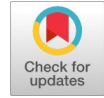# Chan-Vese segmentation of SEM ferrite-pearlite microstructure and prediction of grain boundary

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Abstract: The image processing of microstructure for design, measure and control of metal processing has been emerging as a new area of research for advancement towards the development of Industry 4.0 framework. However, exact steel phase segmentation is the key challenge for phase identification and quantification in microstructure employing proper image processing tool. In this article, we report effectiveness of a region based segmentation tool, Chan-Vese in phase segmentation task from a ferrite- pearlite steel microstructure captured in scanning electron microscopy image (SEM) image. The algorithm has been applied on microstructure images and the results are discussed in light of the effectiveness of Chan-Vese algorithms on microstructure image processing and phase segmentation application. Experiments on the ferrite perlite microstructure data set covering a wide range of resolution revealed that the Chan-Vese algorithm is efficient in segmentation of phase region and predicting the grain boundary.

Keywords: Ferrite-Pearlite steel, Phase segmentation, image processing, grain boundary prediction, Chang-Vese.

I. INTRODUCTION

Steel is the most common material which forms an integrated part of daily human life with different types and grades of steel being widely used for property-specific applications. Steel provides higher strength and toughness at reasonably lower cost than any other materials and thus widely used in industries, automobiles, structures, line-pipes, aerospace and defense applications. The mechanical properties exhibit by any steel depends primarily on the carbon content of the steel, the presence and content of different alloying elements and the different types of heat treatments and/or thermo-mechanical treatments given to the steel during subsequent processing stages. These factors determine the final microstructure occurring in any steel and the microstructures in turn control the strength-toughness properties exhibited by the steel. Different types of steels like plain carbon, alloy, stainless, C-Mn, HSS, DP, HSLA, TRIP, TWIP, IF shows different combination of strength and toughness properties depending on their processing schedules and final microstructures. Plain carbon steels can be defined mostly as an alloy of iron and less than 2.1% carbon and also contain negligible amount of alloying elements which cannot cause any effect to the microstructures and mechanical properties. The

microstructure is the key factor in design, control and measure of the product in a steel processing industry. The interpretation of microstructure essentially requires human skill for correlating with its properties. Nevertheless, in context of Industry 4.0 the development of interpretation of microstructure in computer is a pragmatic problem of interest[1][2]. Therefore, the processing of microstructural image and accurate segmentation of phases with the advanced image processing tools are evolving as new area of research[3][4]. Correct identification and appropriate quantification of various phases in steels are the primary concern for any image analysis technique which further helps to establish perfect structure-property relationships[5]. Manually quantitative analysis is also difficult, tedious and time consuming with more chances of human error. Modern image analysis techniques are based on the use of different commercially available image analysis software which calculates the grain size, quantify the phases and segment the phases on SEM images. But most of this software cannot effectively identify and quantify the phases due to the presence of different phases with close similar contrast and difficult to distinguish. Though several industrially important techniques were proposed to acquire and enhance images of steel microstructure, yet it is an established fact that the advanced tools are far effective in the field of image analysis. Maintaining a satisfactory level of accuracy in image analysis, it helps in noise reduction, pattern recognition, feature extraction and segmentation. Image processing has been extraordinarily improved by current development of computer techniques and provide the further opportunity of improvise the SEM microstructure image processing algorithms[6][7]. The present study aims to develop a framework for segmentation and image processing of SEM images of steel microstructure using Chan-vese segmentation algorithms[8]. The effect of region based segmentation algorithm on phase segmentation has been reported and discussed[9].

II. MATERIALS AND METHODS

A. Acquisition of steel microstructure

The image dataset developed by in house experiments and the specimens are prepare through standard procedure of metallographic study under scanning electron microscopy. The primary interest of the present study was segmentation of ferrite and pearlite phases from a SEM microstructure[10]. For this purpose steel samples with 0.22 wt. %C were used as the materials of interest for this work.

In order to keep reasonable variation in the image data all the steel sample were subjected to, two different heat treatments, annealing and normalizing. The two phase microstructures involving ferrite and pearlite having different volume fraction were captured at in a wide range of resolution 500X to 5000X. For the metallographic experiment the polished samples were eached with 1 % to 2% nital solution and the SEM images were captured in a scanning electron microscope at 500X, 1000X, 1500X, 2000X, 3000X and 5000X magnification. These SEM images are used for image processing and segmentation study and discussed this article.

B. Image Segmentation

Out of many different segmentation approaches[11], Region based methods are gaining due attention and popularity for its inherent adaptive nature[12][13][14]. Therefore, in this study a state of the art of region based segmentation algorithm Chan-Vese has been chosen and applied to microstructure segmentation application. Brief descriptions of segmentation technique and flow of phase identification and quantification are presented below.

Chan-Vese segmentation

Chan-Vese segmentation algorithm is built on an active contours model that aims to perceive the objects in an image[15]. The evolution of curve, level sets and Mumford–Shah functional are the three fundamental steps of the algorithm. The beauty of the technique is that it identifies the objects where boundaries are not clearly defined with gradient. In contrast to the classical methods this techniques attempt to minimize an energy function seems as a minimal partition problem. For the level set task the algorithm perform a "mean-curvature flow" operation that break at the desired boundary independent of the slope of the image in contrast to the conventional active contour models. The numerical algorithm using finite differences is described by the following equations.

Given the curve $C = \partial \omega$, with $\omega \subset \Omega$ is open subset of two unknown constants namely c_1 and c_2 which follows $\Omega_1 = \omega$ and $\Omega_2 = \Omega - \omega$.

Therefore energy minimize equation with respect of c_1, c_2 and C is

$$F(c_1, c_2, C) = \int_{\Omega_1 = \omega} (u_0(x,y) - c_1)^2 dxdy + \int_{\Omega_2 = \Omega - \omega} (u_0(x,y) - c_2)^2 dxdy + v|C|$$

Where first term calculate the force using shrink inside and second term determine the force using expand outside. This two force are balanced with $v|C|$.

So it calculate final force using

$$F_1(C) + F_2(C) = \int_{inside(C)} |u_0 - c_1|^2 dx + \int_{outside(C)} |u_0 - c_2|^2 dx$$

III. RESULTS AND DISCUSSIONS

In this work we have analysed the influence of region based segmentation in phase identification of ferrite and pearlite region in a scanning electron microscope (SEM) microstructure. The microstructures for this work were found from low carbon steel samples which containing 0.22, wt% C and were subjected to together annealing and normalizing treatments. Nevertheless, the microstructures

database used for experiments under the image processing route for the analysis has been captured in SEM under secondary electron (SE) mode over a collection of magnification 500-5000X. The Figure 4 shows a typical set of ferrite pearlite original microstructure captured in a SEM. The acquired grey scale images were processed for contrast enhancement using histogram equalization. The microstructures shown in Figure 5 are predominantly ferrite pearlite microstructure. The phase region of interest, i.e., ferrite and pearlite regions are revealed as dark and bright region as expected.
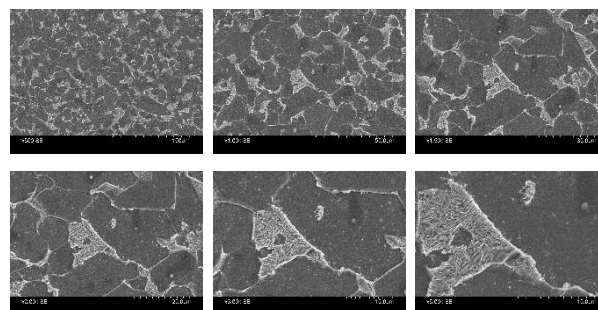
Fig 1: A typical set of original SEM image captured at magnification of 500x, 1000x, 1500x, 2000x, 3000x, and 5000x respectively obtained from steel specimen of 0.22% steel after applying normalization heat treatment.

The acquired greyscale images were processed for contrast enhancement using histogram equalization. This processed image revealed the phase identification and quantification of the two phase's ferrite-pearlite region in the microstructures along with the grain boundary area[16]. The Chan-Vese processes the SEM microstructure image segmentation by energy minimization, contour evolution and set levels. The Figure 2 shows the processed images corresponding to the original SEM images at five different resolutions (500X to 5000X) obtained by Chan-Vese algorithm. The set of processed images it can clearly seen that the pearlite (bright region in the original image) and the ferreit (dark region in the original images) are efficiently segmented by the Chan-Vese algorithm
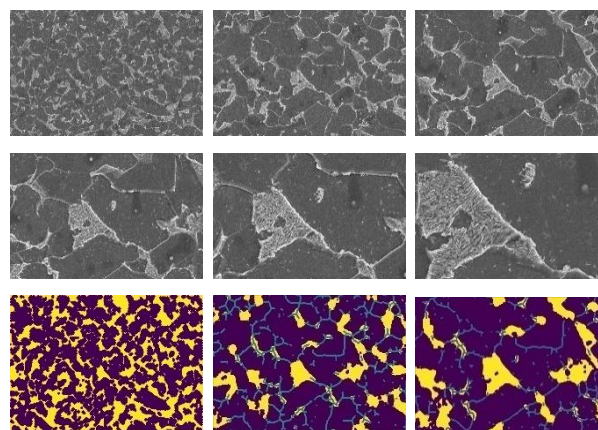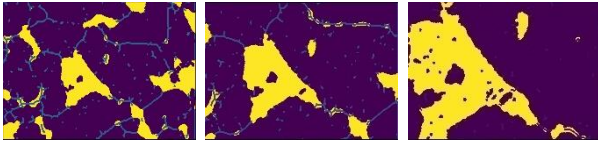
Fig.2: processed images corresponding to the original SEM images (row 1&2) at six different resolutions (500X to 5000X) obtained by Chan-Vese (row 3&4) algorithm.

It is worthy to note tha in the processed images discontineous grain boundary regions are efficiently segmented and the and contineous boundaries are developed. These results demonstrate the efficacy of the Chan-Vese segmentation algorithm of microstructure where the boundaries are rough or disconnected.
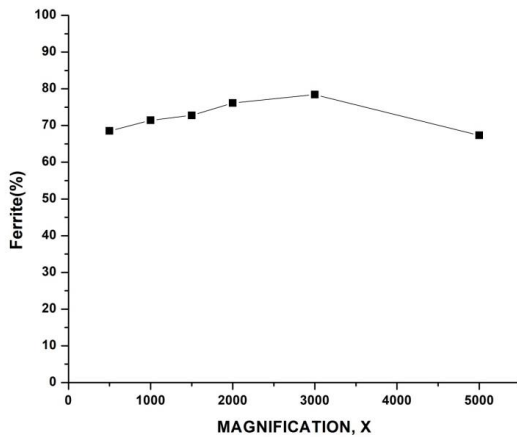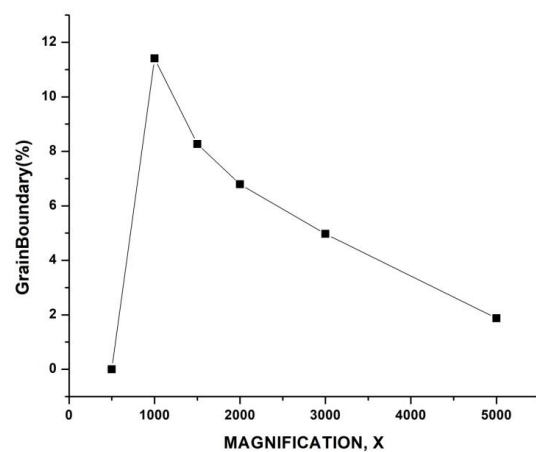

Fig. 3: Performance of Ferrite phase quantification by Chan-Vese segmentation technique

Figure 3 and 4 shows the ferrite and pearlite phase quantification obtained from Chane-Vese segmentation against the magnification. It is evident from the Fig. 3 variation of ferrite fraction against the magnification is approximately ±5%, which is metallurgically convincing and acceptable prediction. On the other hand, in the case of pearlite phase as can be seen in Fig. 4 the phase fraction is slightly consistent in the range of 17.5 %, to 35% over the magnification range of 500X to 3000X. Nevertheless, the variation in phase faction over magnification can be attributed as a reasonable degree of variation can be possible due to the decrease in field of view with magnification. Also how the grain boundary region has been treated in the segmentation process may significantly affect the phase quantification. This issue has been discussed below.
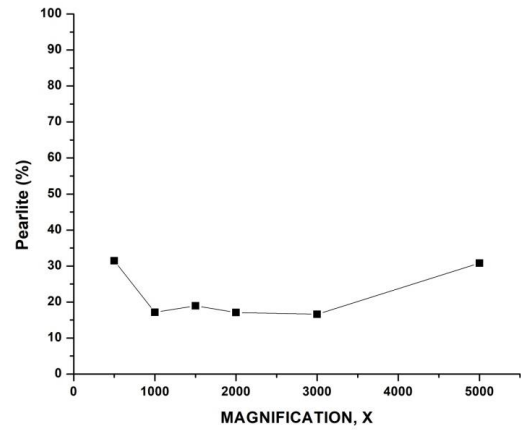
Fig. 4: Performance of pearlite phase quantification by Chan-Vese segmentation technique

The predicted grain boundary zone with the magnification change is presented in Figure 5. It shows that the grain boundary area is continuously reduced from higher magnification to lower magnification from 1000X to 5000X as expected. The reduction of the grain boundary area is metallurgical expected with the increase in the magnification effectively reduced the field of view. However, the algorithm shows that at low magnification the 500X the segmentation algorithm completely failed to detect the grain boundary region as it appears zero grain boundaries. This error in grain boundary conversely effect the phase quantification that is ferrite and pearlite phase detection especially at low magnification as appears in the grain boundary detection data. Therefore the overall study of phase quantification revealed that the Chan-Vese segmentation should be limited to 1000X and above magnification only, for microstructure image processing and analysis.

Fig. 5: Performance of Grain Boundary quantification by Chan-Vese segmentation technique

IV. CONCLUSION

The Chan-Vese based image processing technique successfully employed in segmentation of ferrite – perlite type microstructure of steel. The segmentation of microstructure experiemnts revealed that the Chang-Vese type region based technique perform well even if the phase boundaries are inexact or discontinuous. The present application on ferrite pearlite microstructure images found to be efficient in the magnification range of 1000X to 5000X as the results ion these range appears to be metallurgically significant. Nevertheless, the segmentation tool seems to be unsuitable to apply on the images at lower resolution i.e., below 1000X.

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