LETTER

No Reference Quality Assessment of Contrast-Distorted SEM Images Based on Global Features

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SUMMARY This letter presents a global feature-based method for evaluating the no reference quality of scanning electron microscopy (SEM) contrast-distorted images. Based on the characteristics of SEM images and the human visual system, the global features of SEM images are extracted as the score for evaluating image quality. In this letter, the texture information of SEM images is first extracted using a low-pass filter with orientation, and the amount of information in the texture part is calculated based on the entropy reflecting the complexity of the texture. The singular values with four scales of the original image are then calculated, and the amount of structural change between different scales is calculated and averaged. Finally, the amounts of texture information and structural change are pooled to generate the final quality score of the SEM image. Experimental results show that the method can effectively evaluate the quality of SEM contrast-distorted images.

key words: *image quality assessment, contrast distorted, global features, scanning electron microscopy*

1. Introduction

Along with the development of science and technology, people are becoming increasingly concerned about quality control at the microscopic scale. Scanning electron miscroscopy (SEM) is a widely used scientific technique that uses an electronic system to magnify the observed object and display its microscopic structure. SEM images are realistic and three-dimensional, providing access to fine structure information. However, the acquisition of SEM images can cause contrast distortions that directly affect the researcher's judgment of the sample. In practice, the imaging parameters need to be adjusted constantly to obtain high-resolution SEM images, a practice that is time-consuming and laborious. Therefore, for SEM images with contrast distortion, an automated objective quality evaluation algorithm is required to guide the selection of imaging parameters.

For contrast distortion no reference (NR) image quality assessment (IQA), inspired by natural scene statistics (NSS) of images, Fang et al. [1] proposed an NR quality evaluation method for contrast-distorted images. The quality score was evaluated based on the unnaturalness of the contrast-distorted image, which was characterized by the degree of deviation from the NSS model. Nafchi et al. [2] used the high-order Minkowski distance and entropy to provide an accurate quality prediction for contrast-distorted images. Gu et al. [3] proposed a method based on the concept of information maximization without training. The weight of global and local features is calculated as the index to evaluate image quality. Wu et al. [4] extracted five statistical features from the original image, while two features were extracted from the phase congruence map. To train the model with these features. Khosravi et al. [5] proposed a learning-based blind image quality evaluation model. The randomness of the image feature histograms and the magnitude of the corresponding feature values can reliably reflect changes in image contrast. Zhang et al. [6] transformed images into YCbCr spatial images and extracted gradient features from regions sensitive to compression artifacts. The Log-Gabor transform was used to further analyze the texture differences. Finally, the obtained features were fused into a quality score.

Since SEM images are different from natural images, the above methods do not apply to SEM images and there is relatively little literature dedicated to SEM images. For example, Li et al. [7] proposed an evaluation sharpness method based on dark channel priori for SEM blurred images. The method extracted a dark channel map of SEM images, and a filter was used to remove the noise with edge of map. Finally, the maximum gradient and average gradient were weighted as the quality score. Zotta et al. [8] applied the image quality evaluation metric of the average structural similarity index to SEM images. Ruan et al. [9] used Fourier transform and derivative and contrast methods to measure sharpness. Although these methods have achieved great advances, they cannot estimate contrast distortion in SEM images.

According to the characteristics of the human visual system, this method proposes an NR quality evaluation method for SEM contrast distorted images based on global features. The texture information of the image is first extracted using a low-pass filter with orientation. Then the amount of information in the texture part is calculated. Moreover, the gradient values with four scales of the original image are calculated to measure the differences between different scales with the weighted structural variation. Finally, the texture information and structural variation are integrated to generate the final quality score of the SEM image. The experimental results demonstrate that the proposed

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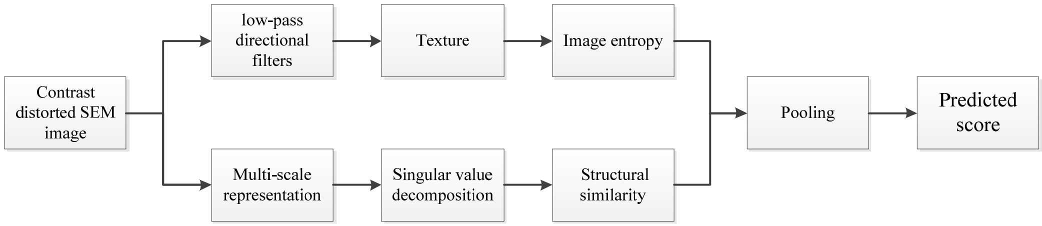

Fig. 1 Flowchart of the proposed method

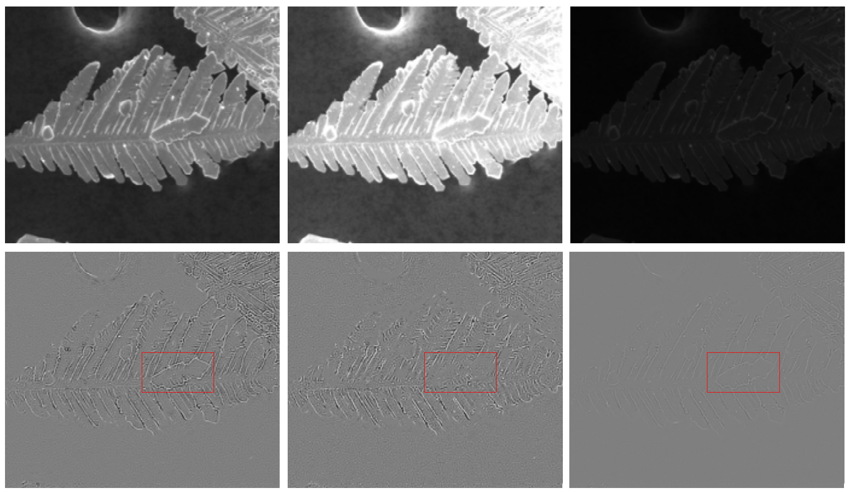

Fig. 2 Original image and two contrast-distorted images with their corresponding texture maps

method outperforms state-of-the-art IQA metrics.

2. Proposed SEM Contrast-Distorted Image Metric

The evaluation of structural loss can be a good way to evaluate visual quality. Thus, the global structural information of the image is taken into account for SEM image quality evaluation. Figure 1 illustrates the flow of this method. Firstly, two features of SEM images are extracted, one is Texture information entropy, the other is the similarity of multi-scale singular values. Then, the two features are pooled into a single number to represent the quality score of the image.

2.1 Texture Information Feature

The method first uses a group of low-pass directional filters [10] to smooth and texture decompose the SEM image. For an SEM image f, if a pixel belongs to a smooth region, then its local total variation (LTV) will basically not decrease. If it belongs to a texture region, the LTV will decrease rapidly. The LTV at pixel point (x, y) is defined as

$$LTV_\sigma(x,y) = L_\sigma * \left|G_f\right| \tag{1}$$

$$G_f = \int_\Omega \sqrt{(f_x)^2 + (f_y)^2} dxdy \tag{2}$$

where L_σ is a low-pass filter with standard deviation σ. f_x and f_y are the gradient values of image f in the x and y directions, respectively.

For a low-pass directional filter, $L_{\sigma,0}$ is defined as

$$L_{\sigma,0}(x,y) = \begin{cases} CL_\sigma(x,y) & x \geq 0 \\ Ce^{-\frac{x^2}{2\alpha^2}} L_\sigma(x,y) & x \leq 0 \end{cases} \tag{3}$$

where C is a constant and α is empirically set to 0.75.

The group of filters L_{σ,θ_i} is defined as a rotating version around the $L_{\sigma,0}$, and the rotation angle θ_i is defined as

$$\theta_i = i \cdot \theta_s, \; i = 0, \ldots, \left\lfloor \frac{360}{\theta_s} \right\rfloor \tag{4}$$

where θ_s is the angle step length. In this work, θ_s is set to 8°.

According to Eqs. (3) and (4), Eq. (1) becomes

$$LTV_{\sigma,\theta_i}(x,y) = L_{\sigma,\theta_i} * \left|G_f\right| \tag{5}$$

The relative reduction rate $\lambda_\sigma(x,y)$ is defined as

$$\lambda_\sigma(x,y) = \max\left\{\lambda_{\sigma,\theta_i}(x,y), i = 0, \ldots, \left\lfloor \frac{360}{\theta_s} \right\rfloor\right\} \tag{6}$$

where, $\lambda_{\sigma,\theta_i}(x,y) = \dfrac{LTV_{\sigma,\theta_i}(x,y) - LTV_{\sigma,\theta_i}(L_{\sigma,\theta_i} * f)(x,y)}{LTV_{\sigma,\theta_i}(x,y)}$.

Figure 2 shows the original image and the two contrast-distorted images from left to right, and the bottom row shows their corresponding texture maps. The images in the red boxes show that the information of the contrast-distorted SEM image is lost through decomposition. Since entropy reflects the amount of information in an image and the complexity of the texture, it is used as a parameter to measure contrast distortion. Image entropy H is defined as

$$H = -\sum_{i=0}^{255} p_i \log p_i \tag{7}$$

where p_i represents the probability of different gray levels in the SEM image. The calculated entropy is used as one of the indicators to measure the distortion degree of SEM image.

2.2 Multi-Scale Singular Value Similarity

The singular value decomposition (SVD) can represent the structure of the image well, and any changes introduced in the image due to distortion can significantly affect the singular vector. Therefore, changes in the structure of SEM images can be evaluated by the extraction of multiscale features of SEM images in the SVD domain. In this letter, the singular values of four scales are extracted to calculate the similarity.

For an SEM image f with the number of pixels $M * N$, the SVD process is as follows:

$$\boldsymbol{I} = \boldsymbol{U}\boldsymbol{S}\boldsymbol{V}^T \tag{8}$$

where $\boldsymbol{U}$ is the unitary matrix of order M, $\boldsymbol{V}$ is a unitary matrix of order N, $\boldsymbol{S} = (\sigma_1, \sigma_2, \cdots, \sigma_r)$, r is the rank of image matrix f, and σ_i (i = $1, 2, \ldots, r,$) is the singular value.

The singular value vector of different scales is S_i, and i can be taken as 0, 1, 2, 3, 4. Calculate the singular value similarity between the original image and four scale images. The formula is as follows:

$$A_k = \frac{2S_k S_0 + c}{S_k^2 + S_0^2 + c} \tag{9}$$

where k = 1, 2, 3, 4, c is a very small constant that guarantees the stability of the value. The final singular value similarity feature Q_2 is calculated using the following equation:

$$Q_1 = \frac{1}{6}(3A_1 + A_2 + A_3 + A_4) \tag{10}$$

2.3 SEM Image Quality Index

The amount of information in the texture image and the amount of structural change in the distorted image are pooled together as the final SEM image quality evaluation metric. The metrics Q is generated by

$$Q = \beta H + (1 - \beta)Q_1 \tag{11}$$

where β is a constant between 0 and 1. It is used to balance the importance of information H and similarity feature Q_1 to SEM image quality indicators. In this work, β is set to 0.6538 according to the experiment.

3. Experimental Results and Analysis

To evaluate the performance of the method in this letter, we used three commonly parameters, including Pearson linear correlation coefficient (PLCC), root mean square error (RMSE), and Spearman correlation coefficient (SRCC). The values of these three indicators are between 0 and 1. PLCC describes the correlation between the evaluation value of the algorithm and the subjective score of the human eye, and RMSE measures the accuracy of the method prediction. SRCC measures the monotonic consistency of the method prediction. The objective quality score obtained by the image quality evaluation algorithm is nonlinearly related to the subjective quality score. Therefore, the objective quality score and subjective quality score of the image are mapped to the same scale by a nonlinear fitting function with the following equation:

$$f(v) = \tau_1\left(\frac{1}{2} - \frac{1}{1 + e^{\tau_2(v-\tau_3)}}\right) + \tau_4 v + \tau_5 \tag{12}$$

where τ_i ($i = 1, 2, \ldots 5$) are the fitted parameters.

We compare the method proposed in this letter with the classical three full-reference (FR) methods, nine NR quality evaluation methods, two methods for SEM image in SEM database. Table 1 shows the results of the experiments, with the best performance in bold.

As can be seen in Table 1, the performance of the proposed method for SEM contrast-distorted image outperforms that of the mainstream image quality evaluation methods in terms of monotonicity and prediction accuracy.

To further validate the performance of the proposed method metric, F-test is used to compare the error between

Table 1 Results of mainstream quality assessment methods and proposed method tested in the SEM database

Algorithms		PLCC	SRCC	RMSE
FR	MSSIM [8]	0.6116	0.6017	0.6846
	GMSD [11]	0.5877	0.5561	0.5859
	PCQI [12]	0.4721	0.4462	0.6792
NR	DESIQUE [13]	0.7621	0.7309	0.451
	BRISQUE [14]	0.7299	0.7038	0.4761
	Bliinds2 [15]	0.7216	0.6965	0.4786
	BIQI [16]	0.6462	0.6301	0.5356
	DIIVINE [17]	0.5854	0.5608	0.5611
	SSEQ [18]	0.5789	0.5464	0.5672
	QAC [19]	0.4251	0.4300	0.6554
	NIQE [20]	0.3518	0.4234	0.6782
	NR-CD [1]	0.4864	0.4772	0.6170
FOR SEM image	Method [9]	0.5732	0.5213	0.6077
	Method [7]	0.2288	0.2108	0.7049
	proposed	**0.8632**	**0.8398**	**0.3522**

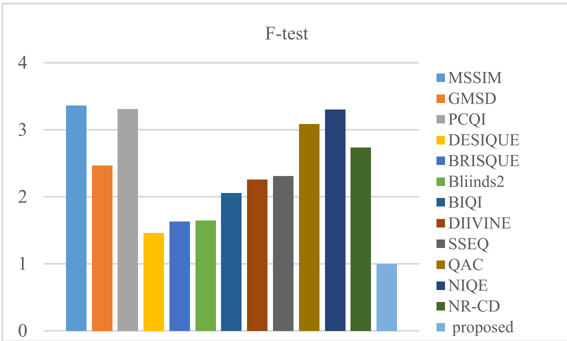

Fig. 3 F statistics of the other metrics against the proposed method

the objective prediction scores and the subjective scores. The F-test score is defined as

$$F\text{-}test = \frac{(RMSE_E)^2}{(RMSE_P)^2} \tag{13}$$

where E is the comparative indicator and P is the proposed indicator.

Figure 3 shows the values of the F-statistics of the other methods relative to the method in this letter. The figure reveals that the proposed method has the smallest prediction error. The 95% confidence interval is chosen for the process of the experiment.

4. Conclusion

In this letter, we propose a global feature-based method to evaluate the image quality of SEM contrast distortion using the image features of SEM and the property that the human visual system has multiple scales. The method takes advantage of the property of SVD, namely, it is sensitive to capturing structural changes in the visual signal. It then calculates the singular values of the four scales of the original image and then weights the averages of the amount of structural changes between different scales. The original SEM image texture information is extracted using a low-pass filter with orientation, and the amount of information in the image is reflected by calculating the entropy. Finally, the amount of structural variation and texture information are pooled to generate the final quality score of the SEM image. Experimental results show that the algorithm proposed can effectively evaluate the quality of SEM images and maintains a high degree of consistency with the subjective evaluation.

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