IMAGE NOISE LEVEL ESTIMATION BASED ON A NEW ADAPTIVE SUPERPIXEL CLASSIFICATION

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ABSTRACT

Accurate estimation of noise level in images plays an important role in different image processing applications. The current algorithms can precisely estimate noise with smooth images, but it is still the challenge to approximate noise level from richly textured images. In this paper, we proposed a new adaptive superpixel classification algorithm for noise estimation in complicated textured images. Firstly, our new superpixel algorithm adapts the finite Gaussian clustering approach, which can better approximate homogeneous patches in noisy images. Then noise information is obtained locally from each superpixel patch. Finally, the best estimation of noise level is calculated with a statistical approach. Experimental results with various kinds of images demonstrate that our method is more accurate and robust compared to the five existing common used algorithms.

Index Terms— Noise level estimation, superpixel, distance measure, additive white Gaussian noise

1. INTRODUCTION

Random noise is usually introduced into the image during the acquisition and transmission processes, which significantly degrades the image quality. Accurate approximation of noise level is critical to benefit a variety of digital image processing applications, such as denoising [1], image segmentation [2], classification [3], restoration [4] and feature extraction [5].

Noise types vary in different images. To be simplified, the noise in images is often assumed to be an additive white Gaussian noise (AWGN) with zero mean and unknown standard deviation (SD) [6]. Usually, the noise SD is regarded as a good representation of the noise level. Various methods [7–16] have been proposed to estimate noise SD, and they are generally classified into two categories, including homogeneous patch-based methods [7–9] and filter-based methods [10–12].

In most of homogeneous patch-based methods, an image is divided into small patches first, then different techniques are utilized for detecting homogeneous patches, i.e., the patches without edges or textures. Since changes of intensity value in homogeneous patches are mainly caused by the noise, the noise SD of an image can be approximated from these homogeneous patches. In filter-based methods, a low-pass / high-pass filter is applied to remove the noise / structures of the given image, then the noise map is formulated for noise estimation. However, the existence of edges and textures may lead to an over-estimation of the noise. Thus, a pre-processing for homogeneous region detection is essential in a majority of filtered-based methods, which can be regarded as hybrid approaches [13–16].

Although these methods can effectively estimate noise from simply textured images, they have difficulty in dealing with the images with complicated textures and details. The challenging task is to accurately detect homogeneous regions in images with abundant structures. Conventionally, the image is partitioned into regular blocks. However, regular blocks with fixed size may contain large amount of edges and textures, which greatly decreases the accuracy of noise estimation. If the segmented local patches can adhere to image boundaries, they are more likely to be homogeneous regions which are nature representation of image scene and thus better for noise level estimation.

Superpixel techniques [17, 18] can group pixels into perceptually meaningful regions to provide primitive for the computation of image noise. However, most of the current superpixel algorithms were designed without considering the noise in images. In this paper, we propose a noise level estimation method by using a new adaptive superpixel classification. Based on the finite Gaussian model, a new distance measure is suggested to overcome the defects of the existing superpixel algorithms when partitioning high-level noisy images into optimal homogeneous patches adherence to image boundaries. The image noise level is estimated with the segmented superpixels based on a statistical approach. Compared with the existing homogeneous-patch based and hybrid algorithms for noise estimation, the proposed method is more accurate and stable, which is demonstrated by experiments with different kinds of images.

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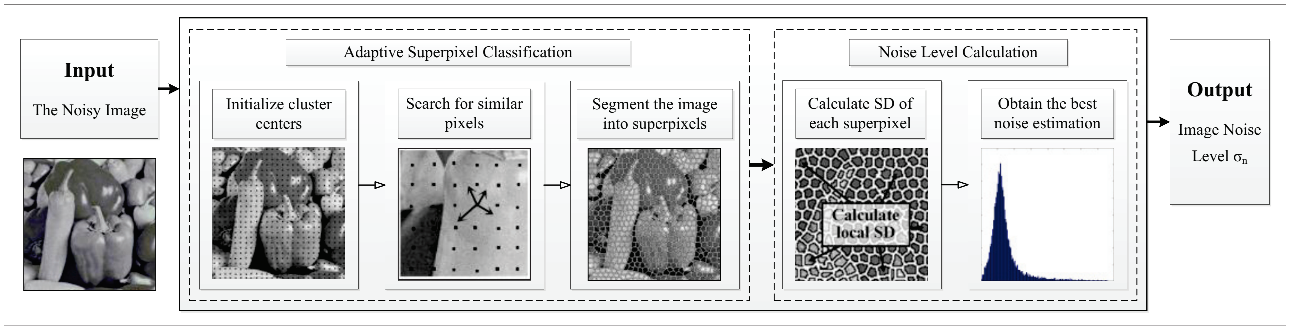

Fig. 1. Producer for the proposed algorithm

2. METHOLODGY

The framework of our algorithm (illustrated in Fig. 1) consists of two major steps, including adaptive superpixel classification and noise level calculation. Through adaptive superpixel algorithm, the input of noisy image can be segmented into homogeneous patches with nature size. The generated homogeneous superpixels are utilized for estimating the noise level of the entire image through the step of noise level calculation.

2.1. Adaptive Superpixel Classification

In order to accurately estimate noise from homogeneous areas, we use the notion of superpixels, which smoothly adheres to the local image structures. To improve the robustness of the superpixel classification on noisy images, a finite Gaussian is used in the new distance measure to determine the mean value and standard deviation value of their intensity similarity and proximity in the image.

A. Superpixel Initialization

As shown in Fig. 1, the first step of our superpixel classification algorithm is the initialization of cluster centers, where the initial size S for each patch is required. Firstly, the total patch number K can be approximated as $K = [H/S^2]$, where H is the total pixel number in the image and $[\cdot]$ means round to the nearest integer. The K initial centers are sampled uniformly in the image. To avoid centering on edges, the centers are moved to the lowest gradient position in a 3×3 neighborhood. As shown in Fig. 2, the initial center is moved from pixel a to j after reselection. At the beginning, pixels in the block with the size $S\times S$ around the center j are utilized. In order to distinguish the Gaussian distributed random noise from image structures, the center j is initialized with the mean value μ_j and the standard deviations value σ_j:

$$\begin{aligned} \mu_j &= [x_j \;\; y_j \;\; z_j] \\ \sigma_j &= [\sigma_{x_j} \;\; \sigma_{y_j} \;\; \sigma_{z_j}] \\ &= \frac{1}{N}\sum_{i\in\phi_j}[(x_i - x_j)^2 \;\; (y_i - y_j)^2 \;\; (z_i - z_j)^2] \end{aligned} \tag{1}$$

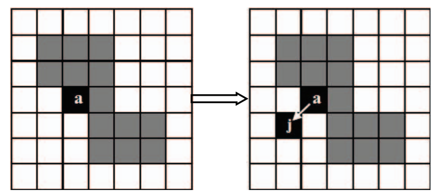

Fig. 2. Initial center reselection

where $[x_j \;\; y_j]$ and z_j represent coordinates and intensity value of center j. ϕ_j denotes the pixels belonging to the cluster j and N is the corresponding pixel number.

B. Assignment and Distance Measure

Conventional distance measure for k-mean clustering algorithm is sensitive to noise, which may cause a failure detection of local edges and textures when the image is corrupted seriously by the random noise. A new distance measure is proposed to solve this problem, which is composed of the spatial distance and intensity distance with considering their mean values and standard deviation values, making our superpixel classification algorithm more robust with noisy images.

Each pixel is labeled to the nearest cluster center based on the new distance D as shown in Eq. (2):

$$\begin{aligned} d_s(i,j) &= \sqrt{\frac{(x_i - x_j)^2}{\sigma_{x_j}^2} + \frac{(y_i - y_j)^2}{\sigma_{y_j}^2}} \\ d_c(i,j) &= \sqrt{\frac{(z_i - z_j)^2}{\sigma_{z_j}^2}} \\ D(i,j) &= \sqrt{d_c^2 + (\frac{d_s}{S})^2\lambda^2} \end{aligned} \tag{2}$$

where $d_s(i,j)$ and $d_c(i,j)$ denote the spatial distance and intensity distance between pixel i and cluster center j, respectively. λ is defined to weight the relative importance between the intensity similarity and spatial proximity. Based on the new distance measure, pixels are assigned to the closest center with a limited search region of $2S\times 2S$ around the clustering center, which may significantly speed up the algorithm.

C. Optimization

After clustering, the centers are updated according to the following equation:

$$
\begin{aligned}
\mu'_j &= [x'_j \;\; y'_j \;\; z'_j] \\
&= \frac{1}{N'} \sum_{i \in \phi'_j} [x_i \;\; y_i \;\; z_i] \\
\sigma'_j &= [\sigma'_{x_j} \;\; \sigma'_{y_j} \;\; \sigma'_{z_j}] \\
&= \frac{1}{N'} \sum_{i \in \phi'_j} [(x_i - x'_j)^2 \;\; (y_i - y'_j)^2 \;\; (z_i - z'_j)^2]
\end{aligned}
\tag{3}
$$

where ϕ'_j represents the update cluster and N' is the number of pixels in ϕ'_j , μ'_j and σ'_j denote the mean value and the standard deviation value of these pixels.

Based on the expectation-maximization (EM) optimization algorithm, the procedures of clustering and updating are repeated until the residual error, calculated as the L_2 norm between the new cluster center locations and old cluster center locations, converges. Finally, a connected-components algorithm is required to enforce the connectivity of the generated patches, which are local, coherent, and homogeneous groups of pixels.

2.2. Noise Level Calculation

When the whole image is segmented into amount of superpixels, the local standard deviation (LSD) of each superpixel is calculated as:

$$
LSD = \sqrt{\frac{1}{\hat{N}-1} \sum_{i=1}^{\hat{N}} (z_i - \frac{1}{\hat{N}} \sum_{i=1}^{\hat{N}} z_i)^2} \tag{4}
$$

where z_i denotes the intensity value of pixel i and $\hat{N}$ is the number of pixels in the corresponding superpixel.

If all of the superpixels are completely uniform without edges and textures, noise SD of the image can be calculated by averaging LSDs of the total generated superpixels. However, it is not always applicable for real applications. We found that in simply textured regions, e.g. in the Block 1 illustrated in Fig. 3, the generated superpixels are homogeneous and respect to the boundaries. However, when the regions grow with more rich textures, for example, in the Block 2 as shown in Fig. 3, the segmented patches are not strictly homogenous. Thus, we exploit a histogram-based statistical method to calculate the image noise SD as shown in Fig. 4. Bins with equal width are set up to form a histogram between the minimum and maximum of the LSDs, where peak of the histogram, i.e., the bin containing most number of superpixels is obtained. The best estimate of the noise SD in the image is calculated according to:

$$
SD = \frac{1}{\Gamma} \sum_{\gamma=1}^{\Gamma} LSD_{\gamma} \tag{5}
$$

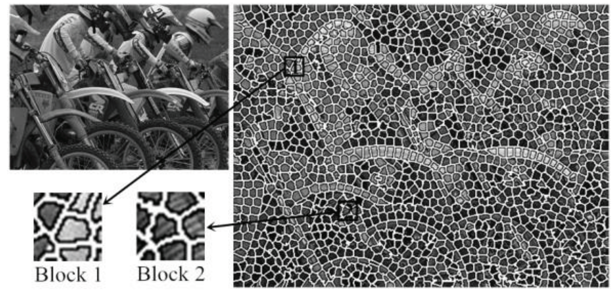

Fig. 3. Visualization of enlarged superpixels using the proposed algorithm in the motorcycle image.

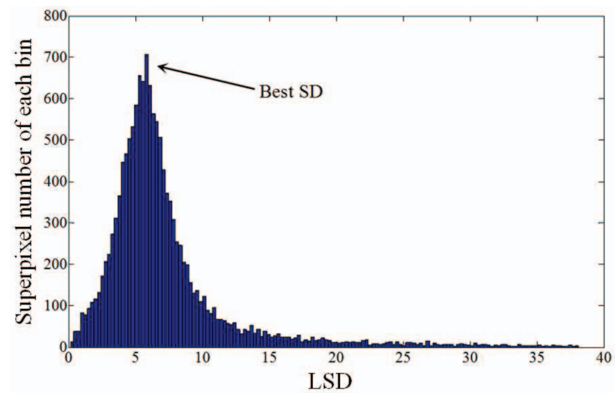

Fig. 4. Best estimate of noise SD for the proposed algorithm

where LSD_{γ} is the LSD value of the superpixel γ in the peak bin and Γ represents the number of superpixels in this bin.

3. EXPERIMENT RESULTS

In this section, we compare the proposed method with five commonly used homogeneous patch-based and hybrid algorithms, including Amer [14], Corner [13], Fu [16], Marais [8] and Yang [15]. Experimental images in this study are chosen from TID2008 database [19], Brodatz texture database [20] and the benchmark test images; 15 typical examples are shown in Fig. 5. To quantitatively evaluate the accuracy and robustness of our method, images with simple textures and complex textures are all included. Synthetic Gaussian distributed noise with zero mean and one of the variance values (σ_t^2): 10, 25, 50, 100 are added to the test images, while the noise level is estimated from the simulated noisy images using different algorithms. The test images are not completely noise-free as they still contain noise with a small level, which will be estimated firstly. Assuming that the noise distributions are independent, all the noise variance estimates σ_e^2 are corrected as:

$$
\sigma_c^2 = \sigma_e^2 - \sigma_o^2 \tag{6}
$$

where σ_o^2 is the noise variance in the original image and σ_c^2 is the corrected noise variance.

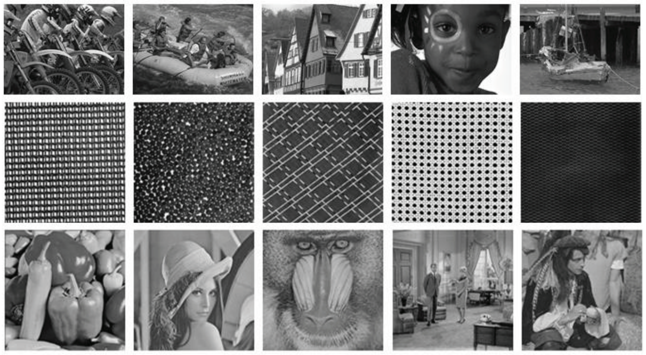

Fig. 5. Examples of experimental images. 1^{st} row from TID2008 database; 2^{nd} row from Brodatz texture database; 3^{rd} row from classical benchmark images.

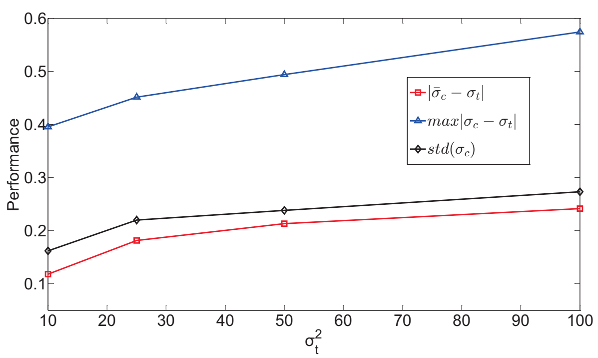

Fig. 6. Performance of our method with different noise levels

In our experiment, we set parameters $S = 5$ and $\lambda = 7$ based on the estimation performance. The comparison results are listed in Table 1. In this table, bias of the corrected estimates $|\bar{\sigma}_c - \sigma_t|$ is calculated to evaluate the accuracy of the algorithms, where $\bar{\sigma}_c$ is the mean value of all test images. The maximum difference between the corrected estimate and the true value $max|\sigma_c - \sigma_t|$ and the standard deviation of the corrected estimates $std(\sigma_c)$ are defined to test the robustness of the algorithms.

As indicated in Table1, our method exhibits better accuracy over the other cases. With regard to the robustness evaluation, the standard deviation of our method is the smallest compared to the other algorithms. Regarding the performance of estimating noise from exactly complex images, i.e., $max|\sigma_c - \sigma_t|$, our method has the lowest error among all the algorithms, except Yang [15] which get comparable results with our proposed method.

We also analyze the performance of our method when estimating noise from images with various noise levels. It is observed from Fig. 6 that the accuracy and robustness of our method are slightly reduced with the increasing of the noise levels. Our method can achieve accurate noise estimates and is insensitive to the noise with a reasonable intensity range.

Table 1. Accuracy comparison of six noise detection algorithms on the experimental images

Method	$|\bar{\sigma}_c - \sigma_t|$	$max|\sigma_c - \sigma_t|$	$std(\sigma_c)$
$\sigma_t^2 = 10$ ($\sigma_t \approx 3.162$)			
Proposed	**0.118**	**0.395**	**0.162**
Amer [14]	0.493	1.569	0.444
Corner [13]	0.233	1.336	0.413
Fu [16]	0.326	0.843	0.251
Marais [8]	0.416	2.426	0.584
Yang [15]	0.313	0.431	0.430
$\sigma_t^2 = 25$ ($\sigma_t = 5$)			
Proposed	**0.181**	**0.451**	**0.220**
Amer [14]	0.634	2.076	0.573
Corner [13]	0.210	1.202	0.339
Fu [16]	0.249	0.855	0.313
Marais [8]	0.335	1.811	0.442
Yang [15]	0.285	0.498	0.349
$\sigma_t^2 = 50$ ($\sigma_t \approx 7.071$)			
Proposed	**0.213**	0.509	**0.238**
Amer [14]	0.573	1.576	0.481
Corner [13]	0.239	0.738	0.269
Fu [16]	0.342	0.623	0.411
Marais [8]	0.376	1.612	0.526
Yang [15]	0.267	**0.494**	0.314
$\sigma_t^2 = 100$ ($\sigma_t = 10$)			
Proposed	**0.241**	0.604	**0.273**
Amer [14]	0.808	2.473	0.673
Corner [13]	0.429	0.853	0.338
Fu [16]	0.563	1.199	0.548
Marais [8]	0.569	2.157	0.713
Yang [15]	0.257	**0.574**	0.294

4. CONCLUSION

In this paper, we have presented a framework of image noise level estimation based on an adaptive superpixel classification. Superpixel techniques are introduced into the domain of the image noise estimation for the first time, where a novel distance measure is proposed to better segment homogenous patches adherent to the boundaries in the noisy images. The local standard deviation of each superpixel is calculated, and the best estimate of the noise level is obtained by a histogram-based statistical approach. Compared with the existing homogeneous patch-based and hybrid algorithms, our method is more accurate and stable for both simply textured and complicated images with various noise levels.

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