MVA '98 IAPR Workshop on Machine Vision Applications, Nov. 17-19, 1998, Makuhari, Chiba, Japan

13—20

Average Grain Size Determination using Mathematical Morphology and Texture Analysis

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Abstract

Many industrial processes need information about material grain size. In this work we examined rolled chrome concentrate to determine the average grain size. Test material was sieved into 15 fractions, from 37 μm to 500 μm.

The analysis method can be divided in three sections: preprocessing, feature extraction and classification. Mathematical morphology was used as preprocessing method, with gray-scale erosion and opening as operations. Feature extraction was implemented with first and second-order statistics. Finally, classification was performed with k-NN and minimum distance classifiers using leave-out method.

We conclude that mathematical morphology with texture analysis can be used to determine average grain size of material. It is computationally easy and fast although less accurate to smaller grain classes. This is due to imaging errors and noise but also the fact that the ratio grain size versus size of structuring element must be large enough.

Both opening and erosion operations can be used. Erosion is two times faster than opening to perform. Also the number of preprocessing operations can be, for example, reduced to three without the classification result will have a remarkable change.

1 Introduction

In process control the information about material grain size can be very important. Measurement method must be simple and fast but accurate enough so that it can be used to control the process.

Various methods have been introduced to solve the problem[1]. Traditional method is to use sieves of different size to mechanically separate different size grains. Other methods are for example Fourier analysis and ultrasonic attenuation[2]. Wang and Bergholm used moments to define individual grain edge density[3]. Previously, we have used distribution classification to define the average grain size[4].

Our idea is to find analogue method to mechanical sieving process. Mathematical morphology is the key method to solve this problem.

The analysis method can be divided in three sections: preprocessing, feature extraction and classification. Firstly, a global histogram equalisation was performed. This smooths the difference between the test images that is caused by asymmetrical light distribution and the ability of different size grains to reflect light. Mathematical morphology was used as preprocessing method, with gray-scale erosion and opening as operations (see Figure 1). Feature extraction was implemented with first and second-order statistics (altogether 21 features). Finally, classification was performed with k-NN and minimum distance classifiers using leave-out method.

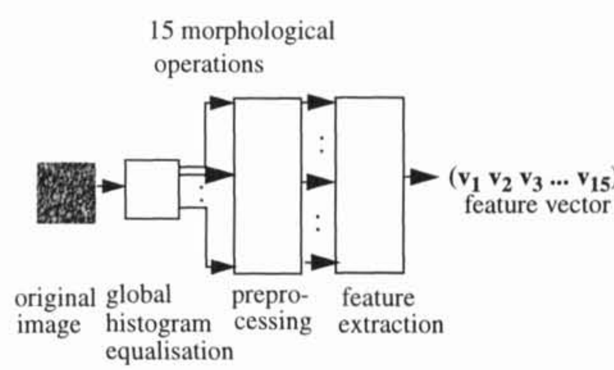

Figure 1. Preprocessing and feature extraction.

2 Background for the Experiments

2.1 Preprocessing

Gray-scale erosion and opening are used at the preprocessing stage. For every image 15 morphological (erosion or opening) operations were performed with different size disk structuring elements. The size of the elements was chosen to be closest to grain diameter upper boundary.

Figure 2a shows a function[5] that describes one line in

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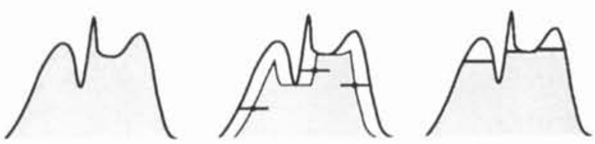
gray-scale image. The structural function is flat.

Typically gray-scale erosion darkens the image and particularly reduces lighter areas that are smaller than structure element (Figure 2b).

Gray scale opening effects only to areas that are smaller or equal size than structure element (Figure 2 c).



(a) (b) (c)

Figure 2. a) Function, b) its erosion and c) opening

2.2 Feature Analysis

The preprocessed images were analysed with first and second-order statistics. One image was taken as one sample. From each preprocessed image one scalar feature value was calculated using a single feature. Finally, all 15 feature values were converted to a feature vector that characterise the original image.

First-order statistics were calculated with Khoros 2 image processing software module called ***kstats***[6]. The following statistics were used: MEAN, VAR, SD, RMS, PSUM, MAXVAL, SKEW and KUR.

MEAN calculates the average of the image, VAR is the variance, SD is standard deviation and RMS is root mean square of image. PSUM is the sum of (positive) pixel values and MAXVAL is the maximum value of the image. SKEW is skewness that measures the asymmetry of pixel value distribution. Positive SKEW values means that distribution is more focused to positive values of x and vice versa. KUR is kurtosis that measures 'the heaviness of tail distribution'. Bigger values means broader distribution.

Co-occurrence features[7] are extracted from a co-occurrence matrix. This included the use of the EPQ method that smooths the histogram of the image[8]. The analysed image was converted to a region graph using a segmented method where the image was divided into squares. These were connected to other neighbour squares using 4- or 8-connection rule. Finally, the region graph was turned to sample set that includes the extracted feature values.

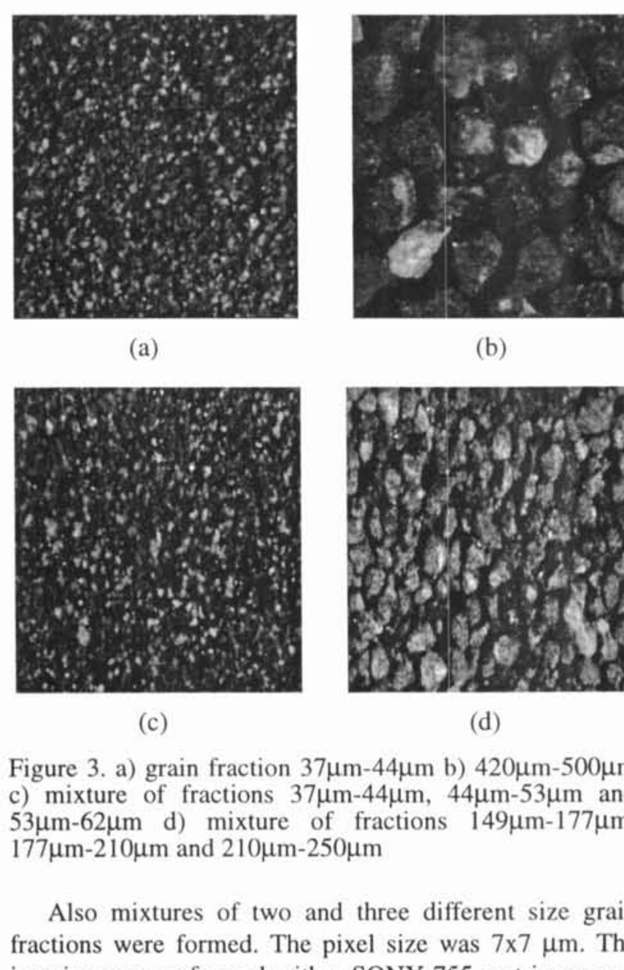
2.3 Classification

Classification was performed with minimum distance and k-NN classifiers using leave-out method.

3 Test Setups

The material was rolled chrome concentrate from where 15 fractions was separated with mechanical sieves. Sieving was performed according Tylers series, where the sieves change according to geometrical series. The diameter of grains range from 37 μm to 500 μm. Smaller classes are dust-like so individual grain boundaries cannot be clearly separated from each other.

The image database consists of over 500 images with size 488x512 pixels (see examples in Figure 3).



(a) (b)

(c) (d)

Figure 3. a) grain fraction 37μm-44μm b) 420μm-500μm c) mixture of fractions 37μm-44μm, 44μm-53μm and 53μm-62μm d) mixture of fractions 149μm-177μm, 177μm-210μm and 210μm-250μm

Also mixtures of two and three different size grain fractions were formed. The pixel size was 7x7 μm. The imaging was performed with a SONY 755 matrix camera and Datacube digitizer. A polarizer was used to eliminate reflections from flat grain surfaces.

Our test environment consists of SUN 20 workstation and KHOROS 2 image processing software with MMach morphology toolbox (version 1.2b)[9]. The material in leave-1-out tests included 60 images, 4 images per one grain class. The sample size was 488 by 512 pixels.

4 Results

4.1 Opening

Firstly, opening operation was tested as a preprocessing method. When calculating co-occurrence features the EPQ smoothing was used with k as 8. The three best results are presented in Table 1.

Table 1. Three best error rates with opening as the preprocessing method using co-occurrence features.

Feature	k-NN (k=1) Error rate (%)	k-NN (k=3) Error rate (%)	minimum distance classifier Error rate (%)
DV	30.00	36.67	51.67
IDM	30.00	33.33	46.67
IM1C	30.00	28.33	55.00

From 13 co-occurrence features best results (28,33%) gave IM1C feature when using k-NN classifier (k as 3). Nearly same results (30,00%) gave features DV, IDM and IM1C (k-NN classifier, value of k as 1).

From the confusion diagram (Figure 4) it can be seen that the worst results focus on the first four classes of samples.

TIP Confusion Matrix created out of an Sample Set
Confusion matrix has 60 samples
Confusion matrix has 15 classes
Total error is 28.33 %
Confusion matrix is:

	d_037-044um	d_044-053um	d_053-062um	d_062-074um	d_074-088um	d_088-105um	d_105-125um	d_125-149um	d_149-177um	d_177-210um	d_210-250um	d_250-297um	d_297-350um	d_350-420um	d_420-500um	
d_037-044um	3	.	1	.	.	.	.	.	.	.	.	.	.	.	.	25.0 %
d_044-053um	.	.	.	3	1	.	.	.	.	.	.	.	.	.	.	100.0 %
d_053-062um	.	1	3	.	.	.	.	.	.	.	.	.	.	.	.	25.0 %
d_062-074um	.	2	.	2	.	.	.	.	.	.	.	.	.	.	.	50.0 %
d_074-088um	.	.	.	.	4	.	.	.	.	.	.	.	.	.	.	0.0 %
d_088-105um	.	.	.	.	.	3	1	.	.	.	.	.	.	.	.	25.0 %
d_105-125um	.	.	.	.	.	2	1	1	.	.	.	.	.	.	.	75.0 %
d_125-149um	.	.	.	.	.	.	.	4	.	.	.	.	.	.	.	0.0 %
d_149-177um	.	.	.	.	.	.	.	.	4	.	.	.	.	.	.	0.0 %
d_177-210um	.	.	.	.	.	.	.	.	.	4	.	.	.	.	.	0.0 %
d_210-250um	.	.	.	.	.	.	.	.	.	2	1	1	.	.	.	75.0 %
d_250-297um	.	.	.	.	.	.	.	.	.	.	1	3	.	.	.	25.0 %
d_297-350um	.	.	.	.	.	.	.	.	.	.	.	.	4	.	.	0.0 %
d_350-420um	.	.	.	.	.	.	.	.	.	.	.	.	.	3	1	25.0 %
d_420-500um	.	.	.	.	.	.	.	.	.	.	.	.	.	.	4	0.0 %

undefined 0

Figure 4. Confusion matrix for feature IM1C (k-NN classifier when value of k is 3).

One reason for this is that for the smallest grain fractions the amount of pixel noise and geometrical image errors is relatively bigger than for the largest grain fractions.

The three best results with stats features are presented in Table 2.

Table 2. Three best error rates with opening as the preprocessing method using stats features.

Feature	k-NN (k=1) Error rate (%)	k-NN (k=3) Error rate (%)	minimum distance classifier Error rate (%)
MEAN	13.33	23.33	33.33
PSUM	13.33	23.33	33.33
RMS	16.67	31.67	46.67

The best results (13,33%) with stats features gave MEAN and PSUM features (k-NN classifier, k as 1). The second best results (16,67%) gave feature RMS with k as 1. The results of features MEAN and PSUM are identical. One reason for this is that their discrimination ability is equally good.

4.2 Erosion

Next step was to investigate erosion as a preprocessing method with the same test material as before. Table 3 presents the three best error rates with co-occurrence features.

Table 3. Three best error rates with erosion as the preprocessing method using co-occurrence features.

Feature	k-NN (k=1) Error rate (%)	k-NN (k=3) Error rate (%)	minimum distance classifier Error rate (%)
DE	21.67	36.67	50.00
IDM	21.67	23.33	46.67
IM1C	13.33	31.67	45.00

IM1C feature gave best results (13,33%) from co-occurrence features with k-NN classifier (k as 1). The second best results (21,67%) was obtained with features DE and IDM (k-NN classifier, k as 1).

Three best results with stats features are presented in Table 4. The best results (20,00%) gave features MEAN and PSUM (k-NN classifier with k as 1). The second best result (25,00%) was obtained with SD, also with k-NN classifier and k as 1.

If we compare opening and erosion as preprocessing methods we found that erosion gave better results with co-

Table 4. Three best error rates with erosion as the preprocessing method using stats features.

Feature	k-NN (k=1) Error rate (%)	k-NN (k=3) Error rate (%)	minimum distance classifier Error rate (%)
MEAN	20.00	36.67	41.67
PSUM	20.00	36.67	41.67
SD	25.00	38.33	43.33

occurrence features. On the other hand, opening with stats features was better than with co-occurrence features.

Computationally erosion takes only half of opening time. With 15 operations this time save is considerable.

4.3 Reduction of operations

So far we have used 15 preprocessing operations per image. The calculation time can be shortened if for example only three operations are used. Table 5 shows the effect when the number of preprocessing operations was reduced to three with PSUM feature. Only first, 8th and last preprocessing operation was performed. The value of k in k-nearest-neighbour classification was 1.

Table 5. The effect of reducing preprocessing operations to three with PSUM feature

Morphological operation	Error rate (%)
erosion	21.67
opening	31.67

The error rate is much bigger with opening operations than with erosion. This leads to conclusion that the reduction method can be used with erosion because error rate (21,67%) does not considerably differ from 15 preprocessing erosion operation error rate (20,00%).

5 Discussion

The number of samples per class is only four, because one image is one sample.

6 Conclusions

Morphology as preprocessing method can characterize average grain size of material. It is computationally easy and fast but less accurate to smaller grain classes. This is due to imaging errors and noise but also the fact that the ratio grain size versus size of structuring element must be large enough. In this way the morphological filtering, which is analogue to mechanical sieving, can be effective.

The same results can be achieved with opening and erosion operations. Erosion is two times faster than opening to perform. Also the number of preprocessing operations can be reduced, for example, to three without the classification result will have a remarkable change.

Acknowledgments

We wish to thank Outokumpu Oy for providing us rolled chrome concentrate.

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