

## 잡음종속 Watershed 변환을 이용한 이미지 위조 검출

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## Image Forgery Detection Using a Noise Dependent Watershed Transformation

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### Abstract

Noise is unwanted in high quality images, but it can aid image tampering. For example, noise can be intentionally added in image to conceal tampered regions or to create special visual effects. It may also be introduced unknowingly during camera imaging process, which makes the noise levels inconsistent in splicing images. In this paper, we present an image forgery detection method using a noise dependent watershed transformation. Image is segmented into objects for initial noise estimation by the watershed transformation, and different noise level in objects are estimated to obtain final decision result. Experimental results of the proposed method on natural images are presented.

### 1. Introduction

In the last decade digital cameras have become so popular that enormous numbers of photographs and videos are taken by amateur photographers. On the other hand, the recent development of digital editing techniques can be used to synthesize realistic images and videos that could also be used in courts of law. Unfortunately, photographs taken by amateur photographers are not protected from tampering. The issue of verifying the authenticity and integrity of digital contents is increasingly becoming important. This motivates the need of techniques which can be used to validate the authenticity of digital content.

Recently a number of forgery detecting techniques for images without watermarking have been studied [1]. These techniques exploit inconsistencies or unnaturally high coherence observed in an image. Jonson et al. used inconsistencies in lighting [2] and chromatic aberration [3]. Lin et al. [4] estimated camera response function and verified its uniformity across an image. Luk'a's et al. [5] extracted fixed pattern noise from an image and compared it with a reference pattern. Fridrich et al. [6] computed correlation between segments in an image and detected cloned regions. Ye

et al. [7] used an estimated JPEG quantization table and evaluated its consistency. The different digital image forensic methods mentioned above help us to aggressively estimate the authenticity of digital images.

Image noise is the variation of brightness for pixels intrinsic in the image acquisition and processing. Due to the inherent characteristics of each individual camera sensor, the variance of noise in an untampered image is in general uniform across the entire image. When image regions from different images with different intrinsic noise levels are combined together to create a forgery, or noises are intentionally added in forged regions to conceal tampering or to add special visual effects, the inconsistency of noise level in different regions of the image can be used to expose the tampered regions. Image splicing and composition are types of tampering that commonly used for manipulating digital image. A part of an image is copied and pasted into another region of different image with using a pre-processing operations. In this case, the forgery detection methods search for tampered image regions using inconsistencies in statistical measure.

In this paper, we present an image forgery detection

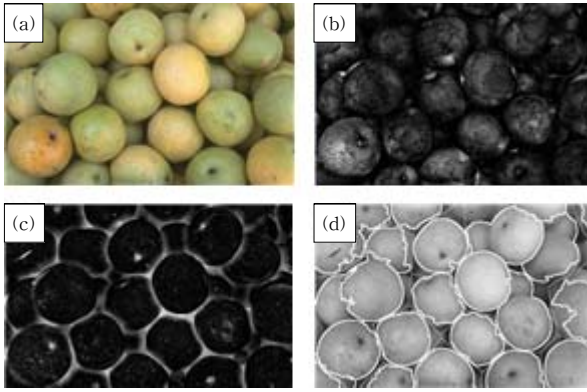


Figure 1. (a) Test image, (b) Foreground marker, (c) Background marker, (d) Segmentation.

method using a noise characteristics based on the watershed transformation. Our solution is based on the idea that copied and pasted region into image from different image must have the different noise pattern. The proposed method depends on marker-controlled watershed transformation and noise estimation for each image segment. The noise patterns of the image segments are then compared for identifying forgery. Image segments with different noise patterns are detected as tampered region. The proposed method outperforms state of the art methods.

The rest of the paper is organized as follows: Section 2 introduces a preliminaries and processing used in our proposed method. Experimental results and performance comparison are shown in Section 3. Finally, we conclude this paper in Section 4.

## 2. Preliminaries and Processing

### 2.1 Watershed Transformation

The watershed concept is tools in the field of topography. It was proposed as a potential method for image segmentation [8]. It is the line that determines where a drop of water will fall into particular region. In mathematical morphology, gray-scale images are considered as topographic relieves. In the topographic

representation of a given image  $I$ , the intensity value of each pixel stands for the elevation at the point. The complete division of the image through watershed transformation relies mostly on a good estimation of image gradients. The result of the watershed transform is degraded by the background noise which produces the over segmentation. Also, under segmentation is produced by low contrast edges generate a small magnitude gradients, causing distinct regions to be erroneously merged.

**Marker-Controlled Watershed Segmentation.** Let us consider the image segmentation, the input image  $I$  of size  $m \times n$  is segmented by using the watershed method into  $k$  segments  $S_1, S_2, \dots, S_k$ . Each object is fully contained in a single segment, and the segments are homogeneous.

Segmentation using the watershed transform works well if we can identify, or “mark”, foreground objects and background locations, as shown in Figure 1. The basic procedures of the marker-controlled watershed segmentation is determined as follows:

1. Compute a segmentation function. This is an image whose dark regions are the objects.
2. Compute foreground markers. These are connected blobs of pixels with in each of the objects.
3. Compute background markers. These are pixels that are not part of any object.
4. Modify the segmentation function so that it only has minima at the foreground and background marker locations.
5. Compute the watershed transform of the modified segmentation function.

### 2.2 Noise Estimation

The CCD (Charge-Coupled Device) digital camera converts the irradiance, the photons coming into the imaging sensor, to electrons and finally to bits. Figure 2 presents the imaging pipeline of CCD camera. There are mainly five noise sources as stated in that namely

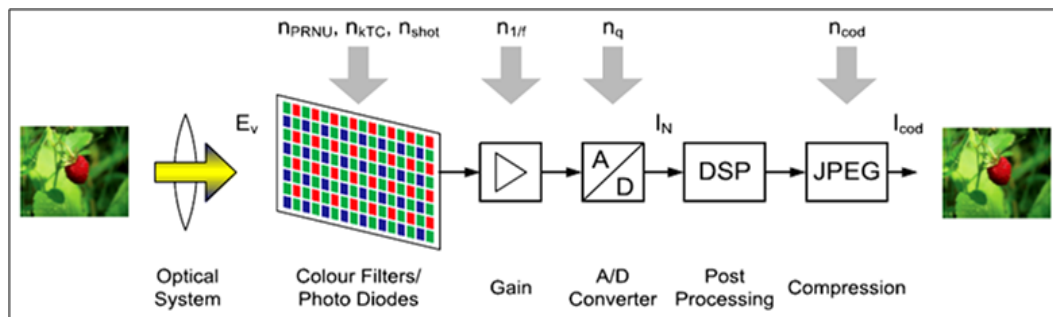


Figure 2. CCD camera imaging process.

fixed pattern noise  $n_{PRNU}$ , photon shot noise  $n_{shot}$ , reset noise  $n_{kTC}$ , amplifier noise  $n_{1/f}$  and quantization noise  $n_q$ , respectively. As following the imaging equation, we define the noise model of a CCD camera:

$$x = F(G(Q(n_{PRNU} + n_{shot}) + n_{kTC} + n_{1/f})) + n_q \quad (1)$$

where  $F(\cdot)$  denotes the camera response function (CRF),  $G$  is electric gain and  $Q$  is the quantum efficiency of the CCD camera. In this work, we focus on photon shot noise for the following two reasons:

- 1) Photon shot noise is the dominant noise source for most images in a scene (excluding those taken in extremely dark environments).
- 2) The relationship between scene brightness and noise intensity is useful for forgery detection, since this relationship should be consistent in an image.

$$x = F(G(Q \cdot n_{PRNU}) + G(Q \cdot n_{shot})) \quad (2)$$

$n_{kTC} = 0, n_{1/f} = 0, \text{ and } n_q = 0$

The number of photons that fall onto a CCD element fluctuates temporally, behaving as noise. Due to the quantum nature of photons, this fluctuation follows the Poisson distribution, the variance of which is closely related to its mean. Therefore, the noise intensity (the temporal variance of pixel values) depends on the mean of the pixel values. In this paper, we assume that the distribution that photon shot noise obeys is Gaussian because the number of photons is large enough to approximate the Poisson distribution by the Gaussian distribution. Note, however, that while the mean and the variance of Gaussian distribution are independent from each other, those of photon shot noise we consider here have relationships because of the characteristic of the Poisson distribution. While it is impossible to measure the distribution of photons directly, we can compute the relationship between the mean and the variance of the observed pixel values instead. Our method uses this relationship as a measure of forgery in images.

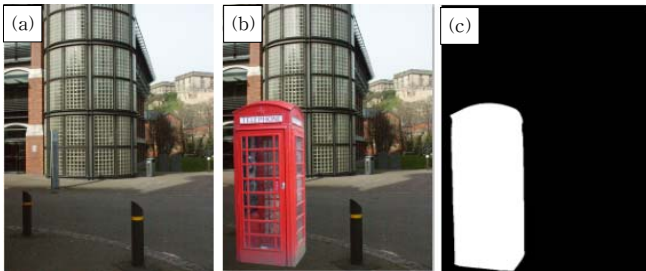


Figure 3. Forgery detection. (a) Original image, (b) Composed image, (c) Localization (by noise variance).

Let  $\mu_{x'}$  and  $\sigma_{x'}^2$  be the mean and variance of observed pixel intensity, respectively, when the noiseless observation is  $x'$ . Consider the variance  $\sigma_{x'}^2$  as a function with respect to the mean  $\mu_{x'}$  and define a NLF(Noise Level Function) as,

$$\tau(\mu_{x'}) = E[(x - \mu_{x'})^2] \quad (3)$$

NLF is the variation of the standard deviation of noise with respect to image intensity. This function represents how the variance changes with respect to the mean of observed pixel value. When we obtain the mean observation  $\mu_{x'}$ , the variance is described by a function with respect to the mean as

$$\sigma_x^2 = \tau(\mu_{x'}) \quad (4)$$

Finally, we can define the standard deviation for the number of interactions per pixel, which called the photon shot noise  $n_{shot}$ . Then such noise variance is used as an evidence for identifying image composition, as shown in Figure 3.

### 3. Experimental Results

We test the performance of our forgery detection method through simulation experiments on a several tampered images. Our test set is formed starting from 72 high-resolution photos of the Dresden Image Database [9]. Each image is then subject to splicing forgery by means of the Photoshop scripts of the University of Catania [10].

In order to provide homogeneous results, the image is segmented into non-overlapping objects, with decisions taken independently for each of them considered as a whole. We compute on the entire database the quantities for blocks of each object:

- *TP* (true positive): forged blocks are declared forgeries
- *FP* (false positive): genuine blocks are declared forgeries
- *TN* (true negative): genuine blocks are declared genuine
- *FN* (false negative): forged blocks are declared genuine

Results are then given in terms of sensitivity, specificity, and accuracy, respectively, are computed as

$$\begin{aligned} \text{Sensitivity} &= \frac{TP}{TP + FN}; & \text{Specificity} &= \frac{TN}{TN + FP}; \\ \text{Accuracy} &= \frac{TN + TP}{TN + FP + TP + FN}. \end{aligned} \quad (5)$$

Each measure implies, respectively, the ability to detect the presence of forgery, the ability to confirm

the absence of forgery, and the overall classification accuracy, independent of the nature of the blocks. Figures 4 and 5 report results for block-sizes  $2 \times 2$  and  $5 \times 5$ , respectively. The first observation is that camera-based techniques, Chen et al. [11] and Zheng et al. [12], perform generally better under all points of view, but accuracy of our scheme higher than the others in block sizes  $2 \times 2$  and  $5 \times 5$ , respectively.

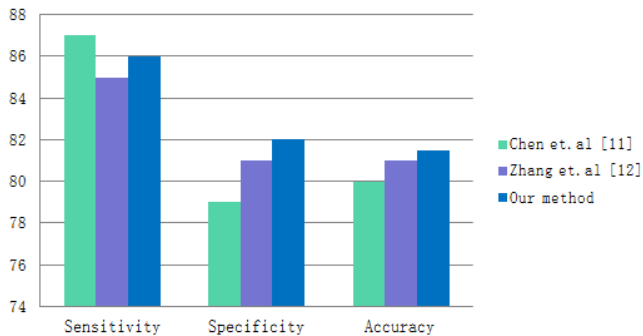


Figure 4. Results for blocks of size  $2 \times 2$ .

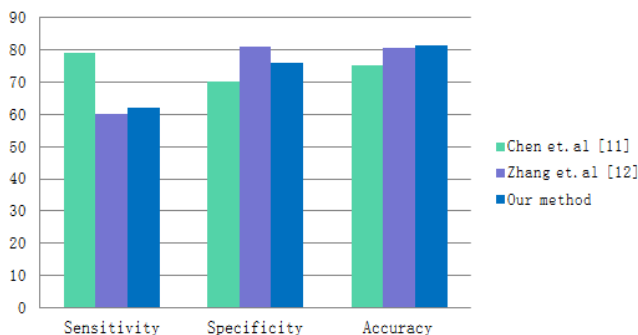


Figure 5. Results for blocks of size  $5 \times 5$ .

#### 4. Conclusion

In this paper, we described an image forgery detection method using the watershed segmentation. The variance of image noise at each local image object is estimated blindly using a properties of natural images. Our method finds both the extent and location of the tampered region by segmentation according to their estimated noise levels. The advantage of the proposed method is that it requires no prior knowledge of the imaging device or the original image. Experimental results show that the proposed method can expose tampered regions concealed by image noise and forgeries created using image composition for special visual effects. The forgeries are generated by image splicing can also be effectively identified using our method based on the inconsistency of noise level in the spliced image regions.

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