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Grain size measurement in optical microstructure using support vector regression

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ABSTRACT

The objective of this study is to develop an image processing algorithm to determine the average grain size in a metallic microstructure by counting the number of grains using support vector regression (SVR). Automatic grain size measurement algorithm is implemented in the microstructural analysis to attain high speed along with accuracy than manual methods The grain boundaries of various metals were determined using Otsu and canny edge detection techniques. The edge detected image is divided into blocks and the number of white to black transitions in each block is used as feature. The extracted features are used to train the support vector machine in regression mode. The number of grains in test image is determined using support vector regression. The accuracy of developed algorithm is verified using the manual intercept method. The experimental results show that the canny edge detection based feature extraction achieves low root mean square error (RMSE) when compared to Otsu method for detecting the grain count.

1. Introduction

Microstructure of a metal describes the structure of grains and its boundaries (interface between two grains) arranged at higher magnification (>25×) observed under an optical microscope. Microstructural analysis is performed by material scientists to determine the nature of grain and its orientation, grain boundary, grain size and its count. Identification of boundaries in metallic microstructure is tedious, as the grain boundaries are not well defined [1]. The boundary of the grain characterizes the size of the grain, and which influences the mechanical properties of the metals viz., strain, ductility and resistance to stress. Image processing in the field of material science is a relatively new research area gaining importance nowadays. Image processing technique improves the visual appearance of the microstructural images to compute the features and structures present, thereby improving reproducibility and repeatability [1].

Various researchers employed automatic methods and mathematical morphologies to determine the features present during processing of metals. Dutta et al. [2] adopted automatic texture and fractal analysis to analyze the fracture surface of HSLA steel. Coster et al. [3] determined the grain boundaries of Ceria during sintering process employing top-hat transformation. Dengiz et al. [4] employed neural network and fuzzy logic algorithms to detect the grain boundary of steel alloys. Colás [5] and Maropoulos et al. [6] reported the relationship between grain size and thermal treatment in stainless steel and low alloy steel respectively. Tarpani and Spinelli [7] correlated the nature of fracture with the grain size during Charpy impact

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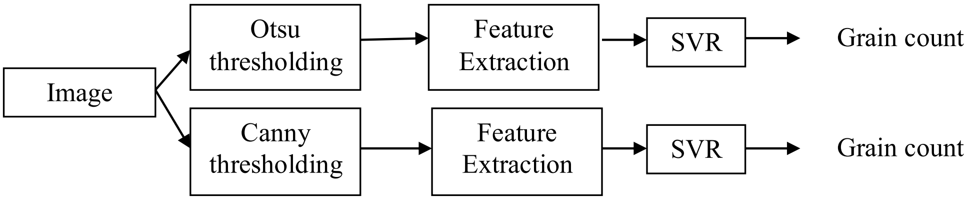

Fig. 1. Work flow diagram for counting the grain in an optical microstructure.

test. Lu et al. [8] proposed a grain boundary identification procedure by processing two input polarizing images. Though, earlier researchers [9] employed image processing techniques in microstructural analysis, the studies on the determination of grain boundary and its size of an optical metallic microstructure using support vector machine-regression (SVR) is scarce, and is attempted herein.

In this study, a novel approach to determine the grain size of various metals, employing SVM regression technique, accounting the ASTM E112-13 standard is attempted. Further, the grain boundaries of metals are detected using Otsu and canny thresholding techniques. Experimental analysis based on three state-of-the-art data sets for the microstructural images are evaluated. In addition, the grain size of various metals is determined physically using intercept method [19], and employed as target value for regression technique.

2. Perception and description

2.1. Methodology overview

The detailed procedure of determining the grain count and its size of a metallic microstructure obtained from an optical microscope is given in Fig. 1. Preprocessing steps were performed on the images collected in the database, followed by conversion of images into Otsu and canny images. From the Otsu and canny edge detected images, number of white to black transition in each block of the image is extracted and it is used as features. The features are subjected to SVM-Regression through 'k' fold training and testing, and the error between manual count and predicted value is determined through root mean square error (RMSE).

2.2. Data set

The rapid development of computer vision and pattern recognition technologies is applied in detecting and accountability of grains in a metallic microstructure. The optical microstructures of various metals were determined following standard metallurgical practices viz., grinding, polishing and etching in an optical microscope (VERSAMAT–3) equipped with Clemex image analyzing system and stored in an image database. The microstructural images of different metals viz., aluminum, copper, different grades of stainless steel and brass were collected from the Department of Manufacturing Engineering, Annamalai University to create an unbiased image database. The database consisits of 100 microstructual images. The proposed algorithm automatic grain size dertemination is implemeted in matlab using a system with a 2.50 GHz Intel core i5 processor.

2.3. Otsu thresholding

The identification of grain boundaries or region of interest in gray level image is determined using Otsu thresholding. Otsu thresholding performs clustering, based on image thresholding, or the reduction of a gray level image to a binary image is utilized for the determination of region of interest [10].

2.4. Canny edge detection

Edge detection, a multi stage process, is a powerful technique employed by earlier researchers to determine the region of interest for images having abrupt changes in intensity. The objectives of canny technique viz., lower error rate, edge points should be well localised and single edge point response were achieved by (a) smoothening using Gaussian filter, (b) computing the gradient magnitude (c) double thresholding and (d) detecting connectivity and link edges [11].

2.5. Feature extraction

Feature represents the part of information relevant for solving the computational task related to a certain application. In this work, Otsu/canny edge detected image is divided into blocks. Number of white to black transitions in each block is counted automatically, and it is used as feature.

2.6. Support vector machine-regression (SVR)

The primary objective of SVR is to determine a function that approximates target values, accurately, by mapping the training data from the input space to a high dimensional feature space through a function ‘Φ’, followed by constructing a separating hyperplane with utmost margin within the feature space [12–15].

Consider a set of training data $\{(x_1,y_1),\ldots\ldots(x_i,y_i)\}$, where each x_i R^n, denotes the input space of the sample and has a corresponding target value $x_i \subset R$ for i = 1,2. . . . l, where l corresponds to the size of the training data. The generic SVR estimating function takes the form

$$f(x) = (w.\Phi(x)) + b \tag{1}$$

Where, $W \subset R^n$, $b \subset R$, and Φ denotes a nonlinear transformation from R^n to high-dimensional space. Our goal is to find the value of ω and b such that values of x can be determined by minimizing the regression risk

$$R_{reg}(f) = C\sum_{i=0}^{l}\Gamma(f(x_i) - y_i) + \frac{1}{2}\|w\|^2 \tag{2}$$

Where Γ(.) is a cost function, C is a constant, and vector ω can be written in terms of data points as

$$w = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\Phi(x_i) \tag{3}$$

By substituting Eq. (3) into Eq. (1), the generic equation can be rewritten as

$$\begin{aligned} f(x) &= \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)(\Phi(x_i).\Phi(x)) + b \\ &= \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)k(x_i, x) + b \end{aligned} \tag{4}$$

In Eq. (4), the dot product can be replaced with function, known as the kernel function. Kernel functions enable the dot product to be performed in high-dimensional feature space using low-dimensional space data input without knowing the transformation. All kernel functions must satisfy Mercer’s condition that corresponds to the inner product of some feature space.

3. Results and discussion

3.1. Microstructural images

Hundred numbers of optical microstructural images of varied metals viz., low carbon steel, copper, stainless steel, aluminum and brass at 100× magnification were collected and stored to create an unbiased database. Microstructures were resized to 240 pixels × 240 pixels to extract equal number of features and thereby determining the grain count and its size. For determination of grain count and its size of a low carbon steel (LCS) microstructure shown in Fig. 2 is used in this study.

3.2. Otsu thresholding

Determination of grain boundaries in a low carbon steel microstructure (Fig. 2) is complex owing to wide variation in gray values observed in the histogram as shown in Fig. 3(a). The wide variation leads to difficulty in determination of a threshold (t) which allows an accurate discrimination, being resolved by automatic thresholding [10], a level simplification method, which determines the vanished grain boundaries as observed in Fig. 3(b). Fuang [10] employed automatic thersholding to detect defects in an object, while Nobis and Hunziker [16] used the same to determine the difference between the sky and canopy after a storm.

3.3. Canny edge detection

In addition, canny edge detection technique-a multi-stage algorithm is employed to detect edges in the LCS microstructure and correlated with Otsu technique. Canny image extracts the boundaries of the microstructure and complemented to determine the accurate grain count by removing false edge segments formed due to noise and fine texture. Further, Canny edge detector is used to remove the mixed edges. Expanding (dilating) the edge pixels identified by the canny edge detector into their immediate neighborhood creates a transitional buffer zone around the edge pixels. The canny edge tech-

Fig. 2. Microstructure of low carbon steel.

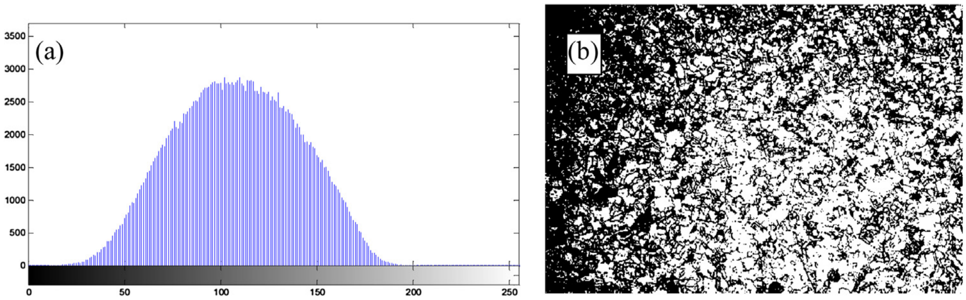

Fig. 3. (a) Histogram of low carbon steel. (b) Binary image using Otsu thresholding.

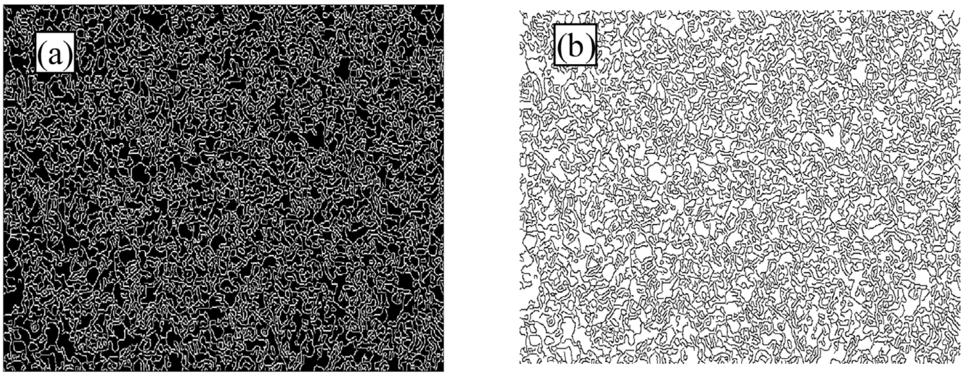

Fig. 4. (a) Canny edge image. (b) Complemented Canny Edge Image.

nique detects the grain boundaries of LCS microstructure in the form of white pixels (Fig. 4(a)), and the detected image is complemented to determine the grain boundaries as shown in Fig. 4(b).

3.4. Feature extraction

The Otsu and canny edge detected images for all the images in the unbiased database are collected and considered for extracting features as described below.

1. Edge detected image is segmented into n horizontal and n vertical blocks

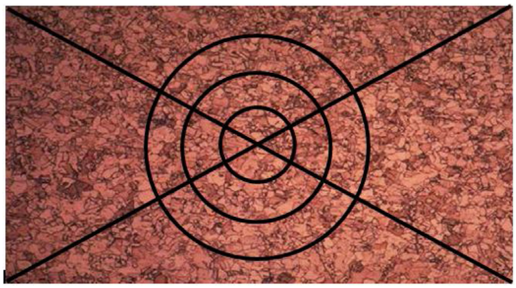

Fig. 5. Grain count determination using Intercept method.

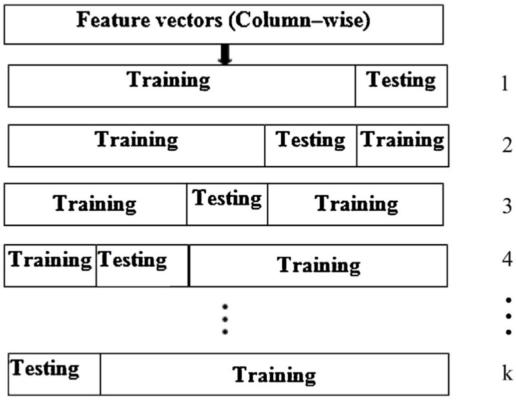

Fig. 6. k-fold Testing strategy.

2. Number of white to black transition in each block is counted automatically and it is used to create a 2n dimensional feature vector for an image.

The determination of number of grains in each microstructure is performed by SVM regression technique [17,18] which demands two inputs viz., target value determined by intercept method detailed below and the extracted feature vectors.

3.5. Intercept method

The manual grain size determination of a metal is influenced by numerous factors viz., surface irregularities, lighting conditions, capability of capturing device and external factors which leads to errors in visual inspection of personnel involved. The size of grain is determined by three principle methods viz., matching, planimetric and intercept methods [8–10]. The matching method is based on the greatest similitude between the sample and a chart of sizes whereas, planimetric and intercept methods consider the amount of grains prevailing inside a defined test area. The ASTM standard E112-13 [19] recommends planimetric and intercept methods for a higher degree of accuracy. In this study, intercept method is implemented on a low carbon steel (LCS) microstructure (Fig. 5) for determining the grain size and is counted physically (observed vector for regression), as recommended by Guisan et al. [13]. The average size of grain (G) in metals depends on the number of grains mean intercept per unit length (N_L) defined by [20]

$$G = 523.2877 + 16.6439\log 10\, N_L \quad (5)$$

3.6. SVR training and testing

The feature vectors extracted from the Otsu and canny images are stored in the unbiased database for training and testing to determine the grain count of each image as per the procedure given in Fig. 6. The preliminary training creates a new model for a feature set, which is used as model for testing all other features in the database employing 'k' fold method [17]. In each fold, 80% of the samples are used for training and the remaining 20% of the samples are used for testing. Five-fold testing strategy is used in this study. Hence there are 100 testing feature vectors.

In this study, 5 fold is used for training and testing, and thereby, 20 images are tested and their grain counts were determined at any point of time by regression technique. 80 out of 100 images stored in the database were used for training, while the remaining 20 images were employed for testing. Similar steps were performed for all the images stored in the database. Different combinations of images viz., aluminum, copper and different grades of steel were tested by leave one out

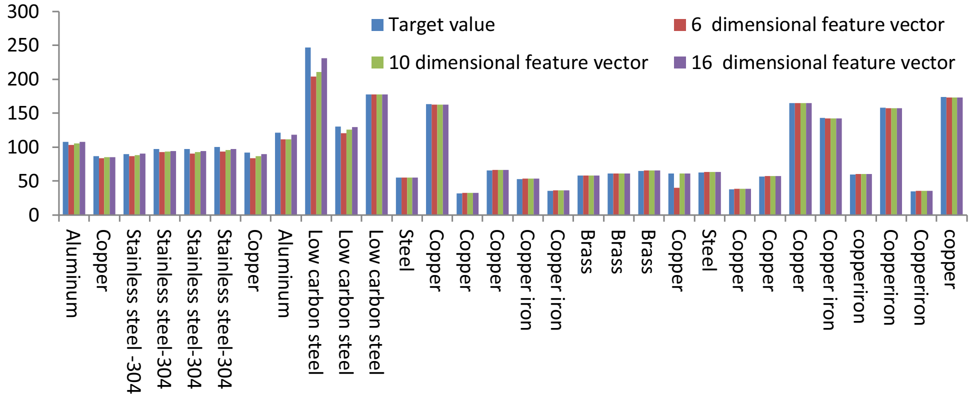

Fig. 7. Number of grains in different metals using Otsu technique.

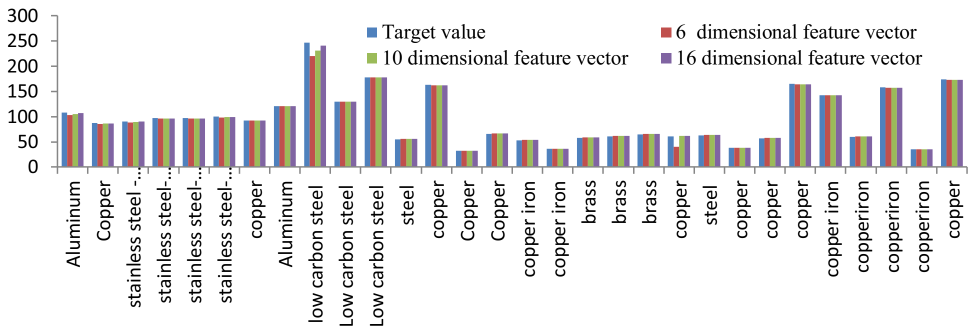

Fig. 8. Number of Grains in different metals using canny technique.

Table 1
Number of grains in LCS by Intercept method for a sample image.

Technique	Grain count	Grain size (μm)
Intercept Method	246	2.6

Table 2
Number of grains in LCS with different features using Otsu and canny technique for a sample image.

Techniques	Grain Count				Grain size (μm)
	Six features	Ten features	Sixteen features	Twenty features	
Otsu Technique	210	220	240	240	2.1
Canny edge Technique	215	230	244	244	2.5

(LOO) process. In addition, the number of grains in each microstructure stored in the image database is physically counted by implementing circular intercept method (detailed in Section 3.5), and employed as target value, y (data set) for implementing regression. In addition the influence of feature set size on the accuracy of grain count prediction by training and testing is attempted and is detailed below.

3.6.1. *Influence of feature size*

Feature sets-a structured approach is chosen with different dimensionality viz., 6 [3 horizontal X 3 vertical], 10 [5 horizontal X 5 vertical] 16[8 horizontal X 8 vertical] as recommended by Antonelli [20], who concluded that, the size of feature set influence the accuracy of the predicted value. In the six dimensional feature set, three features are collected from the horizontal and vertical direction respectively for each image. Similarly, ten and sixteen dimensional features are collected for all the Otsu and canny images stored in the data base. After execution, three feature sets {6 (100 × 6), 10(100 × 10) and 16 (100 × 16)} for each Otsu and canny image is available in the database.

The number of grains in different metallic microstructures with six, ten and sixteen dimensional features using Otsu and canny edge detection techniques is shown in Figs. 7 and 8 respectively. The number of grains and the average size of low carbon steel (Fig. 2) determined by Otsu and canny edge detection technique with six, ten and sixteen dimensional features are shown in Table 2, while Table 1 shows the number of grains and average grain size by manual intercept method.

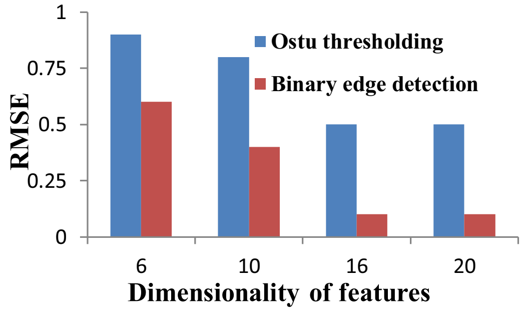

Fig. 9. RMSE for binary and canny images.

The performance of the method is evaluated using root mean square error (RMSE) is given by [21]

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(y_i - y_i^*)^2}{n}} \tag{6}$$

Where y_i is the target grain count and y_i^* is the predicted grain count.

The RMSE for canny edge detection technique is lower than Otsu technique for all six, ten and sixteen dimensional feature sets. Otsu method neglects few grain boundaries leading to reduction in grain count and enhancement in error. Canny edge detection results in more accurate prediction than Otsu method irrespective of feature sets as the canny edge detection detects all the edges of grains. The grain boundaries are clearly defined while employing canny edge detection method (Fig. 4), thereby resulting in prediction of accurate grain count and consequently grain size. In addition, when the number of features (dimensionality) increases to sixteen, canny edge detection holds a lower error percentage (0.1) and a better prediction as shown in Fig. 9. Canny edge detection with 16 dimensional feature vectors results in very closer approximation to the manual intercept method. Further increase in dimensional feature vectors shows no significant variation in prediction for both Otsu and canny techniques. Zhang et al. [22] who measured the grain size of aluminum alloy, opined that the deviation between the proposed method and the manual method should be less than 10%. The implementation of Otsu and canny edge techniques on grain size and grain count measurements overcomes the human errors viz., inaccurate test length measurement, miscounting, and so forth with minimum processing time (<50 s).

4. Conclusion

The grain size of a metallic microstructure employing support vector regression is proposed in this study. The following salient conclusions are drawn from this experimental study. Support vector regression can effectively be employed in predicting the grain size in a metallic microstructure. Canny edge detection technique provides closer prediction than Otsu technique. Sixteen dimensional features results in closer prediction of grain count and size. The root mean square error between manual grain count and the predicted value is less than 5%, if the canny edge image is used for determining the grain count.

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