Comparative Analysis of Spectral and Spatial Features for Classification of Graphite Grains in Cast Iron

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Abstract

The morphology and the distribution of graphite grains are the decisive factors in judging the properties of the material cast iron. There are six classes of graphite grain morphology defined by ISO-945 through reference drawings for cast iron graphite grain classification. These reference drawings are universally accepted for classification of graphite grains. Many shape representations and retrieval methods exist. Among them, methods based on Fourier descriptors (FD) achieve acceptable results in classification compared to other methods. Different shape signatures have been exploited to derive FDs, however, FDs derived from different signatures can have significant effect on the result of classification [17]. In this paper, a performance analysis of classification of graphite grains using spectral and spatial features is performed. The neural network classifier based on radial basis function has been employed for classification. The experimentation is carried out using the metallographic images from the well known microstructures library [6]. For training and testing the network, the grain shapes identified in ISO-945 reference drawings and the grain classification by the experts are used. The FDs derived from centroid distance function and neural network classifier with radial basis function yield better classification results for graphite grains.

***Keywords**: Shape, Fourier descriptors, Feed-forward network, Radial basis function, ISO-945.*

1. Introduction

Shape is one of the most important low level image features due to that shape is a very important feature to human perception. Shape classification involves three primary issues: shape representation, shape similarity measure and shape indexing. Among them, shape representation is the most important issue in shape retrieval. Various shape representation methods, or shape descriptors, exist in the literature, these methods can be classified into two categories: region based versus contour based [7]. In region based techniques, all the pixels within a shape are taken into accounted to obtain the shape representation [5]. Common region based methods use moment descriptors to describe shape. Region moment representations interpret a normalized gray level image function as a probability density of a 2D random variable [3,10]. The first seven invariant moments, derived from the second and third order normalized central moments, are given by Hu [4]. Because moments combine information across an entire object rather than providing information just at a single boundary point, they capture some of the global properties missing from many pure contour-based representations: overall orientation, elongation, etc. The first few terms of the invariant moments, like the first few terms of a Fourier series, capture the more general shape properties while the later terms capture finer detail. However, unlike Fourier series, it is difficult to obtain higher order invariant moments and relate them to shape. Comparing with region based shape representation, contour based shape representation is more popular. Contour based shape representation only exploit shape boundary information, these representation methods can be classified into global shape descriptors, shape signatures and spectral descriptors. Although simple to compute and also robust in representation, global descriptors such as area, circularity, eccentricity, axis orientation can only discriminate shapes with large dissimilarities. Most shape signatures such as complex coordinates, curvature and angular representations are essentially local representations of shape features, they are sensitive to noise and not robust. In addition, shape representation using shape signatures require intensive computation during similarity calculation, due to the hard normalization of rotation invariance. As the result, these representations need further processing using spectral transform such as Fourier transform and wavelet transform. Spectral descriptors include Fourier descriptors (FD) and wavelet descriptors (WD), they are usually derived from spectral transform on shape signatures.

With Fourier descriptors, global shape features are captured by the first few low frequency terms, while higher frequency terms capture finer features of the shape. Apparently, the Fourier descriptors, not only overcomes the weak discrimination ability of the moment descriptors and the global descriptors but also overcome the noise sensitivity in the shape signature representations. Other advantages of FD method include easy normalization and information preserving.

Many FD methods have been reported in the literature, these include using FD for shape analysis [17], character recognition [8], shape coding [18], shape classification [19]. In these methods, different shape signatures have been exploited to obtain FD. In [20], for classification of six classes of graphite grains, FDs are derived from four shape signatures, namely, complex coordinates, centroid distance, curvature signatures and cumulative angular function. However, FD derived from different signatures has significant different effect on shape retrieval. In this paper, we compare graphite grain shape classification using FDs derived from different shape signatures that are discussed in [20] along with one more feature, namely, the cumulative angular function that is discussed in [21]. The signatures considered are central distance, complex coordinates, curvature function and cumulative angular function. The experimental results demonstrate the efficiency of the proposed work.

1.1 Classes of Grains in Cast Iron

The thermo-mechanical properties of cast-iron are strongly dependent on the shape of graphite grains. The nodular cast iron, in which the particles are merely spherical in shape, is normally less brittle than gray iron, where sharp graphite flakes contribute to stress concentration and crack initiation. Thus it is relevant to classify cast iron according to graphite grain shape. The ISO-945 standard defines six classes for cat iron, based on graphite grain shape. These classes are shown in Figure 1. In the manual method, expert chooses the correct class through visual comparison with the reference drawings. Manual method produces varying results in many cases. Instead, the digital image processing and analysis method produces consistent and accurate results [14].

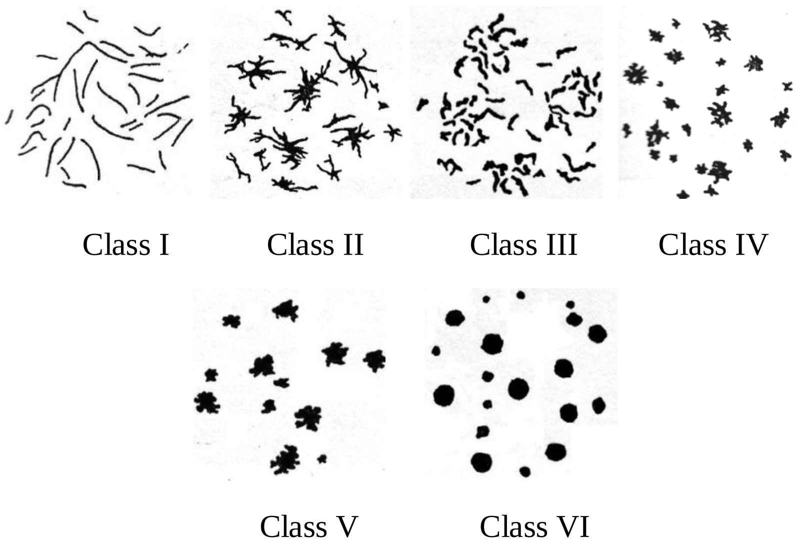


Figure 1. Reference Drawings for the ISO-945 Defined Six Classes of Grains in Cast Iron.

The Figure 2 shows the actual microstructure images of cast iron used for testing.

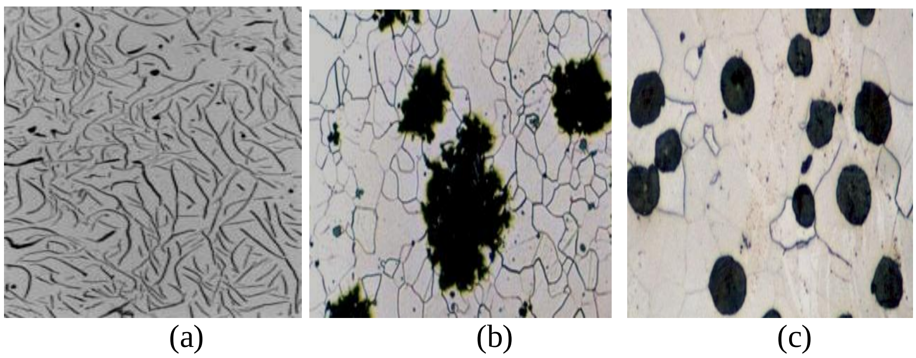


Figure 2. Microstructure Images and Various Grain Shapes in Actual Material Sample Images.

1.2 Materials and Methods

All methods presented in this paper were evaluated and tested on micrographs of cast iron that are obtained using light microscope. The light microscope remains the most important tool for studying microstructure of metallic materials. The images are drawn from microstructure libraries [6]. The etching medium used in the preparation of the specimen is 3% alcoholic nitric acid. The microstructure images used in testing phase are of various compositions and magnifications. In the training phase, the ISO 945 proposed reference drawings of grain morphology [2] of six classes are used for building the knowledge base for the proposed work.

2. Proposed Method

The shapes we consider in this paper are outline shapes which can be described as single plane closed curves. The purpose of the proposed system is to identify six types of graphite grains efficiently using spatial and spectral features using neural network classifier. The Figure 3 shows the frame work of the proposed system.

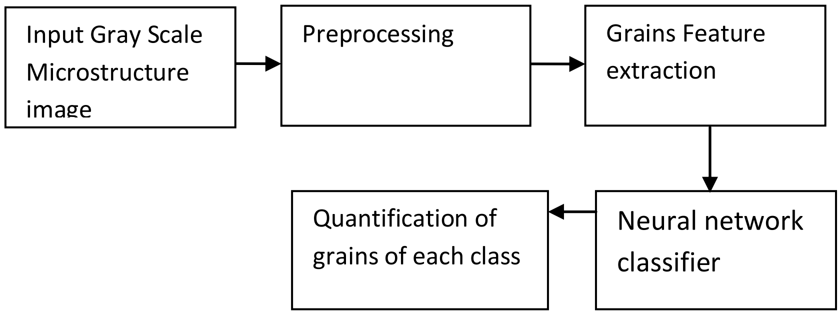


Figure 3. Framework of Proposed System

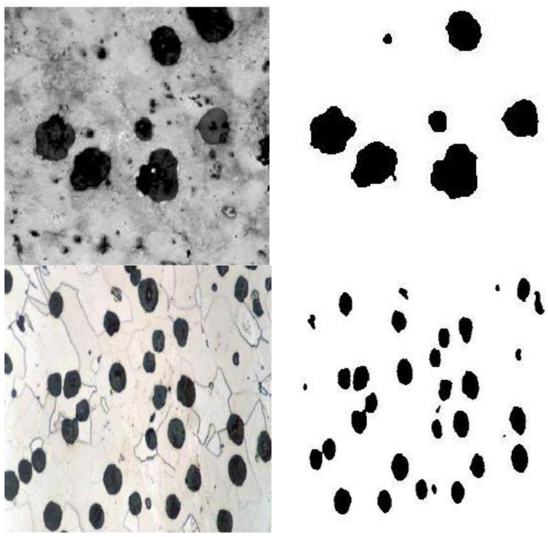
2.1 Preprocessing

Training images:

The scanned images of ISO-945 proposed reference drawings are used as training images, which are shown in the Figure 1. These scanned images are generally free from noise and are stored in JPEG format. These images are converted to gray scale images and then to binary images by global thresholding [1]. The black graphite grains get segmented from the white background. The segmented image is labeled. Each labeled segment is a reference grain structure, which is subjected to extraction of the shape features.

Test images:

Test images are the actual microstructure images acquired from light microscope. Generally, these microstructure images suffer from noise and artifacts developed at the time of specimen preparation. The preprocessing of microstructure images is of very important step in achieving good results in the further analysis of microstructure images. Particularly, in the present work, the grain boundaries must be very clear for identification and quantification processes. Active contour method with initialization of multigrid model is used for segmentation. The output from the segmentation method is a binary image which is used for labeling and feature extraction. The Fig. 4 shows the results that are obtained after these preprocessing operations. The border touching grains are eliminated in quantification process.



(a) (b)

Figure 4. (a) Original Microstructure Image, (b) Segmented Binary Image.

Label the segmented binary image. Each labeled segment's boundary is traced using a 8-connectivity contour tracing technique to obtain the shape boundary coordinates [3]. The set of coordinates (x(t), y(t), t=0,1,2,,…L-1), obtained by tracing the boundary of the segmented grains (object) are used to generate shape signatures.

3. Shape Signatures

A shape signature is a 1-D function representing 2-D boundaries. Four shape signatures are considered in this paper, namely, complex coordinates, central distance, curvature and cumulative angular function.

3.1 Complex Coordinates

A complex coordinates function is simply the complex number generated from the boundary coordinates:

$$z(t) = x(t) + iy(t) \tag{3.1}$$

For suppressing the bias in eq. (3.1) and make the shape representation invariant to translation, shifted coordinates function is used and it is given in eq. (3.2).

$$z(t) = [x(t) - xc] + i[y(t) - yc] \tag{3.2}$$

where (x_c, y_c) is the centroid of the shape, which is the average of the boundary coordinates and it is given as,

.
$$x_c = \frac{1}{L}\sum_t^{L-1} x(t), \quad y_c = \frac{1}{L}\sum_t^{L-1} y(t) \tag{3.3}$$

3.2 Centroid Distance

The centroid distance function is expressed by the distance of the boundary points from the centroid (x_c, y_c) of the shape is given in eq. (3.4).

$$z(t) = ([x(t) - x_c]^2 + i[y(t) - y_c]^2)^{\frac{1}{2}} \tag{3.4}$$

The centroid distance representation is invariant to translation.

3.3 Curvature Signature

Curvature represents the second derivative of the boundary and the first derivative of the boundary tangent. The curvature function given in [19] is defined as the differentiation of successive boundary angles calculated in window *w*,

$$K(t) = \theta(t) - \theta(t-1) \tag{3.5}$$

where

$$\theta(t) = \arctan\left\{\frac{y(t) - y(t-w)}{x(t) - x(t-w)}\right\} \tag{3.6}$$

however, this curvature function defined in this way has discontinuities at size of 2π in the boundary, therefore, the eq. (3.7) is used.

$$K(t) = \varphi(t) - \varphi(t-1) \tag{3.7}$$

where $\varphi(t)$ is defined as in eq. (3.8). The curvature function is invariant under translation and rotation.

3.4 Cumulative Angular Function

The shape also can be represented by boundary angles, but due to that the tangent angle function $\theta(t)$ as in eq. (3.6) can only assume values in the range of length 2π, usually in the interval of [$-\pi,\pi$] or [$0,2\pi$]. Therefore $\theta(t)$ in general contains discontinuities of size 2π. Because of this, a cumulative angular function is introduced to overcome the discontinuity problem. The cumulative angular function is defined by Zahn and Roskies [21] is the net amount of angular bend between the starting position z(0) and position $z(t)$ on the shape boundary,

$$\varphi(t) = [\theta(t) - \theta(t-1)] mod(2\pi). \quad (3.8)$$

A normalized cumulative angular function $\psi(t)$ is used as the shape signature, assuming the shape is traced in anti-clockwise direction.

$$\psi(t) = \varphi\left(\frac{L}{2\pi}\, t\right) - t \quad (3.9)$$

4. Discrete Fourier Descriptors

Fourier transformation on shape signatures is used for shape analysis. The Fourier transformed coefficients form the Fourier descriptors of the shape. These descriptors represent the shape of the object in a frequency domain. The lower frequency descriptors contain information about the general features of the shape, and the higher frequency descriptors contain information about finer details of the shape. Although the number of coefficients generated from the transform is usually large, a subset of the shape. The very high frequency information describes the small details of the shape, it is not so helpful in shape discrimination, therefore, they can be ignored. As the result, the dimensions of the Fourier descriptors used for shape recognition are significantly reduced.

For a given shape signature described in section 3, $s(t), t = 0,1,\ldots,L$, assuming it is normalized to N points in the sampling stage, the discrete Fourier transform of $s(t)$ is given by

$$u_n = \frac{1}{N}\sum_{t=0}^{N-1} s(t)\, exp\left(\frac{-j2\pi nt}{N}\right), n = 0,1,\ldots N-1$$

The coefficients $u_n, n = 0,1,\ldots N-1$, are usually called Fourier descriptors (FD) of shape, denoted as $FD_n, n = 0,1,\ldots N-1$. Rotation invariance of the FDs are achieved by ignoring the phase information and by taking only the magnitude values of the FDs.

For complex coordinates signature, all the N descriptors except the first one i.e. DC component are needed for shape recognition. The DC component depends only on the position of the shape, it is not useful in describing shape thus is discarded. Scale normalization is achieved by dividing the magnitude value of the second descriptor. The invariant feature vector used to represent a shape is given as,

$$f = \left[\frac{|FD_2|}{|FD_1|}, \frac{|FD_3|}{|FD_1|}, \ldots\ldots, \frac{|FD_{N-1}|}{|FD_1|}\right]$$

For centroid distance signature and curvature signature only $N/2$ different frequencies in the Fourier transform, therefore, only half of the FDs are needed for recognition of the shape. Scale invariance is achieved by dividing the magnitude values of the first half of FDs by the DC component. The invariant feature vector used to represent a shape is given as,

$$f = \left[\frac{|FD_1|}{|FD_0|}, \frac{|FD_2|}{|FD_0|}, \ldots\ldots, \frac{|FD_{N/2}|}{|FD_0|}\right]$$

The periodic cumulative angular function of (3.9) is itself invariant under translations, rotations and scales [8], therefore, the FDs derived from this signature can be directly used to index the shape. Also due to its real value, only half of the FDs including the DC component is needed to index the shape. The feature vector to index the shape is then,

$$f = \left[|FD_0|, |FD_1|, \ldots, |FD_{N/2}|\right]$$

The four FDs that are formed using four shape signature functions, namely, complex coordinates, centroid distance, curvature signature and cumulative angular function are used to train the feed-forward neural network for shape identification.

Neural Network Classifier. We use the neural network classifier for grains classification in the segmented image. In the radial basis neural network, the shape features are used as inputs. The error function is 'mean square error(mse)' which is set to 0.15. The spread for radial basis function is 1.0 and the maximum number of neurons allowed to add during training is 300. The input layer has the number of neurons equal to the number of FDs and output layer has one output (grain class number). For each of the signature a separate radial basis network is configured. The training and classification phases of neural network are given in the following algorithms.

Phase 1: Neural network training

Step 1: Input grayscale microstructure image (training image).

Step 2: Perform segmentation by active contour method. The segmented regions are known grains. Label the segmented image.

Step 3: Compute the four types FDs (complex coordinates, centroid distance, Curvature and cumulative angular function) for each labeled region (grain), which are of known grain-class.

Step 4: Repeat the steps 1 to 4 for all training images.

Step 5: Input the shape features computed in step 3 as inputs to the three separate neural networks.

Phase 2: Neural network classifier

Step 1: Input grayscale microstructure image (test image).

Step 2: Perform preprocessing (averaging, morphological operations) and apply active contours segmentation method and obtain segmented image.

Step 3: Label the segmented image.

Step 4: Compute the FDs (complex coordinates, centroid distance, curvature and cumulative angular function)for each labeled region.

Step 5: (Classification)
Input the FDs computed in step 3 for a region to the neural network which is trained using the Algorithm 1 for grains classification.

Step 6: The output of neural network indicates the grain class to which the region belongs.

Step 7: Repeat steps 4 and 5 for all regions of the segmented image.

5. Experimental Results and Discussion

For the experimentation, the neural network is trained using six ISO 945 reference drawings with six grain classes [2]. The grain class I,II,III,IV,V and VI contain 35,18,53,24,19 and 19 grains, respectively. The images are of size 525x525 and the sample images are shown in the Figure1. During the testing phase, 50 microstructure images, each with grains of different types containing 25 grains on an average, are used. These images are drawn from the microstructure library [4] and the sample microstructure images are shown in the Figure 2. The neural network is trained using six ISO-945 reference drawings with six grain classes. The original drawings are scanned and images are stored in JPEG format. The Fourier shape descriptors are used as inputs for the neural network. The radial basis transfer function is used for training. The error function is MSE which is set to 0.01. The spread for radial basis function is 1.0.

During the testing phase, various microstructure images, each with grains of different types containing graphite grains are used. These images are drawn from the microstructure library [6]. The results of classification with the help of FDs derived from four different shape signatures namely, complex coordinates, centroid distance, curvature functions and cumulative angular functions have been compared. The results show that the classification using FDs derived from centroid distance signature is significantly better than that using FDs derived from the other two signatures. The results also compared with the classification achieved in [9,10,11] using the shape features determined in spatial domain. An improved rate of classification is observed in the case of FDs derived from centroid distance function that were determined in spectral domain. The results are shown in Table 1 and Fig. 4. The property that centroid distance captures both local and global features of the shape. It is robust and information preserving.

Table 1. Classification Rate of Six Classes of Grains

Features	Classification Rate %						
	Class I	Class II	Class III	Class IV	Class V	Class VI	Average
FDs(Complex Coords.) [20]	90	88	87	88	81	85	86.50
FDs(Centroid Dist.) [20]	98	94	93	94	95	100	95.66
FDs (Curvature) [20]	95	80	78	80	86	92	85.16
FDs (Cumulative angular function	98	96	95	94	94	100	96.16
SSDs [10,11]	92	91	89	88	88	93	90.16
MIs [10]	96	93	93	92	90	98	94.00

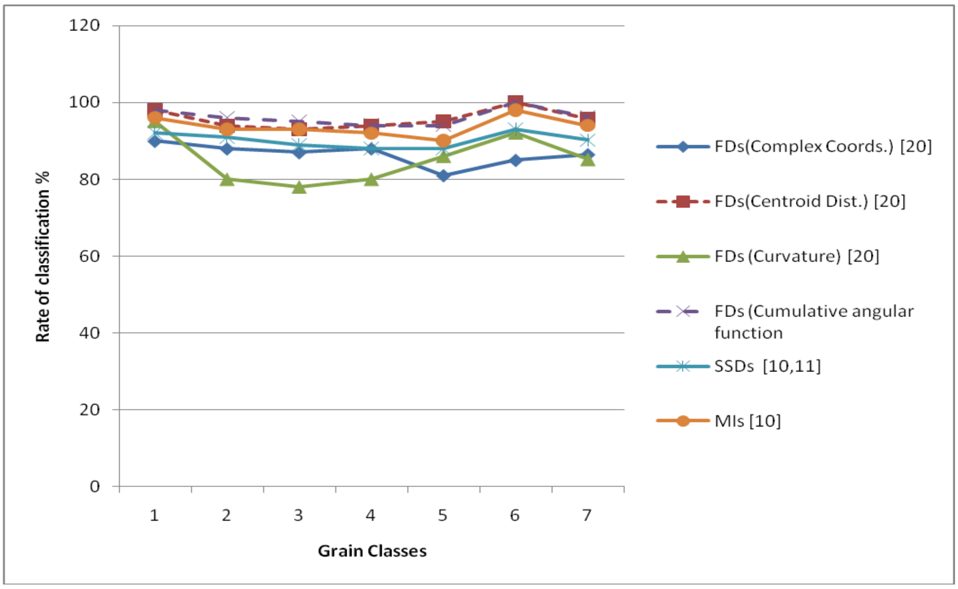


Figure 4. Comparison of Classification Performance of Four FDs,SSDs and Moment Invariants.

6. Conclusion

A comparative study classification using four Fourier descriptors derived from four different shape signatures is performed. The outcome of study show that the classification of graphite grains from microstructure of images of cast iron using FDs derived from centroid distance signature and cumulative angular function are close to each other and significantly better than the FDs derived from the other two signatures. Also, the rate of classification of individual class is much better than the classification made with SSDs and moment invariants that are computed in spatial domain. Therefore, it is clear from our studies that, the shape features of spectral domain yields better results compared to shape features of spatial domain.

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