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AUTOMATIC MICROSTRUCTURE GRAIN COUNT USING SUPPORT VECTOR REGRESSION

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ABSTRACT

Grain count determination is an important task in microstructural analysis, requires long time while performing manually. Nowadays, automatic techniques for the grain size determination are implemented. Although the automatic techniques are documented on the ASTM standards, the major drawback is the non availability of quality digital microstructural images. The quality of microstructure depends on various factors viz., illumination, noise, low contrast, poor boundary definition etc. The present work is focused on a novel methodology that enables a clear definition of the grain and its boundary for an accurate automatic grain count and size through pattern classification technique, employing support vector regression (SVR) method.

Key words: *Support Vector Regression; Microstructure; Grain count; Automatic thresholding.*

1. Introduction

Over the recent years, measurement processes is based on the interaction between handling applications and computer science, comprising a wide field of applications. The image analysis applied to metallography becomes a tool for processes, where maximum reproducibility and repeatability is necessitated. Particularly, in the microstructure analysis of metals, image analysis is useful to obtain grain boundaries, grain size and size distribution, which dictates the mechanical properties viz., ductility, brittleness, stiffness and the tensile strength of metals. The parameters can be estimated through automatic image processing methods and mathematical morphologies. The processing speeds of computers hasten the analysis of many images, in a relatively short duration. The grain boundaries and the grain count of a low carbon steel (LCS) microstructure (Fig.1), is quite cumbersome to determine manually by an expert, owing to its complex nature.

Dutta et al. [1] proposed an automatic characterization of images based on the analysis of texture and fractals to detect the presence of fractures in steel. Coster et al. [2] used automatic image analysis to study the morphological parameters of the microstructure during the sintering of Ceria by using a top-hat transformation to obtain the grain boundaries. Dengiz et al. [3] used a neural network and fuzzy logic algorithms to detect the grain boundary of steel alloys

Other works have focused on the size of the grain in a material, an important parameter in engineering, given its influence in mechanical properties such as strain, ductility, resistance to stress, just to mention a few. Colás [4] and Maropoulos et al. [5] studied the relationship between grain size and thermal treatments by using stainless steel and low alloy steel, respectively.

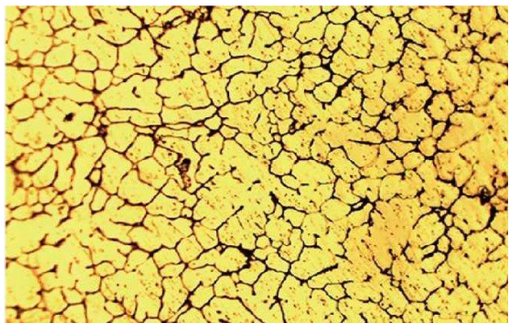

Fig.1 Microstructure of low carbon steel at 100 X

Tarpani and Spinelli [6] correlated the fracture strain with the grain size in the Charpy impact test. Boundary identification and its joining is a major drawback in the grain analysis, being performed manually. Heilbronner [7] developed a methodology that automatically develops grain boundary maps in a reduced time, which is not affected by the grain orientation. Lu et al. [8] also proposed grain identification technique, by processing two input polarizing images to obtain the edges. This work

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takes advantage of the polarized light phenomenon since it uses plane-polarized and a cross polarized images in which the mineral grains are revealed with different values. For automatic methods, the ASTM standard establishes that the grain interior and its boundaries must be well defined. However, there are no established methodologies available to define the grain size and grain count in metallic microstructural images. The automatic grain count was determined by employing box method after improving the microstructural image [9]. Commonly, the analyst determines a threshold value to obtain the best definition of the grain which results in a binary image. In this study, a novel attempt of determining the number of grains using SVM regression technique is attempted and the results are correlated with the manual intercept method. In section 2, procedure for manual intercept method of counting of grains is explained. Section 3 details the support vector regression technique used in this study to predict the number of grains, while section 4 presents the experimental results obtained and conclusion is given in section 5.

2. Intercept Method

Halle Abrams in 1974 introduced the three-concentric circle test grid and a more formal methodology for performing intercept grain size measurements (Fig.2). Three concentric circles were created in such a way that the total circumference was 500 mm (ASTM E112-12 standard), and further suggested adjusting the magnification so that, on average, about 100 grain boundary intersections, P, or grain interceptions, N, would be obtained [10].

In the intercept method, either grain boundary intersections, P, or grains intercepted, N, by the circles are counted. For a single phase structure, it is easier to do P counts. For a two-phase structure, one must do N counts. For a single phase grain structure P=N and either count can be made.

The P or N count is divided by the true line length, L_T, which is the line length divided by the magnification, L/M. This yields P_L or N_L, the number of intersections per unit length or the number of interceptions per unit length. The reciprocal of P_L or N_L is the mean lineal intercept length, L_3, which may be designated as l.

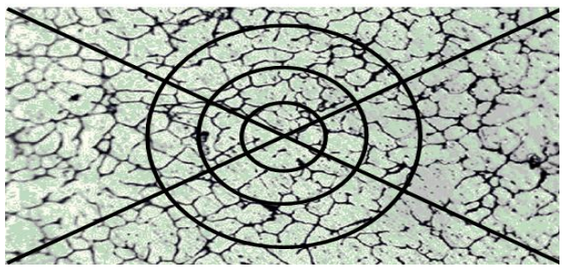

Fig.2 Intercept method

3. Support Vector Regression

The main idea of SVM is to map the training data from the input space into a higher dimensional feature space via function and then construct a separating hyperplane with maximum margin in the feature space. Consider a set of training data $\{(x_1,y_1),\ldots\ldots(x_i, y_i)\}$,where each $x_i \in R^n$ denotes the input space of the sample and has a corresponding target value $x_i \in R$ for i=1,2….. l, where l corresponds to the size of the training data. The idea of the regression problem is to determine a function that can approximate future values accurately [11].

The generic SVR estimating function takes the form

$$f(x) = \omega \times \Phi(x) + b \quad (1)$$

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

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

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

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

By substituting (4) into (3), the generic equation can be rewritten as

$$f(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)(\Phi(x_i)\cdot\Phi(x)) + b$$

$$= \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)k(x_i, x) + b \quad (4)$$

In (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. The RBF is commonly used as the kernel for regression

$$k(x_i, x) = \exp\{-\gamma|x - x_i|^2\} \quad (5)$$

4. Results and Discussion

4.1Methodology

The microstructure of different metals viz., aluminum, copper, brass, low carbon steel, stainless steel and cast iron (50 numbers) are collected and stored in the database. For description, a low carbon steel microstructure at 100 X magnification is shown as a model in this study. The microsructural images stored in the database posses varied gray levels creating difficulty in finding grain boundaries. In order to overcome this, the optical microstructure or gray scale image (Fig.1) is converted into binary image for identifying individual grains, as shown in Fig.3. In this study, regression technique, which demands dual input viz., feature (SVR) and observed vector (intercept method), is employed to determine number of grains. The observed vector is obtained by performing grain count of each microstructural images stored in the database manually, performed by a human expert (detailed in section 2), while binary images are processed to obtain feature vector.

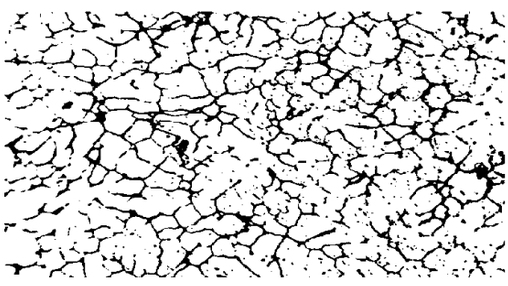

Fig.3 Binary image of LCS

Feature vectors are extracted from each of the binary images and stored in the database. The input binary image is divided into five horizontal and five vertical blocks and the features are extracted by counting the number of white to black transition in horizontal and vertical direction respectively (Fig.3). Of the 50 different metallic microstructural images, 30 microstructures are used for training and the remaining is utilized for testing, and the results are given in Fig. 4. Training and testing is performed using k fold method, i.e., one set of images are utilized for training, while the others are tested adopting leave in leave out process. Different combination of training and testing are performed and accuracy is evaluated by determining the error between feature vectors collected from image dataset and observed value from the manual grain count in the chosen metallic microstructures.

The number of grain in the different microstructural images ranges between from 25 to 250, depending on the nature and texture of particular metal. The maximum grains (Intercept-230, SVR-210) is obtained for the low carbon steel (25^{th} image) microstructure, whereas, the microstructure of copper (13^{th} image) has the minimum number of grains (Intercept-32, SVR-30). For all cases, intercept method shows higher grain than the grain count predicted by SVR. Further, it is observed that, each metal has a different size and quantity of grains, influenced by the ductility and strength of particular metal. The deviation between observed and predicted value is less for all microstructures except LCS, however the deviation is less than 10 % indicating the effectiveness of SVM regression method in determining the number of grains in metallic microstructures.

4.2 Error measurement

The root-mean-square error (RMSE), used to measure the differences between values predicted by a model and the observed is defined by

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - Y_i^{*2}}{Y_i}\right|} \quad (6)$$

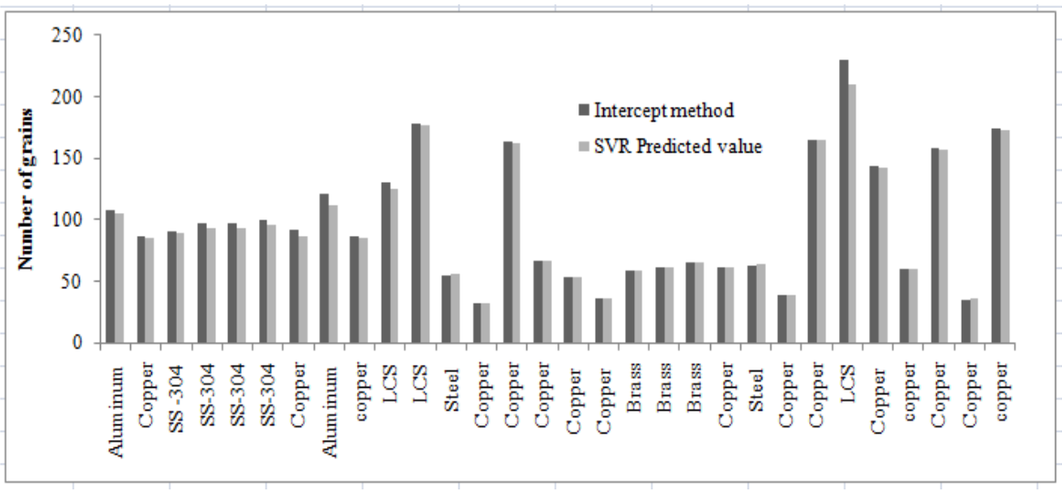

Fig.4 Observed and predicted number of grains

Where 'Y_i' is the observation value and Y_i^* is the predicted value. The error between the observed and processed model using regression technique for predicting the number of grains for various metals stored in the database is 0.90. Zhang et al. [12] reported a deviation less than 10 % is acceptable between the proposed and the manual method.

5. Conclusion

In this work, a new method was processed to determine the grain count in a metallic microstructure using SVR. The proposed method extracts features from the microstructural images and the extracted features were given as input to support vector regression, to determine the grain count. The experimental results show that the RMSE between the manual intercept and the developed method is 0.90.

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