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A high-speed image super-resolution algorithm based on sparse representation for MEMS defect detection

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Abstract—A novel high-speed image super-resolution algorithm based on sparse representation for MEMS defect detection is proposed in this paper. Traditional super-resolution algorithms adopt a single dictionary to represent images， which cannot differentiate varieties of image blocks and leads to slow processing speed. Aiming at overcoming this shortage of traditional super-resolution algorithms, image blocks are divided into different categories by local features and each of these categories possesses the corresponding high and low resolution dictionary pairs. Experimental results of different MEMS defects show that the improved algorithm can obtain images of little lower quality with much less processing time, indicating that the proposed algorithm is more suitable for MEMS defect detection.

Keywords—MEMS defect detection; image super-resolution; sparse representation; fast

I. INTRODUCTION

MEMS devices are widely used because of the outstanding performance in small volume, low cost and easy integration with other components. Traditional defect detection relies on manual operation, which results in low precision, efficiency and strong intensity of labour. In recent years, machine vision systems are adopted to inspect defects or control qualities of many industrial products such as semiconductors and automobiles [1]. At present, machine vision systems for MEMS defect detection are mainly based on SEM or optical microscopes [2-3].The inspection system based on SEM has the characteristics of high magnification, focal depth and resolution, but it is complex and expensive limiting the widespread use. Although the magnification and resolution of the detection system with optical microscopes is not high enough for high-precision defect detection, it has the advantages of simple operation and low cost. So how to obtain images of high quality from low resolution pictures taken by optical microscopes has become a key research issue for MEMS defect detection.

Three different approaches including the interpolation, reconstruction and learning-based method were investigated for image super resolution. Although the interpolation method can realize fast reconstruction and maintain effectively the edges of the image, it is impossible to know the degradation information of the actual images leading to the unstableness of the prior models and the low quality of the acquired images [4-5]. The reconstruction mothed is able to make full use of the non redundant compensation information between multi frames, introduce effectively prior image models and obtain a stable or only super resolution image. However, the mothed requires specific frames of low resolution images, needs accurate registration information and is sensitive to registration errors or noise at high super-resolution magnification [6-7]. Although the algorithms are always complex, the learning-based mothed can break through the limitation of the prior knowledge used in the interpolation and reconstruction method and thus increase the image resolution at high rate especially for high-quality single-frame super resolution [8-9], which signifies that the learning-based method has a good prospect in application for MEMS defect detection.

As a learning-based method, the sparse super-resolution reconstruction [10] has been proposed, which combines the locally linear embedding and sparse signal representation theory. Sparse representation provides a new method of generating a super-resolution image from a single low-resolution input image. Traditional super-resolution algorithms adopt a single dictionary to represent images [10-11]， which cannot differentiate varieties of image blocks. To represent image blocks accurately by the over-complete dictionary, the number of base atoms is always large leading to slow processing speed. Lian Qiu-shen [12] proposed a method based on classification of image blocks to overcome this disadvantage. Although image blocks are divided into smooth blocks, different directional edge blocks and irregular structure blocks, Lian did not classify irregular structure blocks any more. Thus, a novel fast image super-resolution algorithm for MEMS defect detection is proposed based on the work of Lian by classifying irregular structure blocks into different ones.

II. PRINCIPLE OF THE IMPROVED ALGORITHM

A. *Improved classification method of image blocks*

In addition to smooth blocks and different directional edge blocks based on the research of Lian [12], the irregular structure blocks are divided into three different contrast blocks as shown in Fig.1.

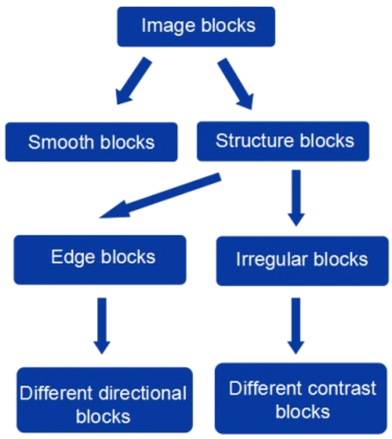


Fig.1. The improved classification method of image blocks

Local variance is adopted to distinguish between smooth and structure blocks via an appropriate threshold because of the small amount of calculation [12]. Edge blocks are differentiated from irregular blocks via the consistency of gradient field direction [12].

The irregular structure blocks are classified by the contrast of the image block and the contrast can be expressed as:

$$C=\sum_{\delta}\delta(i,j)^2 P_\delta(i,j) \qquad (1)$$

where $\delta(i,j)=|i-j|$ is the gray-scale difference between adjacent pixels. $P_\delta(i,j)$ represents the adjacent pixels whose gray-scale difference is δ .

B. *Flowchart of the improved algorithm*

The detailed dictionary training and super-resolution reconstruction of the improved algorithm are presented based on the work of Lian [12] in Fig.2 and Fig.3, respectively. The processing procedure of edge image blocks is left out for clarity because it is identical to the one of irregular structure image blocks.

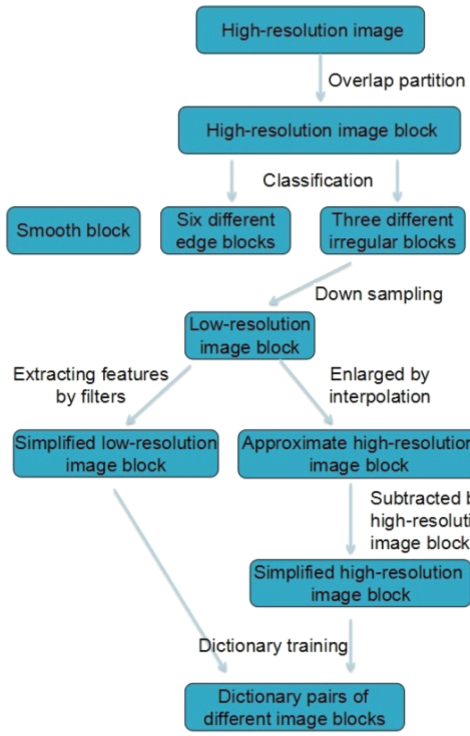


Fig.2. The flowchart of dictionary training

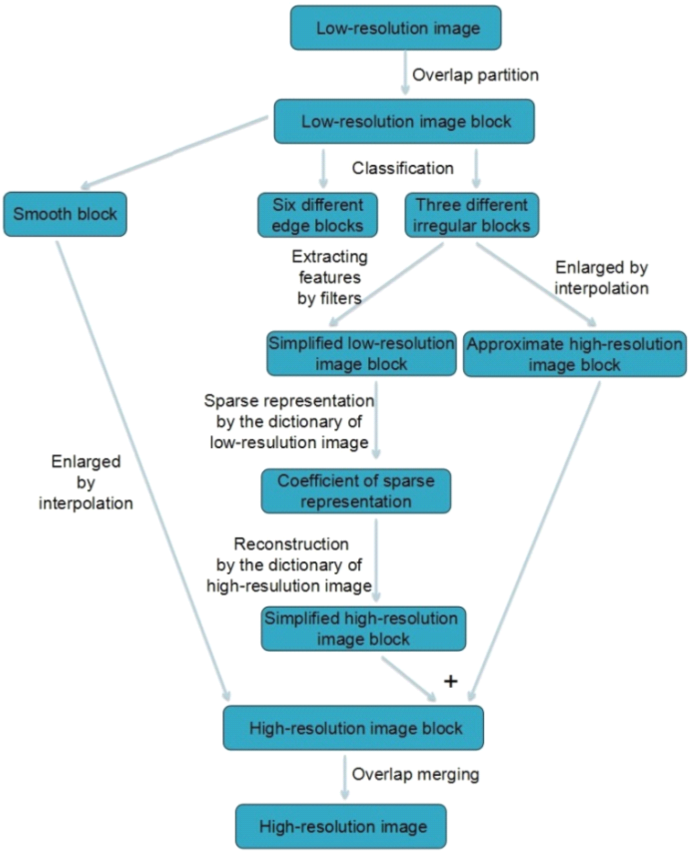
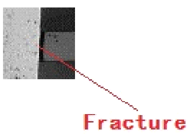


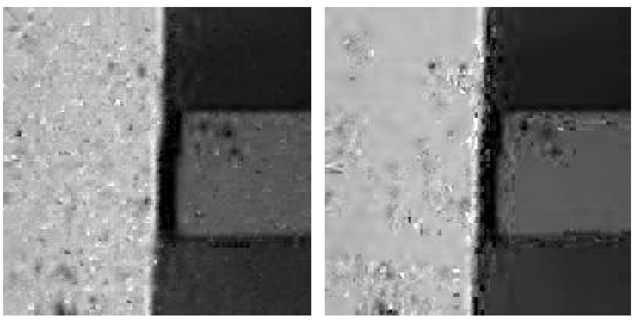
Fig.3. The flowchart of super-resolution reconstruction

III. EXPERIMENTS AND RESULTS

Four kinds of MEMS defect images were chosen for the experiments and each raw image is 150*150. The traditional and improved algorithms were simulated in MATLAB software and the results of 3 times super resolution are shown in Fig.4-7 and Table 1-4.



(a)

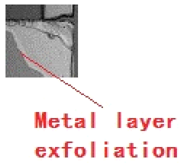


(b) (c)

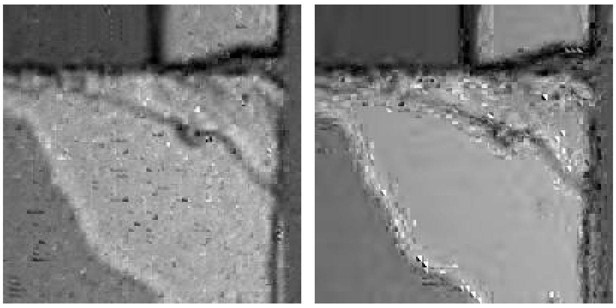
Fig.4. The results of a fracture image. (a) The raw image. (b) The image processed by the traditional super-resolution algorithm. (c) The image processed by the improved super-resolution algorithm.

Table 1. The results of the fracture image

Methods	Processing time(s)	RMSE
Traditional algorithm	16.1898	15.8961
Improved algorithm	5.8198	16.4007



(a)



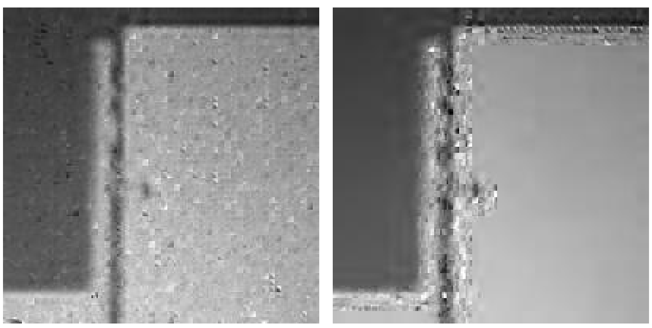
(b) (c)

Fig.5. The results of a metal layer exfoliation image. (a) The raw image. (b) The image processed by the traditional super-resolution algorithm. (c) The image processed by the improved super-resolution algorithm.

Table 2. The results of the metal layer exfoliation image

Methods	Processing time(s)	RMSE
Traditional algorithm	14.1956	16.1901
Improved algorithm	6.0571	18.2112

(a)



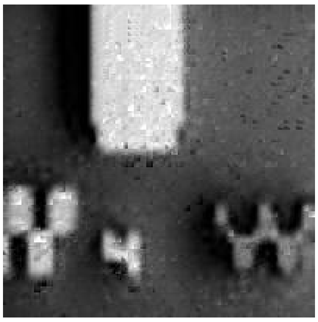
(b) (c)

Fig.6. The results of a malposed overlay image. (a) The raw image. (b) The image processed by the traditional super-resolution algorithm. (c) The image processed by the improved super-resolution algorithm.

Table 3. The results of the malposed overlay image

Methods	Processing time(s)	RMSE
Traditional algorithm	14.1940	12.7994
Improved algorithm	3.4455	14.7978

(a)



(b) (c)

Fig.7. The results of a lateral etching image. (a) The raw image. (b) The image processed by the traditional super-resolution algorithm. (c) The image processed by the improved super-resolution algorithm.

Table 4. The results of the lateral etching image

Methods	Processing time(s)	RMSE
Traditional algorithm	14.0737	16.7243
Improved algorithm	6.5078	20.5055

Although the processing speed varies with different MEMS defects, the improved algorithm is much faster than traditional methods by classifying image blocks into different categories particularly. The RMSE of images processed by the improved method is little larger than the one of traditional algorithms, signifying that the new method can obtain images of little lower quality.

IV. CONCLUSION

A fast image super-resolution algorithm based on sparse representation for MEMS defect detection is proposed in this paper. The classification of image blocks reduces computational complexity greatly leading to high processing speed. The RMSE of images processed by the improved method is little larger than the one of traditional algorithms meaning that the quality of the acquired images is little lower. The experimental results signify that the new algorithm for MEMS defect detection can get clear enough images with much less processing time, indicating that the proposed algorithm is more suitable for MEMS defect detection.

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