives the second-order derivative formula based on 1D periodical lattice and introduces the partial derivative correlation model. With an assumption that Bayer CFA is used, Section IV details the proposed detection framework based on partial derivative correlation model. Section V experimentally compares the proposed detection framework with two existing detection methods based on syntactic images. With features selected using sequential forward floating search algorithm, section VI demonstrates the efficacy of proposed demosaicing features in identification of commercial DSCs and RAW-tools. Section VII concludes this paper and indicates the future works.

## II. DEMOSAICING AND EXISTING DETECTION METHODS

Color filtering and demosaicing are common processes in commercial DSCs to economically produce color. As shown in Fig. 1(a), the color filtering with a CFA allows one specific

color being captured at each pixel. Consequently, only one color is present at each pixel in the resultant RAW image and the missing color samples are reconstructed through demosaicing. The common CFA patterns in Fig. 1 (b) are typically arranged in a mosaic manner on  $2 \times 2$  periodical lattices.

As a key process that determines the fidelity of a color photo, demosaicing has been extensively studied [26–28]. Below we summarize the major differences related with the color filtering and demosaicing.

- *CFA pattern*: The most commonly used is Bayer CFA in Fig. 1(b) [28].
- *Grouping*: The missing color samples are typically grouped before an appropriate demosaicing formula is applied for each group. The grouping can be edge-adaptive or non-adaptive. For edge-adaptive algorithms, the decision criteria differ significantly for distribution of the samples to different edge groups.
- *Reconstructive filtering*: The reconstruction is commonly performed in the color-difference domain. Other possible domains include the intra-channel domain and the color-hue domain. The low-pass reconstruction filters differ significantly in their kernel parameters and sizes.
- *Refinement and enhancement*: As an optional step, the refinement is commonly iterated in updating the green channel and then the red and blue channels. The updating formulas also differ in their parameters.

Several previous forensic works have characterized the demosaicing regularity for both source identification and tampering detection. The work in [3–4] uses an expectation maximization (EM) technique to compute a set of weights for classification of several demosaicing algorithms and for identification of cameras. The works in [5] extends the EM technique by using both the derived EM weights and the average second-order derivative spectrum as features for camera identification. In [6], quadratic pixel correlation coefficients are proposed as demosaicing features for cameras identification. Though reasonable accuracies for identification of 3 to 4 commercial cameras are reported, these methods are not practical due to an overly simplified implicit assumption, i.e. each pixel is equally correlated with its neighboring pixels in a color channel. The work in [7] introduces several new concepts:

1) Detection of the CFA pattern; 2) Heuristic division of the image into 3 regions, the horizontal edges, the vertical edges and the smooth region with an assumption that the demosaicing formula for each region is similar; 3) Each demosaiced sample is written as a weighted average of its neighboring sensor samples in the same color channel and the optimal weights are solved as a total least square solution [24]. Inspired by the new concepts and we also note this detection method has two major drawbacks: 1) the incapability of capturing the cross-color channel correlations caused by demosaicing and 2) the heuristic division is rough, which largely depends on an empirical threshold and cannot accurately reveal the true varying demosaicing grouping for diversified demosaicing algorithms.

In this paper, with assumption that various demosaicing algorithms reconstruct smooth samples from its neighboring sensor samples, we compute in Section III the partial second-order derivative of a demosaiced sample. This provides rich information of the applied demosaicing formula and at the same time, it does not contain the local DC component within a color channel. By proposing a partial derivative correlation model, our estimation of the underlying demosaicing formulas is naturally extended across the boundaries of color channels. In addition, a proposed reverse classification scheme in Section IV precisely classifies samples demosaiced by the same formula into the same category, which minimizes the detection variations due to classification errors. Both the partial derivative correlation model and the reverse classification improve the detection accuracy by suppressing content dependant estimation variations for color images undergone the same demosaicing process. Three types of features computed from 16 categories of demosaiced samples comprehensively represent the regularity introduced by demosaicing. Since forensic challenges are commonly formulated as pattern classification problems, by enhancing the detection accuracy and improving comprehensiveness of the feature description, we suppress the within-class feature variations and enlarge the between-class separation. Consequently, this leads to the superior forensic performances especially when our proposed method is compared with several existing demosaicing detection methods in Section V.

### III. PARTIAL DERIVATIVE CORRELATION MODEL

#### A. Image Derivative on 1D Periodical Lattice

Since common CFAs reside on a  $2 \times 2$  periodical lattice as in Fig 1(b) and demosaicing is frequently carried out along one axis, we first derive the second-order derivative formula based on a 1D periodical mosaic lattice in Fig. 2, where  $\{F(n), n=1, 2, \dots\}$  can be viewed as discrete samples from a smooth continuous function  $f(t)$  at equal sampling intervals. The indexes  $\{\dots, q-1, q+1, \dots\}$  and  $\{\dots, q-2, q, q+2, \dots\}$  are respectively associated with the sensor samples and the demosaiced samples.

Suppose  $F(q)$  is demosaiced along  $t$ -axis, it is reasonable to assume  $f(t)$  is smooth at  $t=q$  such that both the left and the right derivatives of  $f(t)$  are continuous at  $t=q$ , and Taylor series

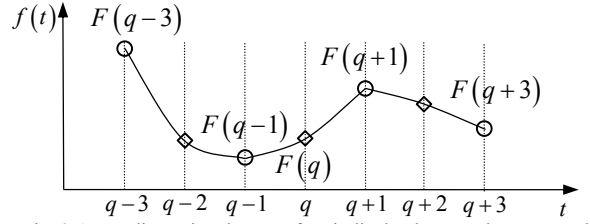


Fig. 2 A one dimensional array of periodical color samples extracted from one color channel of a demosaiced image, where ‘o’s are sensor samples and ‘◇’s are demosaiced samples.  $F(q)$  is demosaiced along  $t$ -axis

expansions are applicable below.

$$F(q+d) = F(q) + \frac{f^1(q)}{1!}d + \frac{f^2(q)}{2!}d^2 + \frac{f^3(q)}{3!}d^3 + \dots \quad (1)$$

With the second-order approximation on the Taylor series expansions, we consider below a small neighborhood including the nearest sensor samples  $F(q-1)$  and  $F(q+1)$ ,

$$\begin{cases} F(q+1) = F(q) + f^{(1)}(q) + f^{(2)}(q)/2 \\ F(q-1) = F(q) - f^{(1)}(q) + f^{(2)}(q)/2 \end{cases} \quad (2)$$

From (2),

$$f^{(2)}(q) = F(q-1) + F(q+1) - 2F(q) \quad (3)$$

Or equivalently,

$$F(q) = \alpha^T \gamma - \beta f^{(2)}(q) \quad (4)$$

where  $\alpha = [0.5 \ 0.5]^T$ ,  $\gamma = [F(q-1) \ F(q+1)]^T$  and  $\beta = 0.5$ . Since  $F(q-1)$  and  $F(q+1)$  are known sensor samples,  $F(q)$  is linearly correlated with and directly computable from  $f^{(2)}(q)$ , its second order derivative along the  $t$ -axis. Therefore, various demosaicing algorithms which estimate  $F(q)$  along the  $t$ -axis are equivalent to estimate  $f^{(2)}(q)$  first, followed by applying a known linear transformation in (4).

The above formulation can be extended to a higher-order approximation by considering a larger neighborhood of sensor samples. For instance, with the fourth-order approximation, we can further include sensor samples  $F(q-3)$  and  $F(q+3)$  to form a set of equations in a similar manner to those in (2). Through elimination process, similar second-order derivative formula to (3) can be derived. In such a case, equation (4) still holds with  $\alpha$ ,  $\gamma$  and  $\beta$  changed correspondingly.

Since only second-order derivatives are used in our formulation, in what follows, we use ‘derivative’ to represent ‘second-order derivative’.

#### B. Derivative-Based Demosaicing Model

To detect the image regularity associated with demosaicing, it is important to have a generalized model to represent the demosaicing processes so that different demosaicing formulas differ only in some free model parameters. Below, we propose a partial derivative correlation model for such a purpose.

To facilitate the discussion, we let  $\mathbf{D} = \{D_{ije}\}$  represent a 3D array of the demosaiced image of size  $H \times W \times K$ , where  $H$  and  $W$

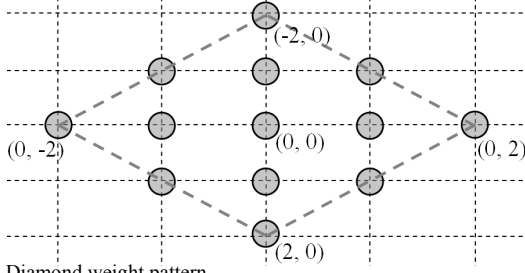


Fig. 3 Diamond weight pattern

are the height and width of the image, respectively, and  $K=3$  denotes the number of color channels.  $c$  is to indicate the red, green and blue channels for a Bayer CFA. Suppose the CFA pattern is known, we can sample the 2D RAW image  $\mathbf{S}=\{S_{ij}\}$  from  $\mathbf{D}$  accordingly. As an example,  $\mathbf{D}$  and  $\mathbf{S}$  for the first Bayer CFA pattern in Fig. 1(b) can be represented as

$$\mathbf{D}=\{D_{ijc}\}=\begin{pmatrix} \{r, G, B\}_{11} & \{R, g, B\}_{12} & \dots \\ \{R, g, B\}_{21} & \{R, G, b\}_{2j} & \\ \vdots & & \ddots \end{pmatrix}, \quad \mathbf{S}=\{S_{ij}\}=\begin{pmatrix} r_{11} & g_{12} & \dots \\ g_{21} & b_{2j} & \\ \vdots & & \ddots \end{pmatrix},$$

where capital letters  $R$ ,  $G$  and  $B$  denote the demosaiced samples in the red, green and blue color channels, respectively, and lower-case letters  $r$ ,  $g$  and  $b$  denote the sensor samples.

Suppose a sample  $D_{ijc}$  is demosaiced along  $t$ -axis, where  $t \in \{x, y, u, v\}$  as depicted in Fig. 1(b) and since from (4), demosaicing  $D_{ijc}$  along  $t$ -axis is equivalent to estimation of its partial derivative  $D_{ijc}^{(t)}$  along the  $t$ -axis, we can write a general demosaicing equation below

$$D_{ijc}^{(t)} = \sum_{\forall (p,q) \in \Omega} w_{pq}^{(t)} S_{i+p, j+q}^{(t)} + e_{ijc}^{(t)} \quad (6)$$

where  $S_{ij}^{(t)}$  denotes a supporting RAW partial derivative computed from  $\mathbf{S}$  along the  $t$ -axis,  $\{w_{pq}^{(t)}\}$  are weights of the supporting derivatives  $\{S_{ij}^{(t)}\}$ , which represent the formula used to demosaic  $D_{ijc}$ ,  $e_{ijc}^{(t)}$  is the corresponding estimation error and  $\Omega=\{(p, q), \text{ where } p^2 + q^2 \leq 4\}$  defines a diamond weight pattern as shown in Fig. 3. Based on the second-order approximation, we use the derived derivative formula in (3) to compute the partial derivatives. For instance, the  $x$ -axis derivatives are

$$\begin{aligned} D_{ijc}^{(x)} &= D_{i-1, jc} + D_{i+1, jc} - 2D_{ijc} \\ S_{ij}^{(x)} &= S_{i-2, j} + S_{i+2, j} - 2S_{ij} \end{aligned} \quad (7)$$

Note that  $\mathbf{S}$  contains sensor samples of all 3 color channels and samples  $S_{i-2, j}$ ,  $S_{ij}$  and  $S_{i+2, j}$  belong to the same color channel due to the  $2 \times 2$  periodicity of the commonly used CFAs in Fig. 1(b). This periodicity of the CFA also applies for other axes including  $y$ ,  $u$  and  $v$ . The partial derivative formulas along the  $y$ -,  $u$ - and  $v$ - axes can be written similar to (7).

We also note that for a number of demosaicing algorithms, one color plane  $c_l$  with rich luminance information (green for a Bayer CFA) is reconstructed first. The reconstruction of

another color plane  $c_c$  with rich chrominance information (red or blue for a Bayer CFA), is based on both the fully-populated color plane  $c_l$  and the RAW  $\mathbf{S}$ . To cater for such cases, we modify the demosaicing equation in (6) accordingly for a demosaiced sample  $D_{ijc}$  in the  $c_c$  color plane as

$$D_{ijc}^{(t)} = \sum_{\forall (p,q) \in \Omega} w_{pq}^{(t)} S_{i+p, j+q}^{(t)} + \sum_{\forall (p,q) \in \Omega} \mu_{pq}^{(t)} D_{i+p, j+q, c_l}^{(t)} + e_{ijc}^{(t)} \quad (8)$$

where  $\{\mu_{pq}^{(t)}\}$  are weights of the supporting derivatives  $\{D_{ijc}^{(t)}\}$  along  $t$ -axis.

Since the supporting derivatives  $\{S_{ij}^{(t)}\}$  are computed from the sensor samples of all 3 color channels, our correlation models in (6) and (8) simultaneously take into account both the cross- and the intra-channel correlation. This is important as the state-of-art demosaicing algorithms often employ color difference or hue domains for demosaicing and this inevitably introduces strong cross-channel correlation. The main advantage of using the partial derivative correlation models is that these derivatives do not contain any local DC component of the respective color channel, which allows estimation of the underlying demosaicing weights, being naturally extended across the boundary of different color channels. Comparatively, the conventional pixel-based correlation model can be hardly extended across the boundary of color channels as the local DC levels in all 3 color channels are highly scenery dependant and generally unequal. By removing the local DC components, the derivative-based formulation focus on the correlation caused by demosaicing and the estimation variations caused by different image sceneries are largely suppressed.

#### IV. PROPOSED DETECTION FRAMEWORK

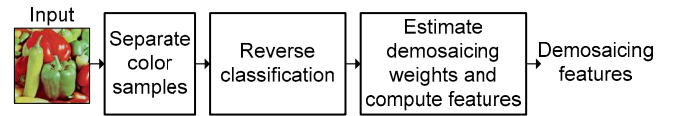


Fig. 4 Overview of the proposed demosaicing detection framework

Fig. 4 shows an overview of the proposed detection framework based on the partial derivative correlation model. Since Bayer CFA has been dominantly used in commercial DSCs [28], we first separate the sensor samples from demosaiced samples according to a Bayer CFA. Then a reverse classification scheme exclusively partitions all demosaiced samples into 16 categories. An expectation maximization reverse classification (EMRC) algorithm is employed to resolve the ambiguous demosaicing axes. After the 16 categories are formed, the partial derivative correlation models are used to form a set of linear demosaicing equations and the weights are estimated as a regularized least square solution. Three types of demosaicing features are computed from the 16 categories for image forensic applications. In the following section, we elaborate the steps in details.

##### A. Reverse Classification to Estimate Demosaicing Weights

After separating the sensor samples  $\mathbf{S}$  and identifying the

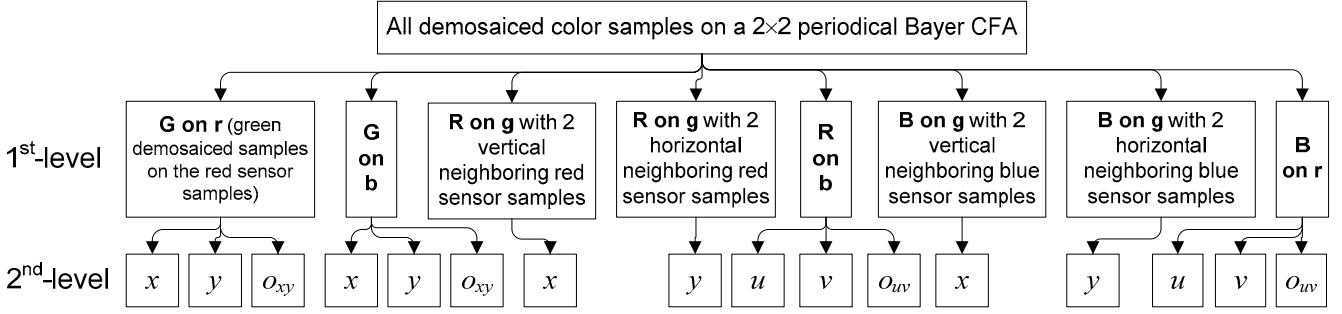


Fig. 5 Two-level reverse classification of the demosaiced samples for Bayer CFA into 16 categories with the demosaicing axes indicated

demosaiced samples from a given demosaiced image  $\mathbf{D}$  according to a Bayer CFA, we perform reverse classification to exclusively classify all demosaiced samples into a number of categories so that each category of demosaiced samples was reconstructed by the same or very similar formulas. The goal of the reverse classification is therefore to best recover the implicit grouping adopted by the underlying demosaicing algorithm. Precise reverse classification is a prerequisite to enable accurate estimation of the demosaicing formulas.

As shown in Fig. 5, our proposed reverse classification is implemented in two levels. In the first level, we divide the demosaiced samples according to their color channel and the relative positions in the  $2 \times 2$  periodical CFA lattice. As a result, we form 8 first-level categories including 2 green categories and 3 each from the red and blue channels. In the second level, we first determine the possible demosaicing axes for each first-level category and further partitions the first-level categories according to their possible demosaicing axes. As the first-level reverse classification is straightforward, below we focus on the second level.

For each of the 8 first-level categories, the possible demosaicing axes are determined by examining pattern of nearest surrounding sensor samples in the same color channel. Fig. 6 shows four possible patterns for Bayer CFA. For patterns (a) and (b) in this figure, ambiguity arises as demosaicing can be conveniently carried out along either one of the two suggested axes or omnidirectionally, i.e. as an average of both axes. To resolve this ambiguity, we further partition such a first-level category into 3 second-level categories according to the 3 demosaicing axes by using an expectation maximization reverse classification (EMRC) algorithm below. The goal of this EMRC algorithm is to jointly assign each sample to its most appropriate demosaicing axes and at the same time, to estimate the corresponding demosaicing formulas.

We first consider the green-channel estimation and let  $\{z_n\}$  for  $1 \leq n \leq N$  denote a first-level green category, where  $N$  is  $\lfloor H \times W / 4 \rfloor$  and the demosaiced samples  $\{z_n\}$  are re-organized based on a single index  $n$ . This category is associated with the pattern in Fig. 6(a) and the possible demosaicing axes are  $x$ ,  $y$  and  $O_{xy}$ , i.e. average of the  $x$ - and  $y$ - axes. Let  $\{z_n^{(1)}\}$ ,  $\{z_n^{(2)}\}$  and  $\{z_n^{(3)} = (z_n^{(1)} + z_n^{(2)})/2\}$  denote the corresponding  $x$ -,  $y$ -axes derivatives and the average derivatives respectively. For each sample  $z_n$  and each axis  $t \in \{1, 2, 3\}$ , we follow (6) to get

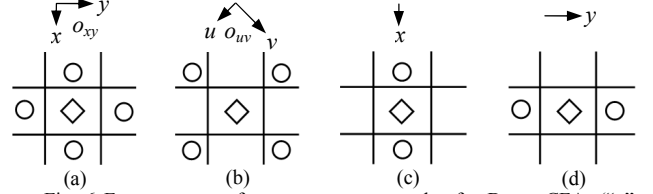


Fig. 6 Four patterns of nearest sensor samples for Bayer CFA, (“o”: sensor samples; “ $\diamond$ ”: demosaiced samples); for green channel (a) four direct neighbors; and for red and blue channels (b) four corner neighbors; (c) two vertical neighbors and (d) two horizontal neighbors.

$$e_n^{(t)} = z_n^{(t)} - \mathbf{w}^{(t)T} \mathbf{s}_n^{(t)} \quad (9)$$

where  $\mathbf{w}^{(t)}$  is a vector of the weights for the  $t^{\text{th}}$  axis,  $\mathbf{s}_n^{(t)}$  is a vector of the corresponding supporting RAW derivatives and  $e_n^{(t)}$  denotes the estimation error. The vectors  $\mathbf{w}^{(t)}$  and  $\mathbf{s}_n^{(t)}$  are formed by re-aligning all elements in the diamond weight pattern defined in Fig. 3 row by row into single-column vectors. For the  $O_{xy}$ -axis,  $\mathbf{s}_n^{(3)}$  contains both the  $x$ - and  $y$ -axes supporting derivatives.

Since the demosaicing weights  $\mathbf{w}^{(t)}$  are unknown, directly assigning the most appropriate demosaicing axis for each sample  $z_n$  is impossible. Therefore, the proposed EMRC algorithm iteratively minimizes

$$J = \sqrt{\frac{1}{N} \sum_{n=1}^N \sum_{t=1}^3 v_n^{(t)} \left( z_n^{(t)} - \mathbf{w}^{(t)T} \mathbf{s}_n^{(t)} \right)^2} \quad (10)$$

where  $v_n^{(t)} \in \{0, 1\}$  is the assignment indicator and  $v_n^{(t)} = 1$  indicates that  $z_n$  is exclusively assigned to the  $t^{\text{th}}$ -axis.

The weights for  $\mathbf{w}^{(t)}$  are initially set to zero. In the **expectation step**, we update

$$v_n^{(t)} = \begin{cases} 1, & \text{if } t = \arg \min \left( \left| z_n^{(t)} - \mathbf{s}_n^{(t)T} \mathbf{w}^{(t)} \right| \right) \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

for  $n=1, \dots, N$  while  $\mathbf{w}^{(t)}$  is fixed.

In the **maximization step**, we fix  $v_n^{(t)}$  and compute  $\mathbf{w}^{(t)}$  as a regularized least square solution [24] below

$$\min \left( \left\| \mathbf{Q}^{(t)} \mathbf{w}^{(t)} - \mathbf{z}^{(t)} \right\|^2 + \lambda \left\| \mathbf{w}^{(t)} \right\|^2 \right) \Rightarrow \mathbf{w}^{(t)} = \mathbf{Q}^{(t)\dagger} \mathbf{z}^{(t)} \quad (12)$$

for  $t = 1, 2$  and  $3$ , where

$$\mathbf{Q}^{(t)} = \begin{bmatrix} \mathbf{v}_1^{(t)} \mathbf{s}_1^{(t)T} \\ \vdots \\ \mathbf{v}_N^{(t)} \mathbf{s}_N^{(t)T} \end{bmatrix}, \mathbf{z}^{(t)} = \begin{bmatrix} \mathbf{v}_1^{(t)} z_1^{(t)} \\ \vdots \\ \mathbf{v}_N^{(t)} z_N^{(t)} \end{bmatrix}, \mathbf{Q}^{(t)\dagger} = (\mathbf{Q}^{(t)T} \mathbf{Q}^{(t)} + \lambda \mathbf{I})^{-1} \mathbf{Q}^{(t)},$$

$\|\cdot\|$  denotes Frobenius norm,  $\lambda$  is a small regularization constant which prevents overfitting and improves stability of the solutions especially under ill conditions.  $\mathbf{I}$  denotes an identity matrix. Since  $\mathbf{w}^{(t)} = \mathbf{0}$  is also a valid solution but equation (12) hardly returns such a special solution, we set  $\mathbf{w}^{(t)} = \mathbf{0}$  if  $\|\mathbf{z}^{(t)}\| \leq \|\mathbf{Q}^{(t)} \mathbf{w}^{(t)} - \mathbf{z}^{(t)}\|$ .

The above expectation and maximization steps are repeated until the following stabilization condition is met,

$$J^{(i-1)} - J^{(i)} < T_h \quad (13)$$

where  $i$  denotes the current iteration number and  $T_h$  is a small experimentally determined constant. Both the expectation and maximization steps are designed to reduce  $J$ , which is sharply reduced at the few initial iterations and gradually stabilized to a low level.  $T_h$  is chosen to speed up the iteration process for the EMRC algorithm. By setting  $T_h=0$ , more iterations are needed. Experimentally, with a small  $T_h$  in the range of [0.001 0.005], the required number of iterations drops significantly. As the outcomes of the EMRC algorithm, the true grouping employed by the underlying demosaicing technique can be largely recovered and the weights  $\mathbf{w}^{(t)}$  representing the underlying demosaicing formulas are more reliably estimated.

For the red and blue ambiguous first-level categories associated with pattern (b) in Fig. 6, the reverse classification is implemented in a similar manner to partition the samples according to the  $u$ ,  $v$  and  $o_{uv}$  axes. The main difference is that the demosaicing equations represented similarly to (9) are written by following the derivative correlation model in (8), where  $\mathbf{s}_n^{(t)}$  contains the supporting derivatives computed from both the RAW image and the green plane.

This EMRC algorithm can be extended to the cases where a first-level category needs to be more thoroughly divided, i.e. when more than 3 sub-categories are needed. Such a scenario is necessary when the regularity of complex demosaicing algorithms needs to be thoroughly investigated.

For patterns (c) and (d) in Fig. 6, the demosaicing axes are clear as the nearest 2 sensor samples are either vertically or horizontally arranged. Such first-level categories are directly exported to the second level and the corresponding demosaicing weights are computed similarly to the maximization step of the above EMRC algorithm.

### B. Computation of Demosaicing Features

With the optimal weights determined for the 16 demosaicing categories, we compute 3 types of features below.

*Weights:* These features represent the applied demosaicing formulas with a total of 312 weights computed for the 16 demosaicing categories.

*Error Statistics:* With the optimal weights  $\mathbf{w}$  available, the absolute errors are given below

$$|\mathbf{e}| = |\mathbf{Q}\mathbf{w} - \mathbf{z}| \quad (14)$$

where  $\mathbf{Q}$  is the matrix of supporting derivatives and  $\mathbf{z}$  is the vector of the corresponding derivatives. For each category, we compute 4 error cumulants including the mean, variance, skewness and kurtosis. For 16 categories, a total of 64 error cumulants are computed, which statistically reveal the goodness that our estimated weights fit the underlying demosaicing algorithm.

*Normalized Group Sizes:* After partitioning an ambiguous first-level category using the EMRC algorithm, percentage of the demosaiced samples distributed to the 3 sub-categories are good indicators of the implicit grouping adopted by the underlying demosaicing algorithm. The normalized sizes of the sub-categories in percentages are also included as our features. For a total of 4 ambiguous first-level categories, we compute 8 such features.

In commercial digital still cameras, the 4 versions of Bayer CFAs in Fig. 1 (b) are most likely adopted equally. Hence we apply our detection method 4 times to cater for the 4 possibilities. Consequently, we obtain  $312 \times 4 = 1248$  weights,  $64 \times 4 = 256$  error cumulants and  $8 \times 4 = 32$  normalized group sizes. Though the feature dimension increases 4-fold, some key advantages are: 1) detection of the correct Bayer CFA is not needed and the discriminative CFA information is automatically included in the overall feature set; 2) the correct Bayer CFA must be present if Bayer CFA is used. We find the features computed based on the 3 incorrect Bayer CFAs also provide useful relative information and the 4 channels of demosaicing features statistically form stable and unique patterns; 3) other non-Bayer CFAs in Fig. 1(b) share common properties as Bayer CFAs including  $2 \times 2$  periodicity and mosaic lattice, which make our derivative correlation models still applicable to such CFAs. Demosaicing based on these CFAs will also cause stable and unique imbalance pattern among these 4 channels of statistical features and our demosaicing features based on 4 Bayer CFAs help comprehensively represent this statistical imbalance.

The proposed total 1536 features comprehensively represent the demosaicing regularity of all 16 demosaicing categories. The overall feature computational time averaged over 100 runs on a P4-2.66 GHz PC with MATLAB 7.4 for 100 different color images of sizes  $512 \times 512$  is about 45 seconds.

In view of the high dimensionality, which requires huge training data and causes slow classifier training and forensic response, we reduce the feature dimension by selecting a compact subset of features using sequential forward floating search (SFFS) algorithm [29]. Starting from an empty feature set, the SFFS algorithm performs stepwise feature inclusion and conditional feature removal to select a subset of features. Compared with simple sequential searching algorithms, the backtracking mechanism employed by SFFS allows removing the previous selected but currently useless features due to

TABLE I  
COMPARISON OF 16 CONVENTIONAL DEMOSAICING ALGORITHMS

ID	Algorithm	Edge Adaptiveness	Domain (Refinement)	Reconstructive Filter (Size)
1	Bilinear	Non-adaptive	Intra-channel	Fixed (3×3)
2	Bicubic	Non-adaptive	Intra-channel	Fixed (7×7)
3	Cok 86	Adaptive	Intra-channel	Mixed (≥3×3)
4	Cok 87	Non-adaptive	Color hue	Fixed (3×3)
5	Freeman 88	Non-adaptive	Color diff.	Median (3×3)
6	Laroche 94	Adaptive	Mixed	Fixed (3×3)
7	Hamilton 97	Adaptive	Color diff.	Fixed (3×3)
8	Kimmel 99	Adaptive	Color hue (Inverse diffusion)	Adaptive (3×3)
9	Li 01	Non-adaptive	Color diff.	Adaptive
10	Gunturk 02	Non-adaptive	Color diff. (Iterative)	Fixed (5×5)
11	Pei 03	Adaptive	Color diff. (Iterative)	Adaptive (3×3)
12	Wu 04	Adaptive	Color diff. (Iterative)	Fixed (3×3)
13	Chang 04	Adaptive	Color diff. (Iterative)	Adaptive (5×5)
14	Wang 05	Adaptive	Color diff. (Iterative)	Adaptive (3×3)
15	Hirokawa 05	Adaptive	Color diff. (Iterative)	Median (5×5)
16	Alleysson 05	Non-adaptive	Chrominance	Fixed (11×11)

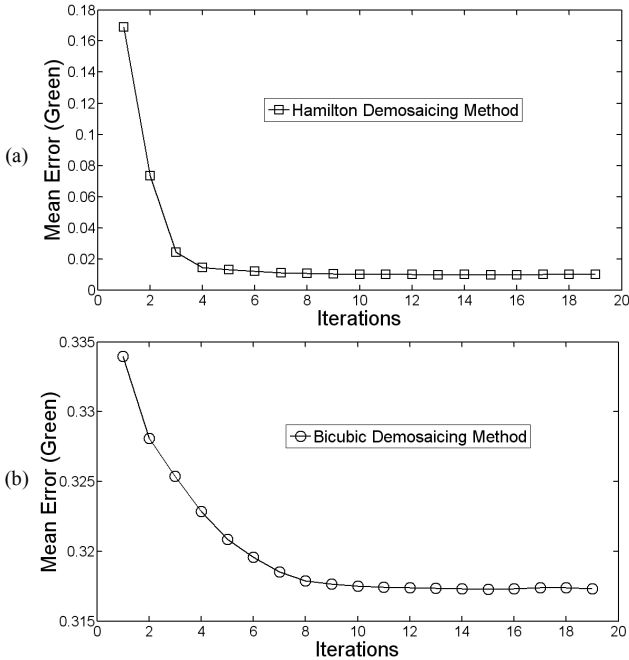


Fig. 8 Mean absolute prediction error versus iterations for (a) an adaptive (Hamilton) and (b) a non-adaptive (Bicubic) demosaicing methods; (c) Test image

inclusion of new features, which more likely result in an optimal feature subset.

## V. SIMULATION RESULTS AND DISCUSSION

In our experiment, we select 16 conventional demosaicing algorithms in Table I. Note these algorithms are highly diversified including the early non-adaptive algorithms as well as the state-of-art highly adaptive algorithms. We have also included two pairs of close demosaicing algorithms, i.e. Chang's and Wang's methods are extensions of Pei's and Kimmel's proposals, respectively. One can refer to [27-28] for details about these 16 methods used.

### A. Re-estimation Accuracy

Our derived demosaicing weights together with (4) can be used to re-estimate the demosaicing samples from the sensor

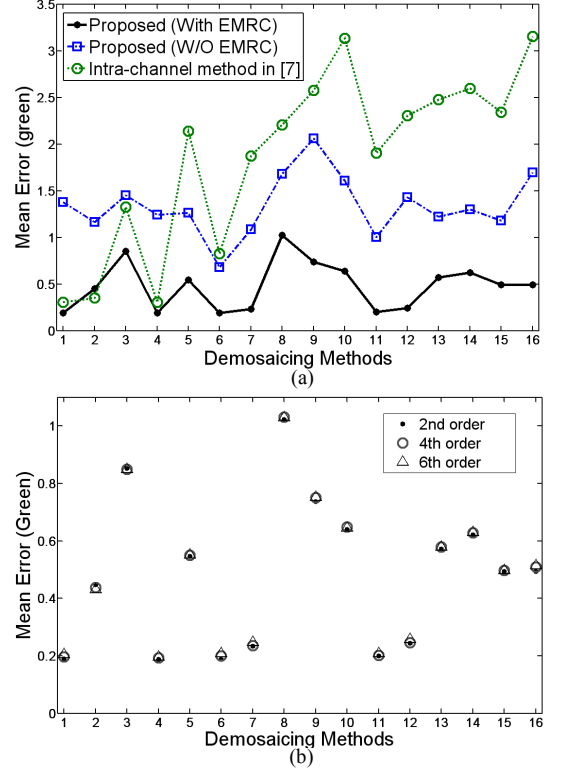


Fig. 7 Comparison of mean absolute re-estimation errors for 16 demosaicing methods based on (a) different detection algorithms and (b) the proposed algorithm with different approximation orders. Refer to Table I for IDs of the demosaicing methods. The mean absolute error is computed when each color sample is represented by 8 bits, i.e. from 0 to 255



samples. The re-estimation accuracy reveals the preciseness that our estimated weights match with the formulas used by the underlying demosaicing algorithm.

In this experiment, we compare our re-estimation accuracies for the 16 demosaicing algorithms in Table I with the detection algorithm [7] based on syntactic images. The syntactic set contains 1000 color images of 512×512, which are cropped from the center of 1000 photos taken with different cameras and then downsampled sufficiently to remove previous filtering characteristics. We first sample the RAWs from these images according to the first Bayer CFA in Fig. 1 (b) and then separately demosaic these RAWs with the 16 demosaicing algorithms. Our proposed detection model is then applied to compute both the optimal weights and the corresponding errors for green channel of each demosaiced image. Based on the same rough reverse classification in [7], our results in Fig. 7(a)

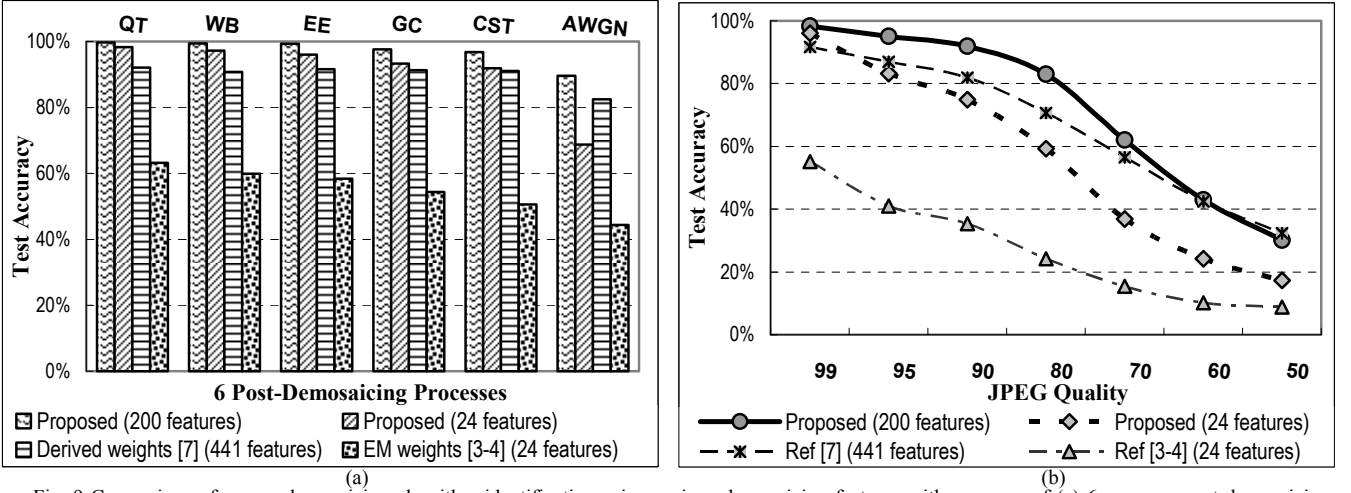


Fig. 9 Comparison of source demosaicing algorithm identification using various demosaicing features with presence of (a) 6 common post-demosaicing processes and (b) lossy JPEG compression of various quality factors. In (a), the post-processes are: **QT**: quantizing color samples of the demosaiced image to  $\{0,1,\dots,255\}$ ; **WB**: white balancing with  $3\times 3$  transformation matrix  $\mathbf{T} = [.85 .07 .08; .01 .88 .11; .03 .08 .89]$ ; **EE**: edge enhancement using unsharp mask (PSNR=30dB); **GC**: gamma correction with  $1/\gamma=1/2.2$ ; **CST**: color space transformation from CIEXYZ to sRGB; **AWGN**: zero-mean white Gaussian random noise (PSNR=30dB).

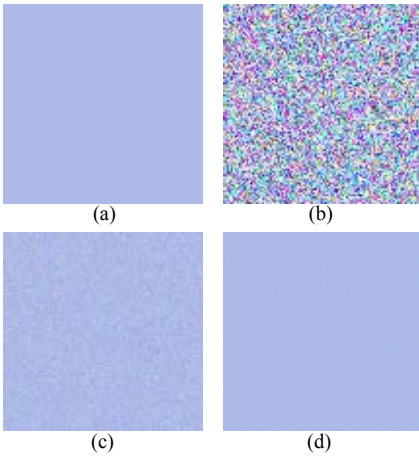


Fig. 10 (a) A uniform 'sky' scenery (256 $\times$ 256) and after adding AWGN camera sensor noises of (b) PSNR = 10 dB; (c) PSNR = 30 dB and (d) PSNR = 50 dB

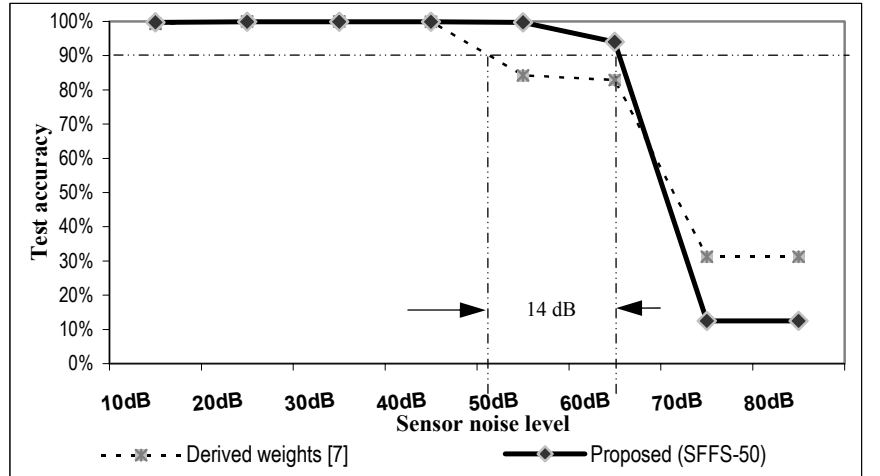


Fig. 11 Comparison of test accuracies in classification of 16 demosaicing algorithms based on uniform blocks with various sensor noise levels

show that the derivative-based correlation model in (6) is more accurate for most of adaptive demosaicing methods that utilize cross-channel information to demosaic the green channel. If the proposed EMRC is applied, the mean absolute errors drop to a very low level for all 16 demosaicing algorithms. The comparison results suggest that our method achieves large margins of improvement on accuracies especially for the adaptive demosaicing methods, where the reconstruction is in cross-channel domains. Fig. 7(b) suggests that the 2<sup>nd</sup>-, the 4<sup>th</sup>- and the 6<sup>th</sup>-order approximations give similar mean errors. In Fig. 8, we can see the iterations in the proposed EMRC algorithm monotonically reduce the average re-estimation error to a low level for two very different demosaicing methods. This demonstrates our proposed EMRC algorithm efficiently improves the detection accuracy for diversified demosaicing algorithms.

### B. Classification of Demosaicing Algorithms

In this experiment, we classify the 16 demosaicing

algorithms using our proposed demosaicing features. Since demosaicing is not the last process in camera processing pipeline, our experiment also takes into account of the common camera post-demosaicing processes including quantization (QT), white balancing (WB), edge enhancement (EE), gamma correction (GC), color space transformation (CST) and lossy JPEG compression. We also include adding zero-mean additive white Gaussian noise (AWGN) as one general form of distortion. The syntactic image set for this experiment is the same as the previous experiment. After demosaicing the 1000 images with these 16 algorithms, the demosaiced images further go through the above post-processing separately. Out of the 1000 syntactic images, 600 images per demosaicing algorithm and per distortion process are randomly selected for training and the rest for testing.

After performing feature extraction, we follow the LIBSVM guild [21] to train two probabilistic support vector machine (PSVM) classifiers with radial basis function (RBF) kernel. For the 6 post-processes excluding JPEG, we use 57600 training

and 38400 testing images. For JPEG of 7 different quality factors, we use 67200 training and 44800 testing images. Compared with the conventional SVM, PSVM also studies distribution of SVM outputs and maps them into probability scores by optimizing a sigmoid function [22, 23]. Based on the same setup, the comparison results in Fig. 9(a) demonstrate that our 200 demosaicing features selected by SFFS result in an average of 2.9% error rate for post-demosaicing processes including QT, WB, EE, GC, CST and AWGN, which reduce the error rates of 10.1% for the derived weights in [7] (441 features) by 2.5 times. With only 24 features selected, our average error rate increases to 9.1%, which is still 3.9 times smaller than 44.8%, the average error rate for the EM weights [3, 4] (24 features). We attribute the significant error rate reduction to our accurate detection model, which more comprehensively captures the differences between the close demosaicing methods and our features contain less content-dependant variations. Our good performance also suggests the uniqueness of demosaicing regularities is still largely preserved after the 6 common post-demosaicing distortion processes.

For lossy JPEG compression, the test accuracies in Fig. 9(b) monotonically decrease as the JPEG quality decreases. As expected, a low JPEG quality factor implies large quantization step sizes especially for the high-frequency DCT components. While demosaicing regularity contains rich high-frequency correspondence among neighboring color samples, low-quality JPEG compression can remove the uniqueness of detected demosaicing regularity. Though JPEG compression could significantly deteriorate the classification performance, at a typical JPEG quality of 80, our 83% top-1 test accuracy based on 200 selected features still suggests a reliable identification performance especially when multiple pairs of close demosaicing algorithms are present. The comparison results show that our average error rate of 28% based on 200 selected features is 17.6% lower than 34%, the average error rate for the derived weights in [7]. With the same number of features, our test accuracy based on 24 features confidently outperforms that of the 24 EM weights in [3-4].

### C. Classification of Post-Processes

Different types of post-demosaicing processes distort the demosaicing regularity in unique manners. In this experiment, with the demosaicing algorithm fixed as Hamilton’s method [26], we classify 7 post-demosaicing processes including quantization (8-bit), WB, EE (PSNR=30dB using unsharp mark), GC ( $1/\gamma=1/2.2$ ), CST(from CIEXYZ to sRGB), AWGN (30 dB) and lossy JPEG compression (Q-factor = 80) using the proposed features. With 600 randomly selected training images and 400 test images per distortion process, i.e. 4200 training and 2800 testing images in total for the 7 distortions, we achieve a test classification accuracy of 97.3% using a similar PSVM classifier based on only 5 selected features. This high classification rate shows our proposed features also effectively capture the unique distortion characteristics of the different post-demosaicing processes. Since the post-processing in

commercial DSCs can differ significantly in the type of inclusive processes, their sequence and the parameters, our good performance implies that the proposed features can be also used as a fingerprint of the post-demosaicing processing.

### D. Sensitivity to Image Variations

Rich content variations in RAW samples make detection of the demosaicing regularity easier. In this simulation, we consider the extreme case of uniform scenery and the only image variations are contributed by sensor imperfections aggregated from sensor noises, dust and process distortions. We assume these noises are AWGN and the required noise level for reliable identification of the 16 demosaicing algorithms based on our proposed features is studied.

We first create a noisy image set containing 1200 images by adding 8 levels (PSNR=10, 20, ..., 80dB) of random AWGN noises to the uniform “sky” scenery in Fig. 10(a). These noisy images are then separately demosaiced with the 16 algorithms. With a similar PSVM classifier and by selecting only 50 proposed features using SFFS, our comparison result in Fig. 11 shows for a cut-off level of 90%, our required PSNR is 66dB, which is about 14 dB higher than [7]. This suggests our proposed features require significant less scenery variations to achieve good identification of source demosaicing algorithms.

## VI. FORENSIC APPLICATIONS

### A. Camera Model Identification

The real camera processing pipelines in commercial DSCs contain proprietary knowledge. In this section, we further test the proposed demosaicing features in distinguishing 14 commercial DSC cameras in Table II. We first establish a photo dataset consisting of 200 photos per camera. All these photos are direct outputs from their cameras and are stored in the default JPEG formats. As illustrated in Fig. 12(a), we crop 12 non-overlapped image blocks from each selected photo at 12 fixed locations to create 2400 image blocks per camera with some samples shown in Fig. 12(b). For each camera, we further divide the image blocks into a training set of 1584 blocks cropped from 132 randomly selected photos and a test set of the remaining image blocks. For 14 cameras, the number of blocks used for training and testing are respectively 22176 and 11424.

With a similar PSVM classifier, our identification results based on 250 selected features by SFFS in Table III demonstrate an excellent performance with an average test accuracy of 97.5%. Since the result is achieved based on individual blocks, the accuracy can be further improved to close to 100% simply by averaging the probabilistic scores of all 12 image blocks cropped from a test photo. The cameras we have tested include multiple models from a same camera manufacturer, e.g. 4 Canon models and 2 models each from Nikon, Lumix, Olympus and Sony. Our results in Table III shows the camera models from different manufacturers can be distinguished almost as accurately as the camera models from the same manufacturers.

With a close examination on the wrongly classified camera

blocks, we found that the 2.5% total classification errors are mainly contributed by some low-quality blocks and we manually classify them into 5 categories as illustrated in Fig. 13. About 49.5% of the total errors are contributed by the “saturated” and the “uniform” categories. Images in these two categories lack content variations, which makes reliable detection almost impossible. The “chromatic” and the “structured” categories also contribute a small portion of errors because these images either lack color variations or edge-type variations which makes comprehensive detection of demosaicing regularity difficult. Though majority of the low-quality test blocks are still correctly classified, our finding suggests that the error rate can be further reduced if we wisely crop the image blocks at locations where rich color and edge information are present.

### B. RAW-Tool Identification

Digital single-lens reflex (DSLR) cameras usually allow the sensor samples to be saved into RAW formats which can be developed into photos using RAW tools at a later time. Similar to the camera processing, these tools demosaic the RAWs and then apply some post-demosaicing processes. However, since these RAW tools are designed for PCs, common constraints such as processor speed, memory size and shot-to-shot delay are no longer among the key design considerations. Hence, these RAW tools are affordable to implement more complex demosaicing and post-processing to achieve higher image quality. In this test, we classify 10 commercial RAW tools in Table IV with our proposed features.

We first develop 200 RAWs (captured by an Olympus E-500 camera) into uncompressed TIFF photos using the 10 commercial RAW tools in Table IV. Based on a similar setup to the camera identification experiment, we use a total of 15840 cropped image blocks for training and 8160 blocks for testing. We identify the source RAW tool using only 50 selected features based on image blocks. Our average identification accuracy of 99.1% in Table V shows that the proposed detection framework can efficiently capture the unique processing characteristics of these RAW tools.

### C. Analysis on Features Selected

Considering that the selected features largely depend on both the datasets used and the SFFS configurations, we show in Table VI the more reliable distribution of the selected features. Among the 3 different types of demosaicing features, we find that for both camera and raw-tool identifications, a dominant percentage of about 80% selected features are the weights features followed by the error statistics features and the least are the normalized group sizes features. Though partially due to the different population sizes of different feature types, these results also suggest that our estimated weights contain the richest discriminant information. The contribution to the selected feature set from the 16 demosaicing categories is rather even. We also note that 36% of selected features are contributed from the green demosaicing categories for camera model identification and only 20% for the RAW-tool

identification. Considering the major difference is that all camera photos in our experiment are in JPEG format and the converted RAW photos are in TIFF format, the difference in contribution percentages from the green categories is likely caused by JPEG compression. In the TIFF photos, we observe in many cases that our detected demosaicing regularity from the different green categories tend to be more similar, exhibiting less diversity information. Hence, fewer features are selected from the green categories.

## VII. CONCLUSIONS

In this paper, we present an accurate detection framework of image demosaicing regularity. Our proposed method addresses the common differences of color filtering and demosaicing algorithms, and the accurate detection is achieved by a precise reverse classification together with partial derivative correlation models. In the reverse classification, an EMRC algorithm is demonstrated to be effective in resolving the ambiguous demosaiced axes. Through using partial derivative correlation models, our method efficiently detects both the cross- and the intra-channel correlation caused by demosaicing. By significantly reducing our feature dimension using sequential forward floating search, the simulation results show that our proposed demosaicing features confidently outperform 2 existing demosaicing detection methods in identifying 16 demosaicing algorithms in the presence of various common post-demosaicing processes. Our proposed features are also highly effective in distinguishing different post-processes and are more sensitive to small scenery variations. When applied to real forensic applications, our reduced sets of demosaicing features achieve nearly perfect average test identification accuracies of 97.5% for 14 commercial DSCs of different models and 99.1% for 10 RAW-tools based on large number of cropped image blocks, which contain a mixture of good and bad quality images.

Complementing the current proposed approach to identify different image software processing pipelines, additional features such as sensor noise pattern [20] are needed in identification of individual cameras of the same model. Further investigation effort also includes verifying the effectiveness of our proposed demosaicing features on the camera models of non-Bayer CFAs.

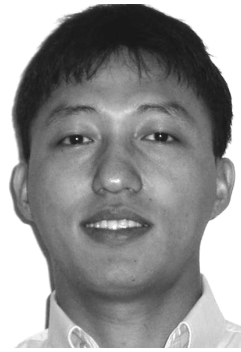
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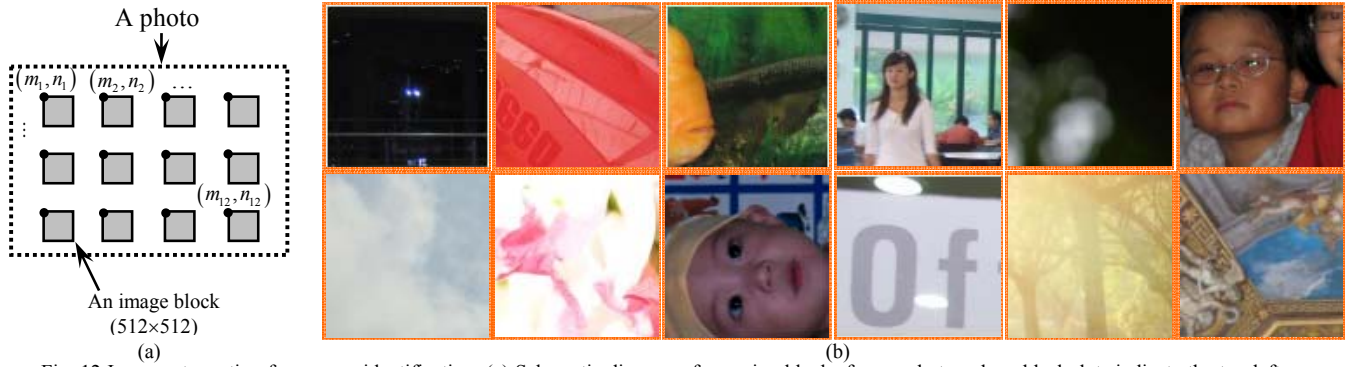


Fig. 12 Image set creation for camera identification; (a) Schematic diagram of cropping blocks from a photo, where black dots indicate the top-left corners  $\{m_i, n_i\}$  of the blocks, which are set to be odd number to avoid shifts to underlying CFA; (b) Samples of cropped image blocks

ID	Camera model
1	Canon Ixus i
2	Canon Powershot A620
3	Canon EOS 400D
4	Canon EOS 10D
5	Nikon Coolpix S210
6	Nikon D70
7	Lumix DMC-FX01
8	Lumix DMC-FX2
9	Olympus U300d
10	Olympus E-500
11	Sony Cybershot DSC-P73
12	Sony Alpha DSLR A350
13	Casio EX-Z60
14	Fujifilm FinePix Z2

Input camera	Ave. rate = 97.5%	Predicted camera														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	
1	1	96.1	1.3	0.1	0.1		2.0		0.4							
2	2	1.1	90.1	1.3			6.5	0.1	0.5							
3	3	0.2		98.5	0.5		0.1	0.1			0.4	0.2				
4	4	Canon			100	Nikon										
5	5	0.1		0.4	0.5	98.0	0.1			0.2	0.1				0.6	
6	6	1.6	2.3		0.6	1.6	93.3		0.1	Lumix	0.3	0.1			0.1	
7	7			0.4			0.1	97.8		1.2	0.2		0.3			
8	8	0.3	0.1	0.8	0.3		0.6		97.8						0.1	
9	9						0.6		0.1		99.3					
10	10							0.1	Olympus	0.1	99.4			0.4		
11	11			0.1	0.1		0.6	0.3				Sony	98.8	0.1		
12	12						0.1	0.1	0.2	0.3		0.5		98.8		
13	13							0.2							Casio	99.5
14	14	0.1	0.1				0.5	1.1				0.1			Fujifilm	98.0

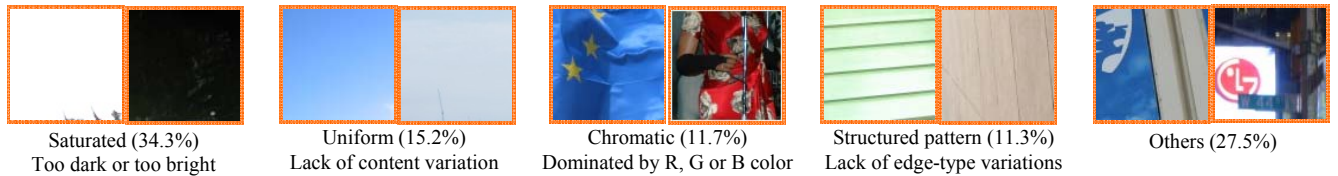


Fig. 13 Samples of wrongly classified camera image blocks

ID	RAW tool
1	ACDSee v10
2	Breeze Browser Pro v1.7
3	Capture One v3.7.8
4	Olympus Master v2
5	Photoshop CS2
6	Picture Window Pro v4.0
7	Rawshooter Essential 2006
8	Silkypix Developer Studio v3.0
9	StepOK v1.1
10	Corel Paintshop Pro 12

Input RAW tool	Ave. rate = 99.1%	Predicted RAW tool									
		1	2	3	4	5	6	7	8	9	10
1	1	98.5	0.1	0.1		0.1		0.2		1.0	
2	2		99.9						0.1		
3	3			98.4	0.4		0.1		1.0	0.1	
4	4				100						
5	5	0.4		0.1		98.4		0.2	0.3	0.6	
6	6	0.1					97.8		0.1	2.0	
7	7				0.1	1.3		98.6			
8	8	0.1			0.1	0.1	0.1		99.6		
9	9						0.1			99.8	0.1
10	10							0.1		0.1	99.6

TABLE VI  
CONTRIBUTION PERCENTAGES (%) TO THE SFFS SELECTED FEATURES FROM 3 DIFFERENT FEATURE TYPES [WEIGHTS (WT), ERROR STATISTICS (ES), NORMALIZED GROUP SIZES (NGS)] AND FROM 16 DIFFERENT DEMAOSAICING CATEGORIES (REFER TO FIG 5 FOR THE DEMAOSAICING CATEGORIES)

Identification application	Feature type			Demaosaicing category															
	WT	ES	NGS	G on r			G on b			R on g		R on b		B on g		B on r			
				x	y	$\sigma_{xy}$	x	y	$\sigma_{xy}$	x	y	u	v	$\sigma_{uv}$	x	y	u	v	$\sigma_{uv}$
Camera models	83	14	3	5	7	9	4	6	5	5	5	7	9	6	5	5	7	7	8
RAW tools	76	24	0	6	2	6	0	4	2	8	4	12	10	4	6	12	6	8	10