APPLICATION OF ADVANCED IMAGE PROCESSING TECHNIQUES TO AUTOMATIC KIKUCHI LINES DETECTION

Rafał Frączek, Tomasz Zieliński

Instrumentation & Measurement Department, AGH University of Science and Technology
Al. Mickiewicza 30, 30-059 Cracow, Poland
tel/fax: +(4812) 6338565, email: tzielin@uci.agh.edu.pl
www.agh.edu.pl

ABSTRACT

Automated crystal orientation measurement (ACOM) in the scanning electron microscope (SEM) is a standard technique of texture analysis (pattern recognition) that is used in materials science. The measurement is carried out by interpreting backscatter Kikuchi patterns, in particular by the extraction of the position of so-called Kikuchi bands, i.e. pairs of parallel lines. Their detection strongly depends on appropriate processing of a source image, which usually is highly corrupted by noise and has uneven background illumination. Such advanced processing is addressed in this paper. It exploits wavelet transform based de-noising as well as curve modification and curvelet transform based contrast enhancement methods. Additionally, directional, ridge detection type 2D filters are used for searching lines missing to pairs.

1. INTRODUCTION

Possibility of reproducible manufacturing of crystal materials with desired physical properties is one of the most important problems in material engineering. The crystal material properties are mainly determined by size and spatial orientation of crystal domains that in turn can be deduced (calculated) from the position of so-called Kikuchi bands, i.e. pairs of parallel lines, existing in electron microscopy images (see figure 1). When an electron beam impinges on a crystalline solid, it is spread out as a wide shower consisting of scattered electrons. After leaving the crystal, a Kikuchi diffraction pattern (a set of pairs of parallel lines) is produced on a phosphor screen. Its geometry is unique for the crystal structure and hence its extraction is essential for the evaluation of the crystal material properties. Kikuchi bands usually form characteristic broad stripes of intensity in the image and their edges (Kikuchi lines) are often fragmented and diffused. Moreover, the microscopy images are usually corrupted by noise. Therefore some of the Kikuchi lines are hardly visible and difficult to detect, and in such situation image processing plays a very important role. Its goal is noise suppression and lines efficient enhancement.

The goal of this paper is to propose significant improvements of the Kikuchi lines detection algorithm developed by authors and described in [1]. Two efficient image pre-pro-

cessing steps have been added to it, namely wavelet transform-based image de-noising and curvelet transform-based contrast enhancement. Additionally, the algorithm has been equipped with special procedure for searching lines missing to pairs that exploits directional, ridge detection type filters.
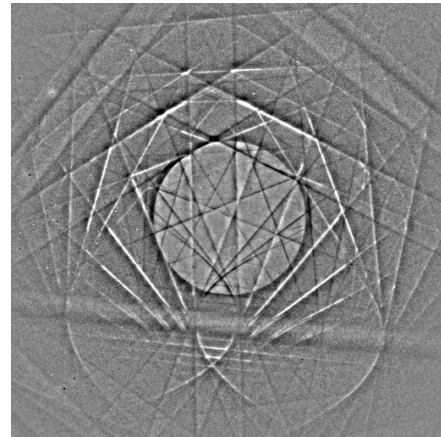

Fig. 1. An example of a source image.

2. KIKUCHI LINES DETECTION ALGORITHM

The discussed method is an extension to the one presented in [1] and can be summarized as follows:

1) *Correction of unequal background illumination* by means of subtraction of local average values.
2) **Image de-noising** by shrinkage of its wavelet coefficients (section 3 and 4).
3) **Contrast enhancement** using curve modification method and curvelet transform (section 3 and 5).
4) *Directional filtering*. The pre-processed image is filtered twice with a mask oriented at each of four orientations: vertical, horizontal and at the angles of 45 and 135 degrees. As a result four filtered images are obtained and they are processed separately later.
5) *Segmentation (binarization)*. At this step each filtered image is segmented into *background* and *objects (lines)*. A global thresholding method is applied.
6) *Binary image enhancement*. A sequence of morphological operations is used to make binary images more suitable for further processing.

7) *Modified Hough transform*. The binary images are pro-cessed with modified Hough transform. It results in a set of detected Kikuchi lines.

8) *Verification*. In order to decrease the probability of non-existing lines detection ("false positives") an additional verification step is performed (see [1] for details).

9) ***Searching for missing lines to pairs***. In the end, for each of detected "single" line (i.e. a line without a correspond-ing parallel partner) we are looking for a missing parallel line that possibly could not have been detected. The im-age is convolved with a *steerable, directional, ridge de-tection type 2D filter* [8] which is oriented in the direction parallel to the found "single" (section 6).

In the following sections extensions added to the previous version of the algorithm will be presented, namely wavelet-based image de-noising, curve modification and curvelet-based contrast improvements, and, finally, directional filter-ing-based searching for missing lines to pairs.

3. NOISE ESTIMATION

After correction of unequal background illumination, realized by subtraction of local average values, estimation of noise standard deviation is carried out. For this purpose it is neces-sary to extract image regions with noise only. First, the global mean value is subtracted from the image. Next, the image is partitioned into square blocks of 4×4 pixels that are trans-formed separately by 2D DFT. Two situations are possible: an individual block includes a Kikuchi line(s) or does not. In order to distinguish between these two cases a special pa-rameter v is calculated:

$$v = F(0,0)^2 + F(0,1)^2 + F(1,0)^2 + F(1,1)^2 \qquad (1)$$

where $F(i, j)$ denotes a magnitude of DFT coefficient. If v is higher than empirically found threshold then it is assumed that relevant block includes a Kikuchi line. The threshold value is found on the basis of the number of incorrectly clas-sified blocks. From figure 2 one can conclude that the opti-mal threshold value is equal to 2.9.
Finally, the entire image is divided into two subsets: the first one consists of blocks that include only noise and the second one is made up of blocks containing lines. At this point, the first subset is used to estimate noise standard deviation σ which is needed in further steps.
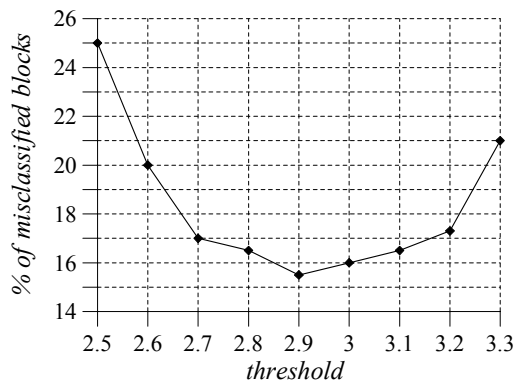

Fig. 2. Percentage of misclassified block against threshold.

4. IMAGE DE-NOISING

Since images from electron microscope are highly corrupted by noise, it is very difficult to detect in them hardly visible lines. The presence of strong noise makes wrong decision and false "detection" of a line (that does not exist) very prob-able.

For that reason several de-noising methods were carefully tested. The following methodology was applied. First, an artificial, noise-free, reference image containing different types of lines was created. Generated lines had different width, length and contrast in respect to the background. Then, the reference image was embedded in noise extracted from original microscope images (ten different 8×8 square blocks containing only noise were added to the reference in random order). Finally, the generated noisy image was proc-essed by several de-noising methods, and obtained results were compared to the reference image using the standard peak signal to noise ratio (PSNR).

The following de-noising methods have been applied and tested: pixel averaging within 3×3 window, median filtering with 3×3 window, adaptive Wiener filtering, linear and non-linear complex diffusion method [2], automatic noise re-moval using fourth order partial differential equations (PDE) [3], standard wavelet de-noising using details' coefficients thresholding [4], wavelet de-noising using pyramidal direc-tional filter bank decomposition (curvelet-like transform) [5] and de-noising using neighbouring wavelet coefficients (*NeighShrink* wavelet de-noising method) [6]. Comparison of the observed efficiency of different approaches is presented in table 1.

In the standard and *NeighShrink* wavelet de-noising methods, application of the following wavelet types was veri-fied: Haar, Beylkin, Coiflet, Daubechies, Symmlet, Vaidya-

Tab. 1. De-noising efficiency of different methods (PSNR$_{in}$=21dB).

Method	PSNR$_{out}$ [dB]
Fourth order PDE [3]	24.81
Linear complex diffusion [2]	25.23
Pixel averaging	25.63
Median filtering	25.78
Non-linear complex diffusion [2]	26.12
Curvelet-like de-noising [5]	28.03
Adaptive Wiener filtering	28.60
Standard wavelet de-noising (Haar) [4]	29.39
NeighShrink wavelet de-noising (Haar) [6]	**30.41**

Tab. 2. Efficiency of wavelet transform-based de-noising methods.

Wavelet type	PSNR$_{out}$[dB]	
	Standard [4]	*NeighShrink* [6]
Haar	**29.39**	**30.41**
Beylkin	27.87	28.88
Coiflet	28.48	29.48
Daubechies	28.72	29.70
Symmlet	28.63	29.64
Vaidyanathan	27.74	28.73
Battle	28.32	29.33

nathan and Battle. The observed maximum PSNR for each wavelet type is shown in table 2. Since the *NeighShrink* algorithm with Haar wavelet outperformed other methods and offered the highest PSNR, it was added to the old version of the Kikuchi line detection algorithm [1] and tested with it in the further part of the paper.

5.   CONTRAST ENHANCEMENT

Some Kikuchi lines are characterized by very low contrast between the line and surrounding background that should be enhanced.

5.1. Contrast enhancement by curve modification

Image curve modification is known to be a very simple and fast technique for modification of the pixel distribution in any image. In order to avoid the amplification of remaining noise only pixels lying in 4×4 blocks already classified as "lines" are mapped to their new values according to the function:

$$y = 128 + 127 \cdot \frac{\operatorname{atan}\big(m \cdot (x - 128)\big)}{\operatorname{atan}(128)} \qquad (2)$$

which is depicted in figure 3. The parameter m controls the function slope. If m is too high then both, possible artefacts after de-nosing step and remaining noise, can be significantly amplified. If parameter m is too low then contrast increase is not sufficient. Thus, a trade-off is necessary and $m = 0.07$ has been chosen experimentally. The values of the transfer function are computed and rounded in advance and stored in an array of integers. Next, for the given input pixel value, the transformed output pixel value is directly obtained from this array.

As it can be observed from the outline of the proposed transfer function presented in figure 3, the applied curve modification yields the contrast increase especially for pixels values lying near 128 where pixels belonging to hardly visible lines are the most frequently concentrated.
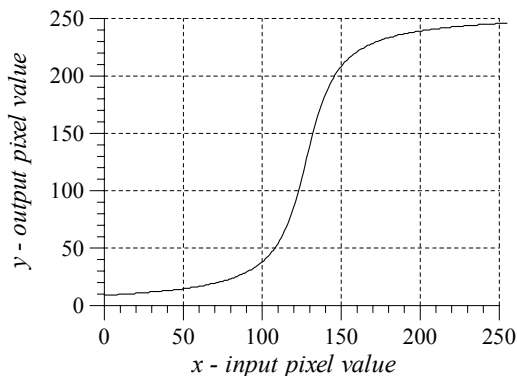

Fig. 3. The outline of the applied transfer function (2)

5.2. Contrast enhancement by curvelet transform

Described above contrast enhancement by curve modification in some cases can be not sufficient in the context of

Kikuchi lines detection since it only offers increasing the image contrast by a limited factor. The problem is that curve modification amplifies not only hardly detectable lines but also remaining noise and possible artefacts that may appear in the image after wavelet de-noising. Therefore looking for an additional more sophisticated method is necessary.

The curvelet transform is a very attractive candidate for such application: it is well-adapted to represent images with lines and edges, and therefore is reported as a very good tool for lines/edges contrast enhancement, especially for noisy images [7]. In case of noisy electron microscope images with Kikuchi lines, its usage enables to achieve two goals simultaneously: line enhancement and not significant noise amplification.

The application of curvelet transform for contrast enhancement consists of the following three basic steps: 1) performing the forward curvelet transform, 2) modification of its coefficients using nonlinear function $f(x)$:

$$f(x) = \begin{cases} 1, & \text{if } x < c \\[1.5ex] \dfrac{x-c}{c}\left(\dfrac{m}{c}\right)^{p} + \dfrac{2c-x}{c}, & \text{if } c \le x < 2c \\[1.5ex] \left(\dfrac{m}{x}\right)^{p}, & \text{if } 2c \le x < m \\[1.5ex] \left(\dfrac{m}{x}\right)^{s}, & \text{if } x \ge m \end{cases} \qquad (3)$$

and 3) calculating the inverse transform. In (3) the p parameter determines the degree of non-linearity whereas s controls dynamic range compression. Nonzero value of s leads to enhancement of weak lines but the same time strong lines can be soften when this value is too high. In turn, the c parameter is a normalization factor. Its value is related to the noise standard deviation σ. If c is larger than 3σ then the noise will not be amplified. Finally, the m parameter determines the value under which curvelet transform coefficients are amplified. The value of m is derived from the maximum curvelet coefficient M of the relative band ($m < kM$, with $k < 1$). Exemplary outline of the $f(x)$ function is presented in figure 4 for $p = 0.5$, $s = 0.6$, $c = 3$, $m = 30$, (the dashed line is drown only as reference). All parameters' values have been chosen experimentally.
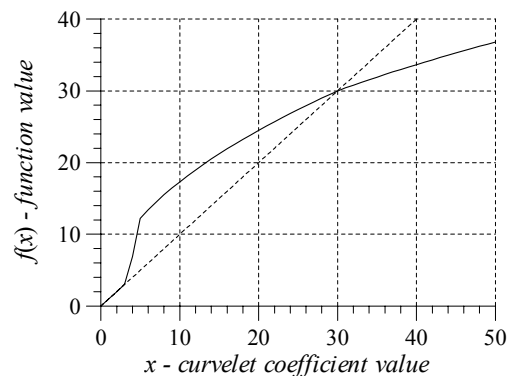

Fig. 4. The exemplary outline of the function $f(x)$ (3).

6. TUNED DIRECTIONAL FILTERING

The directional 2D filter is designed to meet the optimal conditions for a ridge (line) detection and fulfils the following criteria [8].

• *Signal-to-Noise Ratio* (*SNR*). The response of a filter $h(x, y)$ to a particular signal $f(x, y)$ (e.g. an idealised edge or ridge) cantered at the origin is equal:

$$M = \int_{R^2} f(x,y)h(-x,-y)dxdy \qquad (4)$$

M is given by the height of the response at its maximum. It is desired to have a high value of M.

• *Localization.* The estimated feature position corresponds to the maximum of the response in the direction orthogonal to the feature boundary. The localization term which is a measure of the width of the maximum (peak) is given by:

$$L = -\int_{R^2} f(x,y)h_{yy}(-x,-y)dxdy \qquad (5)$$

It is desired to maximize the L term.

• *Elimination of false oscillations.* The response should be relatively free from oscillations orthogonal to the feature boundary. This can be achieved by penalizing the term:

$$R = \int_{R^2}\left|h_{yy}(x,y)\right|^2 dxdy + \int_{R^2}\left|h_{xx}(x,y)\right|^2 dxdy \qquad (6)$$

The individual terms are combined to obtain a single criterion:

$$C = M \cdot L - \mu \cdot R \qquad\qquad .(7)$$

The filter that maximizes this criterion is our optimal filter. The parameter μ controls the smoothness of the filer and in consequence the level of oscillations along the ridge. The higher value results in a filter having less tendency to false maxima. The criterion (7) can be transformed to a matrix form and the optimal solution is found analytically by using Lagrange's multiplier method [8]. We have used 2D filter with $M = 2$ and $\mu = 0$ because this detector is better the than classical detector in terms of SNR and localization. The higher order detector would be more oscillatory and it could give more false detections. In our Kikuchi lines detection method the image is filtered by the directional filter tuned to a detected unpaired line and again processed with the Hough transform.

7. RESULTS

The whole algorithm has been implemented in Matlab and tested with and without the image processing techniques presented in the paper. The tests were carried out on 30 images having 312 Kikuchi bands (pairs of parallel lines), obtained from the Institute of Metallurgy and Materials Science of the Polish Academy of Sciences, Cracow, Poland. The final detection results are presented in table 3. The *standard* algorithm, taken also into account in the table, denotes the program that is routinely used by material science professionals at IMMS-PAS. This method exploits the Hough transform in a typical way and does not utilize advanced: 1) image pre-processing methods, 2) results verification and 3) searching for missing lines to pairs. Numbers of "true" and "false" lines, presented in the table, were evaluated by means of manual verification of automatic decisions (each "detected" line pair was manually verified whether it corresponds to a real Kikuchi pair on the image or not).

Tab. 3. Kikuchi bands detection results

Algorithm	Number of "true" line pairs	Number of "false" line pairs
Standard – used at IMMS-PAS	224 (71.8%)	36
Old – described in [1]	261 (86.2%)	2
[1] + contrast enhancement	**282 (90.4%)**	**4**
[1] + de-noising + contrast	**282 (90.4%)**	**2**
[1] + de-noising + contrast + pairs	**287 (91.9%)**	**2**

The obtained results confirm the fact that proper choice of image pre-processing methods has a big impact on effective Kikuchi bands detection. The most successful was addition of the carefully selected contrast enhancement techniques resulting in significant increase of detected "true" line pairs. In contrary, it turned out that additional sophisticated image de-noising causes only small reduction of the number of detected "false" line pairs (what is also very important in practise). Finally, 5 additional line pars were detected due to extra application of tuned directional 2D filters.

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