# Issues on Selecting Image Features for Robust Source Camera Identification

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## Abstract

Image feature selection is an important issue for source camera identification. Well-selected features should make camera classifiers accurate, efficient as well as robust. Current source camera identification schemes select image features mainly based on classification accuracy and computational efficiency. In this work, we demonstrate that robustness should also be considered for classifiers which aim at real-world tasks. Besides, we reveal what impact the reduced feature subset will have on the robustness of camera classifiers. The dimensionality reduction is often necessary for computational efficiency.

## Keywords

Image Forensics, Camera Identification, Image Feature Selection, Robustness, Dimensionality Reduction

## 1. Introduction

Statistical image features are important clues for uncovering image origin and tracing back source imaging devices. Most statistical image features employed for these purposes were investigated in steganalysis, for example, the statistics of wavelet-like decomposition of natural images and the statistics of prediction errors of wavelet coefficient magnitude (Farid and Lyu, 2002), and the image quality metrics (IQMs) (Avcibas et al., 2003). These statistics and their variants are easily found in previous image forensic studies such as (Kharrazi et al., 2004), (Tsai et al., 2006), (Gou et al., 2009), (Khanna et al., 2009), (Filler et al., 2008), (Tsai et al., 2007), and (Tsai et al., 2008). Usually, specific statistical features related to camera and/or scanner pipelines, e.g., CFA (colour filter array) configuration (Kharrazi et al., 2004), (Tsai et al., 2006), demosaicing algorithms (Gallagher and Chen, 2008), (Cao and Kot, 2009), colour processing/transformation, and the photo response non-uniformity noise (PRNU) (Filler et al., 2008) are used along with steganalysis features. Although there are many similarities in technique between steganalysis and source camera/scanner identification, their difference is fundamental. For the former, we can assume that a stego image has not been changed since the hidden message is embedded. Such an assumption is reasonable; otherwise the hidden message may not be losslessly extracted). For the latter, however, this assumption is often not feasible. In practice, we often have little knowledge about the image in question. A test image may have undergone some image processing and thus becomes a processed one, or it may remain unchanged since it is generated by cameras or scanners so that it keeps an unprocessed one. Consequently, the statistical image features associated with the purpose of forensic investigation should ideally remain unchanged or practically change very little for a test image which has undergone some innocuous image processing.

Since in general, existing camera/scanner identification methods are deemed quite reliable in laboratory tests, one might be tempted to apply them in practice as well. However, little is known about the robustness of forensic algorithms (Gloe et al., 2007). In this work, we use a variant algorithm of (Kharrazi et al., 2004) and (Tsai et al., 2006) as an example to investigate the robustness of camera classifiers as well as the impact the reduced subset of features has on the robustness.

The rest of the paper is organized as follows. In Section 2, we construct our sample camera classifier and evaluate its performance on ten different cameras. In Section 3, we evaluate the performance of our classifier on images under three common image manipulations. In Section 4, we first adopt a classical feature selection algorithm in pattern recognition to search for a suboptimal subset of features, and then evaluate the performance of the camera classifier on unprocessed and processed images, respectively. We will conclude our work in Section 5.

# 2. A Sample Camera Classifier and its Performance

## 2.1. Construction of Feature Vector

In (Kharrazi et al., 2004), Kharrazi et al. proposed a prototype of camera classifier based on the statistical image features derived from steganalysis as well as the statistical features related to camera pipelines. That method was re-implemented by Tsai and Wu on different camera models (Tsai et al., 2006). Their feature vector consists of three types of image features: 9 wavelet features, 12 colour features and 12 image quality metrics (IQMs). The wavelet features consist of the mean of high-frequency subband coefficients in each orientation and at one scale. The colour features consist of the average value of each colour band, the correlation pair between two different colour bands, the neighbour distribution centre of mass for each colour band, and three energy ratios. The IQMs features are directly borrowed from (Avcibas, 2001) and consist of three pixel difference-based features, i.e., Minkowski difference, the mean absolute error, and the mean square error; three correlation-based features, i.e., the structural content, the normalized cross correlation, and Czekonowski correlation; six spectral features, i.e., the spectral magnitude error, the spectral phase error, the spectral phase-magnitude error, the block spectral magnitude error, the block spectral phase error, and the block spectral phase-magnitude error. The reader is referred to (Kharrazi et al., 2004), (Tsai et al., 2006) and (Avcibas, 2001) for more detailed information about the IQMs.

In this work, we propose a variant algorithm of (Kharrazi et al., 2004) and (Tsai et al., 2006) as our sample camera classifier. We adopt all the 33 features in (Tsai et al., 2006). Besides, we add the standard deviation (STD), skewness and kurtosis of high-frequency subband coefficients in each orientation and at one scale in order to more comprehensively reflect the characteristics of wavelet coefficients. As a result, we have $3\times3\times4=36$ wavelet features, which form our Feature Set I. The colour features and IQMs listed in (Tsai et al., 2006) form our Feature Sets II and III, respectively. By combining Feature Sets I, II and III, we generate a new feature vector of 60 dimensions, which is used as the input of our camera classifier. Like (Kharrazi et al., 2004) and (Tsai et al., 2006), we adopt the LIBSVM toolbox (Chang and Lin, 2001) with a nonlinear RBF (Radial Basis Function) kernel to build our camera classifier.

### 2.2. Performance of Our Sample Classifier on Unprocessed Images

Ten cameras employed in our test are five Canon cameras: A40, A620-1, A620-2, A720, 450D; two Nikon cameras: L3-1, L3-2; two Sony cameras: DSC-T10, DSC-W90; one Olympus camera: U820. For simplicity, we represent the above ten cameras as X1, X2, X3, X4, X5, X6, X7, X8, X9, and X10 in sequence. To evaluate the capability of these image features in identifying individual cameras, we purposely use two Canon A620 cameras and two Nikon L3 cameras. Exactly, the photos taken by X3 and X7 are not what we captured ourselves but downloaded from the well-known free photo website: http://www.flickr.com/. Each camera takes 300 photos of natural scenes including buildings, trees, blue sky and clouds, streets and people. All the photos are saved in JPEG format at the highest resolution each camera can support. To facilitate fair comparison, we take a $1024\times1024$ test image block from each photo. Based on the previous analysis (Li, 2010), each test image is cut from the centre of a photo to avoid saturated image regions. This selection strategy makes the test image better reflect the original image content. For each camera, we randomly choose 150 images to form the training set while the rest 150 images form the test set. Experimental results are shown in the form of confusion matrix, where the first column and the first row are the test camera index and the predicted camera index, respectively. To prevent obscuring significant statistics, a classification rate below 3% is simply denoted as $\ast$ in the tables.

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 |
|---|---|---|---|---|---|---|---|---|---|---|
| X1 | 96 | * | * | * | * | * | * | * | * | * |
| X2 | 3 | 96 | * | * | * | * | * | * | * | * |
| X3 | * | * | 87 | 7 | * | * | * | * | * | * |
| X4 | * | * | * | 96 | * | 3 | * | * | * | * |
| X5 | * | * | * | * | 96 | * | 3 | * | * | * |
| X6 | * | * | * | * | * | 95 | * | * | * | * |
| X7 | 5 | 3 | * | * | 15 | 7 | 63 | * | * | * |
| X8 | * | * | * | * | * | * | * | 99 | * | * |
| X9 | * | * | * | * | * | * | * | * | 95 | * |
| X10 | * | * | * | * | * | * | 3 | * | * | 91 |

**Table 1: Confusion matrix for our sample classifier using all the three feature sets. Accuracy = 91% (1370/1500)**

From Table 1, our classifier achieves the average classification accuracy of 91%. It demonstrates that our sample camera classifier is very effective in classifying unprocessed images. As for X3 and X7, the correct rates are 87% and 63%, respectively. We owe the decline in accuracy to different image content. As mentioned before, the photos from X3 and X7 are downloaded from a free photo website. So we are unable to know whether the photos have been altered or not. The only thing we can observe is that the image content from X3 consists of artificial products with various textile patterns and those images looks bright, while the image content from X7 mainly consists of indoors scenes and those images looks dark. In contrast, the content of our photos mainly consists of natural scenes with middle intensity. Our detection results coincide with the observation that identification rate is affected by image content (Tsai et al., 2007), (Li, 2010).

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 |
|---|---|---|---|---|---|---|---|---|---|---|
| X1 | 95 | * | * | * | * | * | * | * | * | * |
| X2 | * | 97 | * | * | * | * | * | * | * | * |
| X3 | * | * | 83 | 7 | * | * | 7 | * | * | * |
| X4 | * | * | * | 91 | * | 6 | * | * | * | * |
| X5 | * | * | * | * | 94 | * | * | * | * | * |
| X6 | * | * | * | * | * | 95 | * | * | * | * |
| X7 | * | * | * | * | 5 | 3 | 87 | * | * | * |
| X8 | * | 3 | * | * | * | * | * | 97 | * | * |
| X9 | 5 | * | * | * | * | * | * | * | 91 | * |
| X10 | * | * | * | * | * | * | 6 | * | * | 93 |

**Table 2: Confusion matrix for our sample classifier using Feature Set I. Accuracy = 92% (1382/1500)**

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 |
|---|---|---|---|---|---|---|---|---|---|---|
| X1 | 64 | * | * | * | 6 | 8 | * | * | 9 | 7 |
| X2 | 20 | 40 | * | * | 13 | 9 | * | 3 | 8 | 5 |
| X3 | * | * | 81 | 3 | * | 7 | * | * | * | 3 |
| X4 | 7 | 17 | * | 45 | 4 | 9 | * | 5 | * | 9 |
| X5 | 4 | 7 | * | 5 | 38 | 17 | * | 3 | 12 | 9 |
| X6 | 15 | 6 | * | 12 | 11 | 43 | * | 3 | 6 | * |
| X7 | 6 | 9 | 13 | 7 | 7 | * | 43 | * | 9 | 4 |
| X8 | 3 | 11 | * | 7 | 24 | 15 | * | 29 | * | 5 |
| X9 | 9 | 10 | 7 | 9 | 13 | 13 | * | 3 | 35 | * |
| X10 | * | 5 | * | 9 | 4 | 12 | * | 10 | 5 | 51 |

**Table 3: Confusion matrix for our sample classifier using Feature Set II. Accuracy = 47% (702/1500)**

We further investigate the performance of each individual feature set. Table 2 indicates that the average accuracy is 92% when only Feature Set I is used. So wavelet features have better identification power than the combined effect of all the three feature sets. In other words, even without Feature Sets II and III, this camera classifier can still achieve satisfactory accuracy for these ten cameras. On the other hand, Table 3 shows that the colour features lead to the average accuracy of 47% while Table 4 shows that the IQMs have the average accuracy of 66%. Apparently, both Feature Sets II and III are not as effective as Feature Set I. In terms of computational complexity, these two feature sets are redundant in this case.

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 |
|---|---|---|---|---|---|---|---|---|---|---|
| X1 | 77 | 7 | * | 11 | * | * | * | * | * | * |
| X2 | 20 | 61 | * | 9 | * | * | * | * | * | * |
| X3 | * | * | 81 | 11 | * | * | * | * | * | * |
| X4 | 11 | 13 | 6 | 58 | * | 5 | * | * | * | * |
| X5 | 5 | * | * | * | 88 | * | 5 | * | * | * |
| X6 | 4 | 5 | * | * | 4 | 70 | * | 4 | 10 | * |
| X7 | * | 7 | * | 7 | 12 | * | 52 | 5 | 4 | 7 |
| X8 | * | 4 | 4 | 5 | 5 | * | 17 | 56 | 3 | * |
| X9 | * | 4 | * | * | 6 | 11 | 17 | 13 | 45 | * |
| X10 | * | * | * | 4 | 3 | * | 11 | 9 | * | 69 |

**Table 4: Confusion matrix for our sample classifier using Feature Set III. Accuracy = 66% (987/1500)**

## 3. Robustness of Our Sample Classifier

Incidental image processing is usually not a malicious attack but a feasible way for saving storage space or emphasizing image regions of interest. Camera identifiers should have the capability in tackling images that have undergone invisible image manipulations. We evaluate the robustness of our classifier under three common image manipulations: JPEG compression, image contrast stretching and image sharpening. Each test image has undergone only one manipulation under each test. We do not consider the combined effect of different manipulations to avoid making our analysis biased. As will be seen, colour features, which have mediocre performance for unprocessed/untouched images, outperform both wavelet features and IQMs for processed images.

### 3.1. Experimental Results under Compression

We take JPEG compression using MATLAB with quality factor 70. The image quality under that level is often acceptable for saving storage space. Table 5 indicates that the average accuracy is 36%. Compared with Table 1, the performance of the classifier greatly decreases. We further investigate the performance of each individual feature set. From Feature Sets I to III, the corresponding correct identification rates are 21%, 46% and 31%, respectively. Apparently, the performance of every feature set degrades. Feature Set I has the sharpest decline in performance. However, the behaviour of Feature Set II is a little surprising. It leads to the average accuracy of 46%. Compared with the accuracy before compression (47%), there is only a slight decline. This result implies that compression has a small impact on Feature Set II. This is because the colour features do not have much relation to the image details which the JPEG compression often discards. So we can say that colour features are more robust than the wavelet features and the IQMs for compressed images.

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 |
|---|---|---|---|---|---|---|---|---|---|---|
| X1 | 89 | * | * | * | * | * | 7 | * | * | * |
| X2 | 68 | 11 | * | * | * | * | 17 | * | * | * |
| X3 | 41 | 5 | 25 | * | * | 4 | 19 | * | * | * |
| X4 | 30 | * | * | * | 4 | * | 47 | * | * | 14 |
| X5 | * | * | * | * | 81 | * | 17 | * | * | * |
| X6 | 48 | * | * | * | 3 | 13 | 29 | * | * | 6 |
| X7 | 15 | * | * | * | 10 | * | 72 | * | * | * |
| X8 | 22 | * | * | * | 39 | * | 36 | * | * | * |
| X9 | 29 | * | * | * | 26 | 7 | 34 | * | * | * |
| X10 | 26 | * | * | * | 3 | * | 7 | * | * | 63 |

**Table 5. Confusion matrix for our sample classifier using all the three feature sets under compression. Accuracy = 36% (534/1500)**

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 |
|---|---|---|---|---|---|---|---|---|---|---|
| X1 | 94 | * | 3 | * | * | * | * | * | * | * |
| X2 | 10 | 86 | 3 | * | * | * | * | * | * | * |
| X3 | * | * | 88 | 7 | * | * | * | * | * | * |
| X4 | * | * | * | 97 | * | * | * | * | * | * |
| X5 | * | * | * | * | 89 | * | 5 | * | * | * |
| X6 | * | * | 4 | 7 | * | 89 | * | * | * | * |
| X7 | 5 | 3 | 7 | * | 17 | 4 | 54 | * | * | 5 |
| X8 | * | * | * | * | * | * | * | 97 | * | * |
| X9 | * | * | * | * | * | * | * | * | 89 | * |
| X10 | * | * | * | 5 | * | * | 4 | * | * | 87 |

**Table 6. Confusion matrix for our sample classifier using all the three feature sets under contrast stretching. Accuracy = 87% (1305/1500)**

### 3.2. Experimental Results under Contrast Stretching

Contrast stretching is a common image processing operation when people want to emphasise image content within an interval of image grey levels. To simulate the process of suppressing some grey-level pixels while emphasising others, we stretch pixel values on each test image with the following contrast stretching function

$$f(x) = \begin{cases} 0, & 0 \le x \le 20 \\ \dfrac{255}{210}(x-20), & 20 < x < 230 \\ 255, & 230 \le x \le 255 \end{cases} \qquad (1)$$

According to Table 6, the average accuracy of the sample classifier is 87%. So the average accuracy of our sample classifier only decreases by 4 percentage points compared with Table 1. From Feature Sets I to III, the corresponding correct identification rates are 90%, 42% and 46%, respectively. Feature Set I only has a slight decline in performance compared with Table 2, but Feature III loses almost 20 percentage points in accuracy. Therefore, the wavelet features are quite robust against contrast stretching while the IQMs do not behave well in this circumstance. In essence, contrast stretching directly changes the shape of the histogram of pixel values and it has little influence on the high frequency wavelet coefficients, so the good performance of Feature Set I is understandable.

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 |
|---|---|---|---|---|---|---|---|---|---|---|
| X1 | * | * | 97 | * | * | * | * | * | * | * |
| X2 | 5 | * | 95 | * | * | * | * | * | * | * |
| X3 | * | * | 100 | * | * | * | * | * | * | * |
| X4 | * | * | 99 | * | * | * | * | * | * | * |
| X5 | * | * | 84 | 16 | * | * | * | * | * | * |
| X6 | * | * | 100 | * | * | * | * | * | * | * |
| X7 | 3 | * | 65 | 20 | * | 6 | 4 | * | * | * |
| X8 | 75 | * | 15 | * | * | * | * | 9 | * | * |
| X9 | * | * | 91 | * | * | * | * | * | 7 | * |
| X10 | * | * | 99 | * | * | * | * | * | * | * |

**Table 7: Confusion matrix for our sample classifier using all the three feature sets under sharpening. Accuracy = 12% (186/1500)**

### 3.3. Experimental Results under Image Sharpening

Image sharpening is often used for enhancing object edges. In our simulation, a weighted median filtering-based sharpening algorithm is used with the recommended parameter (Bovik, 2006). Table 7 shows the average accuracy is 12%. Apparently, image sharpening has the greatest impact on our sample classifier. From Feature Sets I to III, the corresponding correct identification rates are 11%, 43% and 12%, respectively. It means that using the wavelet features or the IQMs can hardly identify cameras correctly. By contrast, the use of the colour features only loses 4 percentage points in accuracy compared with Table 3. Therefore, the colour features are robust against image sharpening. In fact, image sharpening often equally alters pixels on red, blue and green bands, so the selected colour features are not very sensitive.

## 4. Dimensionality Reduction and its Impact on Robustness

Feature selection is one of the important problems in pattern recognition. There are many reasons for reducing the number of features, for instance, computational complexity. The problem in Feature Selection (FS) can be stated as the search for a sufficiently reduced subset of, say, *d* features out of the total number of available ones, *D*, without significantly degrading (or even improving in some cases) the performance of the resulting classifier when using either set of features (Ferri et al., 1994). Some FS algorithms have been introduced to optimize camera classifiers. Tsai and Wang once used the SFFS (Sequential Floating Forward Selection) algorithm (Pudil et al., 1994) as an adaptive feature selection tool to find a suboptimal subset of features which was supposed to improve the classification precision of their SVM-based camera classifier (Tsai et al., 2008). The top 20 important features were selected from 34 features employed in (Kharrazi et al., 2004). In this work, we use the SFFS algorithm to select a subset from our 60 features, but our focus is to investigate the effect of this reduced subset on the robustness of the camera classifier. As will be seen, the SFFS algorithm is able to find a suboptimal subset which enables our sample classifier to achieve almost the same average identification accuracy as the original 60 features. However, the selected feature subset has no way to guarantee the robustness. In fact, feature selection algorithms such as SFFS aim at efficient pattern classification and the criterion functions in SFFS are defined on the basis of classification accuracy.

### 4.1. SFFS and the Criterion Function

The Sequential Forward Selection (SFS) and its backward counterpart (SBS) are suboptimal methods. Both of them suffer from the so-called "nesting effect". Attempts to prevent the nesting of feature subsets led to the development of the plus *l* - take away *r* method. The plus *l* - take away *r* method or called (*l*, *r*) method, consists of applying SFS during *l* steps followed by *r* steps of SBS with the cycle of forward and backward selection until the required number of features is reached. However, it is not easy to find the best parameters *l* and *r*. The improved version of (*l*, *r*) method is the SFFS algorithm, which consists of applying after each forward step a number of backward steps as long as the corresponding subsets are better than the previously evaluated ones at that level (Ferri et al., 1994).

The criterion function determines which feature should be included in and which should be excluded from the subset in the SFFS. Two popular class separability criteria are divergence and scatter matrices. Computation of divergence is not easy for non-Gaussian distribution. Hence, this work uses the criterion function defined on the basis of scatter matrices. Suppose $S_w$, $S_b$ and $S_m$ are Within-class scatter matrix, Between-class scatter matrix and Total mixture matrix, respectively. Our criterion function is defined as $J=|S_m|/|S_w|$, where $|.|$ represents determinant. The reader is referred to (Theodoridis, 2006) for more information about its calculation.

### 4.2. Performance of the Reduced Feature Subset

After performing the SFFS, 26 features are selected from the original 60 ones to form our new feature vector. They are 15 wavelet features (i.e., 7 coefficient averages, 5 STD, 2 skewness values and 1 kurtosis value), 6 colour features (i.e., 2 average values, 2 correlation pairs and 2 energy ratios) and 5 IQMs (i.e., 3 pixel difference-based features and 2 spectral features).

We use these 26 features to repeat our experiments in Subsection 2.2 and Section 3. For unprocessed images, the camera classifier has the average classification accuracy of 90%. Compared with Table 1, the reduced subset achieves very close identification accuracy as the original 60 features. Next we evaluate its performance under three image manipulations. For compressed images, the reduced subset leads to the average accuracy of 29%. Compared with Table 5, it loses 7 percentage points in accuracy. For contrast stretched images, the average accuracy is 86%. Compared with Table 6, it loses only 1 percentage point in accuracy. As for image sharpening, these 26 features have the same identification power (i.e., 12%) as the original 60 features. From the above experiments, we can observe that the performance of these

26 features is very close to that of the original 60 features when test images are not subject to image processing; for processed images; however, the reduced subset may cause the classifier to lose robustness to some extent.

## 5. Conclusions

Image feature selection is an important issue for feature-based camera classifiers. Although different statistical image features have been proposed for camera identification, their robustness has not been thoroughly discussed; moreover, the robustness of the reduced subset of features has seldom been discussed. In this work, we have used a variant of a classical camera classifier as an example to investigate these two aspects. Our experiments have revealed that different statistical image features have different robustness against image manipulations and the reduced subset of features usually does not have the same robustness as the original feature vector. Our work also indicates that the selection of an accurate, efficient and robust reduced subset of image features is a difficult issue since we can not predict which features will be selected by common SF algorithms. This topic is significant for the design of practical camera classifiers and needs further study.

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