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Improved image noise level estimation based on segmentation and block processing

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Abstract: *Accurate estimation of noise parameters in digital images is of great significance to improve the quality of image processing. Principal component analysis is an important means of image denoising, and the traditional method is to estimate the whole image. Due to the complexity of image content, this paper proposes a preprocessing method based on superpixel segmentation to process the largest possible smooth block in the image. Compared with contrast method, the estimated value of the proposed method is closer to the true value.*

Keywords: *Image noise estimation, Superpixel segmentation, Principal component analysis (PCA)*

1. Introduction

In the process of imaging and transmission, due to the interference of external factors, some noise will be introduced into the acquired original image, resulting in the reduction of image quality. In order to obtain an image with higher quality, it is necessary to process the image containing noise by different denoising methods to reduce the influence of noise on the image. In the process of noise reduction, it is necessary to know the distribution model and parameters of the noise. Generally, it is assumed that the image noise is zero-mean Gaussian white noise. At this time, the parameter to be estimated is the noise standard deviation.

The traditional methods of image noise reduction can be roughly divided into two categories. One is based on the spatial characteristics of the image, and the pixels and their surrounding pixels are replaced by convolution, mean substitution and other operations, such as Gaussian filtering, median filtering, mean filtering and bilateral filtering. For example, Deng Zhongdong et al. [1] designed a noise estimation algorithm using median filtering. The other is to mathematically describe the characteristics of the image, process the image information through mathematical transformation formulas, correspond to a certain transformation domain, and then perform image reconstruction. In this process, image noise is eliminated as much as possible. The common methods are wavelet transform, Laplace transform and discrete cosine transform. For example, Chen Zhuan, Hu Zhifeng et al. [2] designed noise estimation algorithm using wavelet threshold. Since the image structure often has local characteristics, the processed pixels can usually be restored to a certain extent through the characteristics of the surrounding neighborhood pixels. Therefore, combining pixels and their neighborhoods into local blocks will often achieve better results.

In 2003, Ren et al. [3] proposed the concept of superpixels. Superpixel segmentation is to gather the pixels with the same features together and combine them into many small blocks. Each block has its own local information, and the pixels in different blocks have great differences. Through these blocks, the information of the original image can be fully preserved, these blocks are called superpixels. Representing an image with superpixels instead of pixels can transform the image from pixel-level representation to regional-level representation, making the image representation more in line with human visual perception without losing image accuracy. Using superpixels as the processing unit reduces the amount of data processing, thereby improving the operating efficiency of the image segmentation algorithm. Therefore, superpixels are widely used in the field of image segmentation, and are often used for image pre-segmentation, which is an extremely important step in the image segmentation process. Principal component analysis (PCA) is a method for dimensionality reduction of large-scale data. Its core idea is to examine the correlation between samples or attributes and perform spatial transformation.

In order to effectively estimate the standard deviation of image noise, this paper proposes a noise estimation method based on superpixel segmentation and principal component analysis (PCA) for image blocks. The method first performs superpixel segmentation on the noise-contaminated image, and adopts the Simple Linear Iterative Clustering Algorithm (SLIC). The pixel blocks generated by this algorithm

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are relatively compact, and the domain features are easy to express. At the same time, there are few parameters that need to be set and adjusted, and the operation is simple. It has a good effect on the compactness and contour retention of the image. The block with the largest number of pixels after segmentation is selected for processing, and the circumscribed rectangle of the block is taken as the input of the PCA algorithm, so as to effectively and quickly estimate the noise of the image.

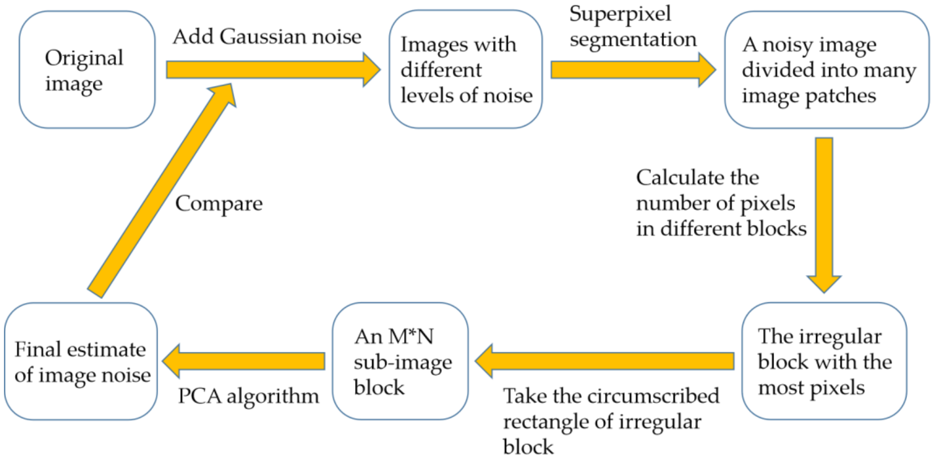

Figure 1: The flow chart of the method.

The noise estimation algorithm designed in this paper is shown in Figure 1. Firstly, we artificially add different levels of Gaussian white noise to the images in the image library. Secondly, we use simple linear iterative clustering (SLIC) to perform superpixel segmentation on the noisy image, and obtain the segmented superpixel image. Then we select the superpixel with the most pixels and take its circumscribed rectangular block as the input of PCA algorithm, that is, obtain the covariance matrix of image data, perform eigendecomposition on the covariance matrix, and take the minimum eigenvalue obtained as the estimation value of noise level.

2. Superpixel segmentation algorithm

Using the similarity of features between pixels to group pixels and use a small number of superpixels to replace a large number of pixels to express image features, which can greatly reduce the complexity of image post-processing, usually as a pre-processing step in image processing. In order to select the smooth area of the image for subsequent image noise estimation, and consider the content information of the image, this paper selects the superpixel segmentation algorithm [4] to divide the image irregularly. The specific content is briefly described as follows:

SLIC is an algorithm with simple idea and convenient implementation. It converts color images into 5-dimensional feature vectors and XY coordinates, and then constructs distance measurement standards for the 5-dimensional feature vectors. It is the process of local clustering of image pixels. The SLIC algorithm can generate compact and approximately uniform superpixels, and has a high comprehensive evaluation in terms of operation speed, object contour preservation, and superpixel shape, which is more in line with the expected segmentation effect.

Step 1- Initialize seed point (cluster center): According to the set number of superpixel groups, we can evenly distribute some seed points in the image.

Step 2- Reselect the seed point within the n*n neighborhood of the seed point: First calculate the gradient values of all pixels in the neighborhood, and then move the seed point to the place with the smallest gradient in the neighborhood. The purpose of this is to avoid the seed point falling on the contour boundary with larger gradient, so as not to affect the subsequent clustering effect.

Step 3- Assign class labels to each pixel in the neighborhood around each seed point: Different from the standard k-means search in the whole image, the search range of SLIC is effectively limited, which can speed up the algorithm convergence.

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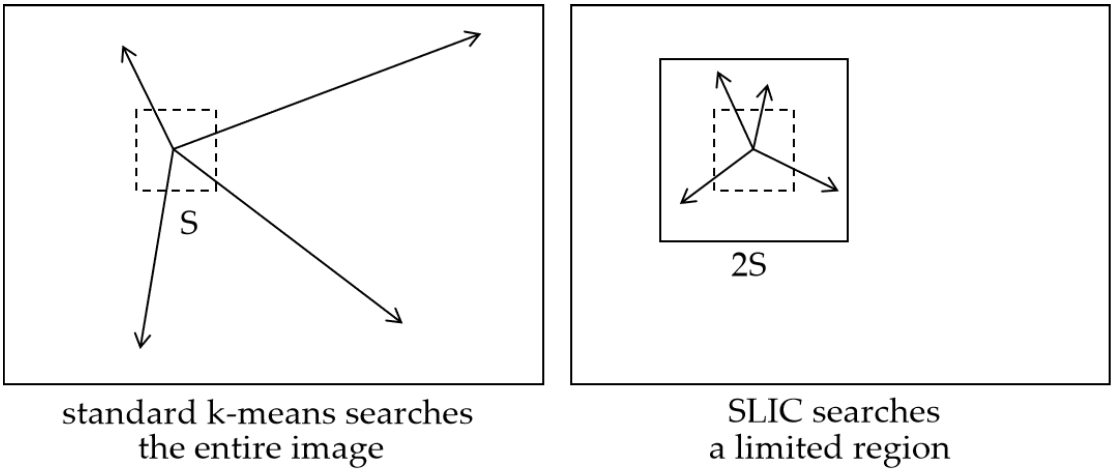

Figure 2: Search range for standard k-means and SLIC.

Step 4- Distance measurement: These include color and spatial distance. For each pixel searched, the distance between it and the seed point is calculated separately. The specific distance formula is as follows:

$$d_c = \sqrt{(l_j - l_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2}$$
$$d_s = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \tag{1}$$
$$D' = \sqrt{\left(\frac{d_c}{N_c}\right)^2 + \left(\frac{d_s}{N_s}\right)^2}$$

Among them, d_c represents the color distance, d_s represents the spatial distance, and N_s is the maximum spatial distance within the class. The maximum color distance N_c varies not only with different pictures, but also with different clusters, so we take a fixed constant m (value ranges [1, 40], generally 10) instead. The final distance measurement D' is as follows:

$$D' = \sqrt{\left(\frac{d_c}{m}\right)^2 + \left(\frac{d_s}{s}\right)^2} \tag{2}$$

Since each pixel point will be searched by multiple seed points, each pixel point will have a distance from the surrounding seed points, and the seed point corresponding to the minimum value is taken as the cluster center of the pixel point.

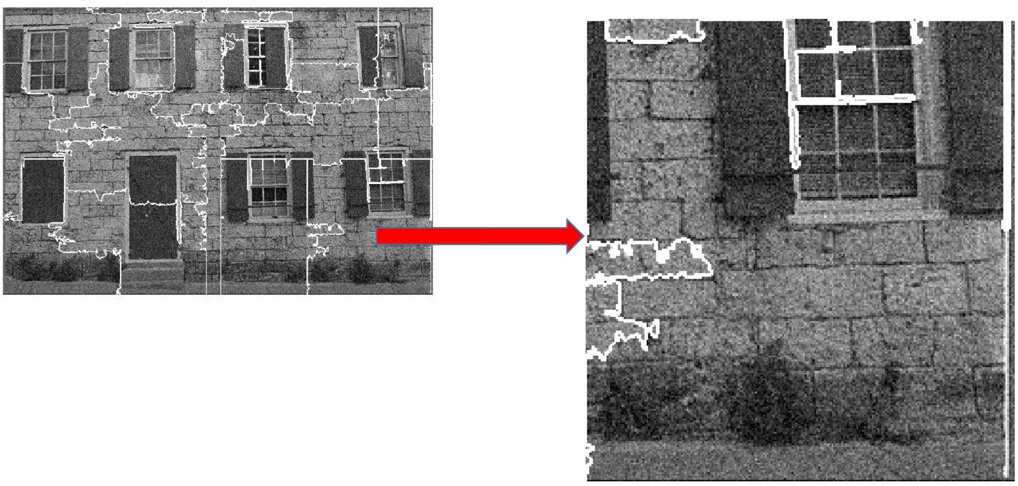

Figure 3: Results of superpixel segmentation.

ISSN 2616-5775 Vol. 5, Issue 6: 31-36, DOI: 10.25236/AJCIS.2022.050606

Step 5- Iterative optimization: In theory, the above steps continue to iterate until the error converges (it can be understood that the cluster center of each pixel point no longer changes). In practice, it is found that 10 iterations can obtain ideal results for most images, so the general number of iterations is 10 .

Step 6- Enhance connectivity: After the above iterative optimization, the follow-ing defects may occur: multi-connectivity, super-pixel size is too small, a single su-per-pixel is cut into multiple discontinuous super-pixels, etc. These situations can be solved by enhancing connectivity.

Figure 3 shows the preliminary results of the selected example image using the above superpixel segmentation method. In order to obtain the largest possible smooth block for subsequent processing, we calculated the number of pixels contained in each image block, and selected the block with the most pixels as our processing object.

3. The principle of PCA noise estimation

We assume that $\boldsymbol{x}$ is a noise-free image (or an image block) of size $S_1 \times S_2$,

where S_1 is the number of columns and S_2 is the number of rows,and $\boldsymbol{y}=\boldsymbol{x}+\boldsymbol{n}$ be the noisy image corrupted with noise. The noise is additive white Gaussian noise independent of the signal, with a mean value of 0 and a noise variance of σ^2 . Both images $\boldsymbol{x}$ and $\boldsymbol{y}$ contain $N=(S_1-M+1)\times(S_1-M+1)$ overlapping sub-image blocks of size $M\times M$. These patches are vectorized as $\boldsymbol{x}_i, \boldsymbol{y}_i, i=1,2,......,N$ and their covariance matrices are denoted as $\Sigma_{x_i}, \Sigma_{y_i}$,which have $M^2\times M^2$ entrances.

To further advance our method, there is an important assumption in the paper [5]:

Assumption 1: $\boldsymbol{x}$ can be sparsely represented by applying PCA, that is, all $\{\boldsymbol{x}_i\}$ take values in the subspace V_{M^2-m} .

When the above assumptions holds, the author in [5] proves that:

$$\lim_{N\to\infty} E(|\lambda_{y,\min}-\sigma^2|)=0 \tag{3}$$

where $\lambda_{y,\min}$ is the smallest eigenvalue of Σ_{yi} and σ^2 is the variance of the added noise. Therefore, we can estimate the standard deviation level of the noise as $\sqrt{\lambda_{y,\min}}$, and at the same time, through the introduction of the paper [5], the accuracy of the estimation is proportional to N . The noise level estimation algorithm can be summarized as the following steps:

(1) $\boldsymbol{y}$ is decomposed into overlapping sub-image blocks $\boldsymbol{y}_i, i=1,2,....N$. The default block size is 5×5 pixels, i.e. ,$M=5$.

(2) The initial estimated value calculated based on the variance distribution of the image block is also used as the upper limit of the entire estimation process. We assume that $s^2(\boldsymbol{y}_i)$ is the sample variance of $\boldsymbol{y}_i$ and $Q(p)$ is the p -quantile of $\{s^2(\boldsymbol{y}_i), i=1,2,...N\}$. The estimated value of the initial noise level is calculated as $C_0Q(p_0)$, and this paper refers to the paper [5] to set C_0 =3.1 and p_0 =0.0005.

(3) By recursively discarding the patch with the largest variance until Assumption 1 is satisfied, we can select a subset of patch $\boldsymbol{Y}_p$

$$\boldsymbol{Y}_p=\{\boldsymbol{y}_i|s^2(\boldsymbol{y}_i)\leqslant Q(p), i=1,......,N\} \tag{4}$$

Assumption 1 is checked by the following condition:

$$\lambda_{Y_p,\mathrm{m}}-\lambda_{Y_p,\min}<49\sigma^2/M \tag{5}$$

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where $\lambda_{Y_P,\min}, \lambda_{Y_P,\mathrm{m}}$ are the smallest and m^{th} smallest eigenvalues of Σ_{Y_P}, respectively, and σ is the estimated noise level in the previous iteration.

(4) $\sqrt{\lambda_{y,\min}}$ is considered to be an estimate of the noise level during the current iteration, and steps 3 and 4 iterate until convergence is reached.

4. Experimental results and analysis

In order to verify the effectiveness of the proposed algorithm, we selected 24 images in the Kodak image library and applied Gaussian white noise respectively. Examples of some images are shown in Figure 4. The noise level is set to 6 levels, which are [1 3 5 10 15 20] and compared with the contrast method [6], the experimental results are shown in Table 1.

Figure 4: Partial experimental images of noise standard deviation estimation experiment

Table 1: Comparison of estimation results between our method and contrast method

Actual value	Contrast method	The method of this paper
1	0.86	1.43
3	2.23	3.19
5	4.56	5.11
10	9.52	9.79
15	14.37	14.63
20	19.25	19.29

Table 1 shows the experimental results of the proposed method and the selected comparison method. Compared with the contrast method, the mean of the noise standard deviation estimation is closer to the true value than the contrast method when the noise level is greater than 1. Our method first performs superpixel segmentation on the image, and selects relatively smooth image blocks with similar texture, color, brightness, etc. between pixels. Using this feature to estimate the noise level is more accurate than estimating the original whole image directly under the partial noise level.

5. Conclusion

This paper proposes an improved image noise level estimation method, which can reduce the amount of data and obtain more accurate estimation results. The method firstly performs superpixel segmentation on the image, then selects the largest irregular smooth block, and takes its smallest circumscribed rectangle. Finally, the PCA algorithm is used to estimate the noise of the rectangular block. We selected 24 images from the Kodak image library and made a comparative test, and the results were more convincing.

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ISSN 2616-5775 Vol. 5, Issue 6: 31-36, DOI: 10.25236/AJCIS.2022.050606

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