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PROGRAMMED SYSTEM FOR IDENTIFYING TYPE OF FLAKE GRAPHITE AS PER ASTM A247 USING MATLAB

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ABSTRACT *:In this paper we presented a program using MATLAB software which automatically identifies the type A form of Flake graphite in Grey cast Iron as per ASTM A247 standard, that has categorized graphite flake forms namely type A, B, C,D and E in Grey cast iron microstructure images. For classification Haralic defined four textural features namely contrast, correlation, energy and homogeneity are employed. An adaptive neuro-fuzzy inference system (ANFIS) is established for classification. The experimentation is done on actual grey cast iron microstructure images and the results are compared with the manually computed results. The comparison indicates good correlation between manual estimation and automated estimation .The programmed system is capable of acquiring and performing analysis online also. The programmed system has shown accuracy, speed and economical capabilities when compared to manual methods.*

KEYWORDS: Automatic Identification, Grey Cast Iron, ASTM A247, Haralic Features, ANFIS

1. INTRODUCTION

Gray iron or grey iron, is a cast iron alloy that has a graphitic microstructure. It is named after the gray color of the fracture it forms, which is due to the presence of graphite. It is the most common cast iron and the most widely used cast material based on weight. Flake form of graphite is the characteristic feature of gray cast iron material. The microstructure analysis system has an important role to play in qualitative and quantitative analysis in the gray cast iron industry. It is used to determine many stereological parameters of graphite inclusion and through which the expected mechanical properties are predicted. For example, the percent area of graphite inclusion in a given sample of gray cast iron is an important stereological parameter which is generally computed in quality control labs for quality assessment [1]. The ASTM A 247 standard has categorized graphite flake forms into types A, B, C, D and E. This project proposes a novel method for classification and quantification of the five types of graphite flakes (lamellar), namely, type A, B, C, D and E in gray cast iron microstructure images and also computes the required stereological parameters. Classification of five forms of graphite in grey cast iron is difficult and laborious for a human expert. Specially, accurate quantification of flake form of graphite is almost impossible by manual method. For classification, Haralic et al., defined four textural features, namely, contrast, correlation, energy and homogeneity, are employed. An adaptive neuro-fuzzy inference system (ANFIS) is developed for classification [2].The experimentation is done on actual gray cast iron microstructure images and the results are compared with the manually computed results. The comparison indicates good correlation between manual estimation and automated estimation. Microstructure images of gray cast iron acquired from light microscope are used in the experimentation. Images acquired from optical micrographs in as polished condition at 100X magnification.

The mechanical properties like tensile strength and hardness values and chemical composition is predicted based on quantification of optical micrograph of gray cast iron and thus the quality of the material is judged [3]. The proposed method has been implemented using MATLAB 7.9 software. The designed system is capable of acquiring and analysis of images online. The method developed is accurate, fast and economical when compared to manual methods.

2. IMPORTANCE OF MICROSTRUCTURAL ANALYSIS AND ASTM A247

The most important aspect of any engineering material is its structure. The structure of a material is related to its composition, properties, processing history and performance. Therefore, studying the microstructure of a material provides information linking its composition and processing to its properties and performance. Interpretation of microstructures requires an understanding of the processes by which various structures are formed. Microstructural analysis is used to gain information on how the material was produced and the quality of the resulting material. Microstructural features, such as grain size, inclusions, impurities, second phases, porosity, segregation or surface effects, are a function of the starting material and subsequent processing treatments. The microstructural features of metals are well defined and documented, and understood to be the result of specific treatments. These microstructural features affect the properties of a material, and certain microstructural features are associated with superior properties [4].

.Microstructural analysis techniques are employed in areas such as routine quality control, failure analysis and research studies. In quality control, microstructural analysis is used to determine if the structural parameters are within certain specifications. It is used as a criterion for acceptance or rejection. The microstructural features sometimes considered are grain size, amount of impurities, second phases, porosity, segregation or defects present. The amount or size of these features can be measured and quantified, and compared to the acceptance criterion. Various techniques for quantifying microstructural features, such as grain size, particle or pore size, volume fraction of a constituent, and inclusion rating, are available for comparative analysis. Microstructural analysis is used in failure analysis to determine the cause of failure. Failures can occur due to improper material selection and poor quality control. Microstructural examination of a failed component is used to identify the material and the condition of the material of the component. Through microstructural examination one can determine if the component was made from specified material and if the material received the proper processing treatments. Failure analysis, examining the fracture surface of the failed component, provides information about the cause of failure. Failure surfaces have been well documented over the years and certain features are associated with certain types of failures. Using failure analysis it is possible to determine the type of stress that caused the component to fail and often times determine the origin of the fracture. Microstructural analysis is used in research studies to determine the microstructural changes that occur as a result of varying parameters such as composition, heat treatment or processing steps [5].

Typical research studies include microstructural analysis and materials property testing. Through these research programs the processing - structure - property relationships are developed.

The flake size and distribution are also important from the point of view of the mechanical properties of gray iron. ASTM has classified the type of distribution, and size of graphite in gray iron according to specification A247.The flake graphite patterns have been subdivided in to five types as shown in figure 1.

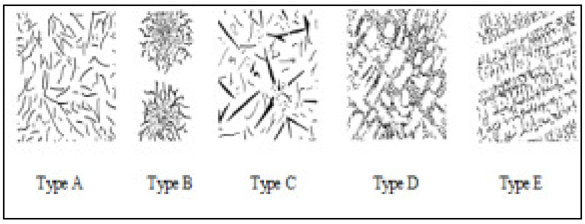


Fig 1.Types of graphite flakes distribution in gray cast iron as per ASTM A247.

Type A has a random distribution of flakes of uniform size and is preferred for mechanical applications. A high degree of nucleation that promotes eutectic is necessary for its formation. Type A flake graphite (random orientation) is preferred for most applications. In the intermediate flake sizes, type A flake graphite is superior to other types in certain wear applications such as the cylinders of internal combustion engines.

In Type B, a rosette pattern of distribution of flakes is obtained. The eutectic cell size is large because of the low degree of nucleation. Fine flakes form at the center of the rosette because eutectic solidification begins at a large under cooling raises the eutectic growth temperature resulting in a coarse, radially growing flake structure. Type B flake graphite (rosette pattern) is typical of fairly rapid cooling, such as is common with moderately thin sections (about 10 mm) and along the surfaces of thicker sections, and sometimes results from poor inoculation.

Type C occurs in hypereutectic irons and forms with coarse primary kishgraphite. The large flakes of type C flake graphite are formed in hypereutectic irons. These large flakes enhance resistance to thermal shock by increasing thermal conductivity and decreasing elastic modulus. On the other hand, large flakes are not conducive to good surface finishes on machined parts or to high strength or good impact resistance.

Type D is fine under cooled graphite which forms when solidification occurs at a large under cooling. This structure forms in the presence of Ti and in rapidly cooled irons that contain sufficient Si to ensure a graphitizing potential that is high enough to avoid chill formation at the high cooling rate. It also exhibits interdendritic segregation with random orientation. The small, randomly oriented interdendritic flakes in type D flake graphite promote a fine machined finish by minimizing surface pitting, but it is difficult to obtain a pearlitic matrix with this type of graphite. Type D flake graphite may be formed near rapidly cooled surfaces or in thin sections. Frequently, such graphite is surrounded by a ferrite matrix, resulting m soft spots in the casting.

Type E form in strongly hypoeutectic irons of low carbon equivalent .This morphology is classified as interdendritic with preferred orientation. Unlike type D graphite, type E graphite can be associated with a pearlitic matrix and thus can produce a casting whose wear properties are as good as those of a casting containing only type A graphite in a pearlite matrix.

3.MANUAL AND AUTOMATED METHODS

Manually, the identification type of graphite distribution of flakes i.e., A, B, C, D or E and determining the flake size is done by visual comparison of optical micrographs in as polished condition at 100X magnification with the reference images from ASTM A247 chart [6]

For determining the percentage area of the ferrite and graphite in microstructure in as polished condition a point count method is used as shown in below figure 2.which shows the microstructure of gray cast iron consisting of two feature sets i.e., light phase ferrite(α) and dark phase graphite flakes (β) the area fraction of these phase is measured using point probes .The population of points in two dimensional is sampled by superimposing a grid of points on the structure [7] [8].

The square grid 5x5 in figure constitute a sample of 25 points (the intersections in the grid) out of this population of all the points that could be identified in the area of specimen. The event of interest that results from the interaction of the probe sample with the structure is, “the points hits the β phase” .The actual measurement is simply a count of these events i.e., the number of points in the 5x5 grid in figure 2 that lie within β areas. In figure 2 this counts gives 6 points in the β phase that count is the result for this placement of the probe sample in this field of the microstructure. This point count is related to the area fraction of the β phase in this two dimensional structure by the fundamental stereological relationship.

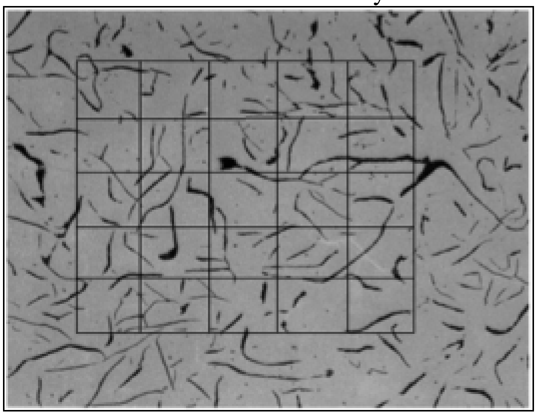


Fig.2 Measurement of area percentage of phases in gray cast iron by point count method

In this example of figure 2 the point fraction is 6/25=0.24 .In practice the grid will be placed on a number of fields, and average is taken. Therefore in the above figure the area of graphite (β phase) is 24% and the ferrite (α phase) is 1-0.24=0.76 i.e., 76%.

In manual methods of identification of graphite flake distribution, size and determining the area percentage of ferrite and graphite needs an expert ,the results may vary from person to person and time consuming, thus to overcome these an automated method is developed.

In an automated method the system automatically characterizes the type of graphite distribution in gray cast iron as per ASTM A247 and quantifies the graphite flake length and area percentage of ferrite and graphite. The automated method lowers the probability of introducing subjective errors in to analysis; this method increases the speed of analysis which can be decisive for example, in the foundry industry when control analysis of the microstructure should be done prior to the final cast, the low cost, relative to the whole process, when used every day for routine analysis.

4. IMAGE ANALYSIS

Image analysis is concerned with making quantitative measurements from an image to produce a description of it [9]. The purpose of image analysis is to extract quantitative information from images produced using various kinds of image sources. In the digital world, an image is represented by a rectangular matrix of image points, or pixels, whose values reflect the gray values (or color values, if the image is a color image) at the corresponding positions. The subsequent processing of these pixel values allows extracting the quantitative information desired.

The sequence normally followed in digital image analysis is as shown in the figure 3.

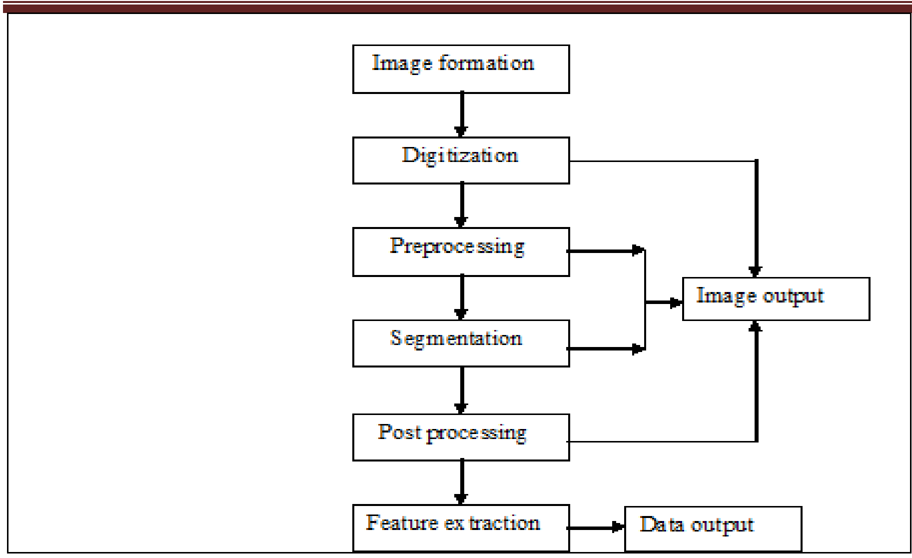


Fig.3The sequence of steps followed in image analysis.

The sequence starts with an image from a given source for example, a microstructure imaged through a light microscope and a video camera. The camera signal goes through the digitization step, and the resulting digital image is stored in the computer memory. At this point, if no further processing is required, the image can be output to a suitable printer. Electronic noise and uneven illumination are typical examples of defects that can be successfully corrected in the preprocessing step [10].

If the goal is to further analyze the image to extract quantitative information, then the sequence follows with the segmentation step, in which the several objects in the image must be identified and discriminated from the background. This is a complex and critical step because the software must mimic a sophisticated human cognition capability. Due to this complexity, it is often necessary to correct the segmentation result in the post processing step where the so-called morphological operators are employed.

The resulting post processed image is then composed of the desired objects, which can be analyzed in the feature extraction step. A large number of quantitative parameters can be obtained including size, shape, position and texture. The data can be output to various plotting and analysis programs

5.EXPERIMENTAL SETUP

The experimental set up consists of trinocular type optical microscope (Censico make) in which microstructure image of the polished gray cast iron specimen is obtained. On the trinocular type optical microscope monochrome Close Circuit TV (CCTV) camera (GW GVC-850 make) is mounted as shown in figure 4. The monochrome CCTV camera grabs the microstructure image of the polished gray cast iron specimen and it converts in to digital image, this digital image is displayed on the monitor of the computer (operating system Windows XP service pack 3) with the help of the Digital Video Recorder (DVR) card which is interfaced with the computer .The displayed image is gray scale image type digital image and this digital image is stored in JPEG format. This stored image is further processed and analyzed using an algorithm developed in MATLAB 7.9 version software for the results.

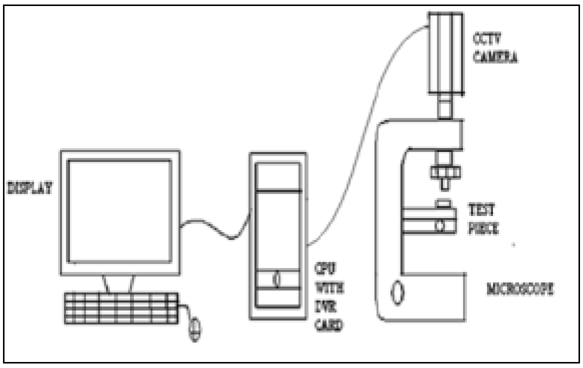


Fig. 4 Experimental setup

6. FEATURE EXTRACTION

In any classification system, the feature selection is a key process in object recognition and accurate classification. In the proposed system, a set of four Haralic features, out of fourteen defined features, namely, contrast, correlation, energy and homogeneity are used. Haralic features are determined using GLCM. A GLCM is constructed with conditional-joint probabilities (C_{ij}) of all pairwise combinations of gray levels for a fixed window size (N), given the two parameters: interpixel distance (δ) and interpixel orientation (θ). A different GLCM is required for each (δ, θ) pair. Each GLCM is dimensioned to the number of quantized gray levels (G). A GLCM is often defined to be symmetric. The textural features are extracted through the statistical calculations applied on GLCM. These features are shift-invariant and they are defined as following:

Contrast: It is the measure of the intensity contrast between a pixel and its neighbor over the whole image. Contrast is 0 for a constant image $f1 = \sum_{i,j=1}^{G} C_{ij}(i-j)^2$

Correlation: It is the measure of how correlated a pixel is to its neighbor over the whole image.

$$f2 = \sum_{i,j=1}^{G} \frac{(i-\mu_x)(j-\mu_y)C_{ij}}{\delta_x \delta_y}$$

Correlation is 1 or -1 for a perfectly positively or negatively correlated image.

Energy: It is the sum of squared elements in the $f3 = \sum_{i,j=1}^{G} C_{ij}(i-j)^2$

Energy is 1 for a constant image.

Homogeneity: It measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$f4 = \sum_{i,j=1}^{G} \frac{C_{ij}}{1+|i-j|}$$

Homogeneity is 1 for a diagonal GLCM.

The algorithm for feature extraction from the binarized microstructure images is given in the Algorithm 1.

Algorithm 1: Feature extraction

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

Step 2: Apply active contours method to the input image and obtain segmented binary image.

Step 3: Construct the $GLCM_1$ through $GLCM_8$ with G=2 in eight angles (0^0,45^0,90^0,135^0,180^0, 225^0, 270^0, and 315^0) at a distance of 1 unit.

Step 4: Compute the Haralic textural features, $f1, f2, f3$ and $f4$ for each GLCM.

Step 5: Compute the mean values, μ_1, μ_2, μ_3 and μ_4 and standard deviation values, SD_1, SD_2, SD_3 and SD_4 of features $f1, f2, f3$ and $f4$, respectively.

Step 6: Repeat Steps 1 through 5 for all the known class of gray cast iron images.

Step 7: Compute μ_1', μ_2', μ_3' and μ_4', the mean values of μ_1, μ_2, μ_3 and μ_4, respectively, of a class of images and tabulate these values .

The feature vector is formed using the μ_1', μ_2', μ_3' and μ_4' values computed in the Algorithm 1. The feature vector is used as input to ANFIS to build the Gaussian membership functions of fuzzy quantities.

7.ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is one of hybrid neuro-fuzzy inference expert systems and it works as Takagi-Sugeno-type fuzzy inference system. ANFIS has a similar structure to a multilayer feed forward neural network, but the links in an ANFIS only indicate the flow direction of signals between nodes and no weights are associated with the links.

7.1 ANFIS Structure

ANFIS architecture consists of five layers of nodes. Out of the five layers, the first and the fourth layers consist of adaptive nodes while the second, third and fifth layers consist of fixed nodes. The adaptive nodes are associated with their respective parameters, get duly updated with each subsequent iteration while the fixed nodes are devoid of any parameters. In general, for two-rule based system, the rules are defined as,

Rule 1: If (a is A_1) and (b is B_1) then (O_1 = p1x +q1y + r1)

Rule 2: If (a is A_2) and (b is B_2) then (O_2 = p2x +q2y + r2)

where x and y are the inputs, A_i and B_i are the fuzzy sets; O_i are the outputs within the fuzzy region specified by the fuzzy rule; pi, qi and ri are the design parameters that are determined during the training process. The general architecture of ANFIS to implement the two if-then rules is shown in the Figure.5, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

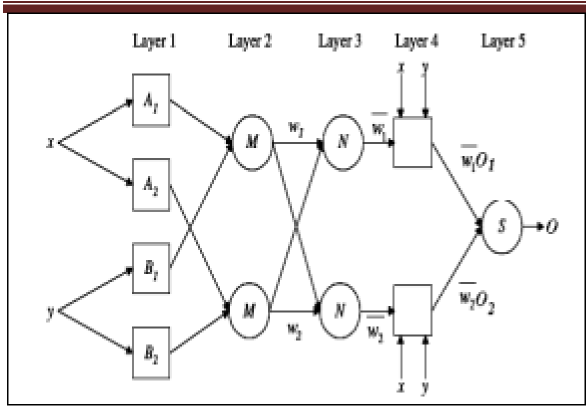


Fig. 5 Two-rule ANFIS architecture

7.2 Classification using ANFIS

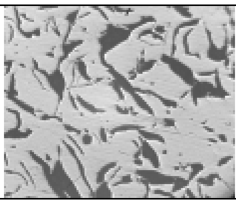
The ANFIS uses a strategy of hybrid approach of adaptive neuro-fuzzy inference and yields good classification results. The objective of classification is to classify five types of grains. The feature vectors were applied as the input to an ANFIS classifier. The ANFIS network has a total of 81 fuzzy rules and one output. The algorithm for classification of grains in a microstructure image by ANFIS is given in the Algorithm 2 and is implemented using MATLAB. The quantification of distribution of grains is also included in the algorithm after the classification step.

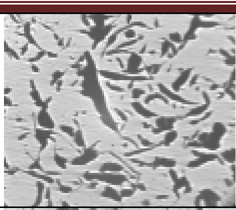
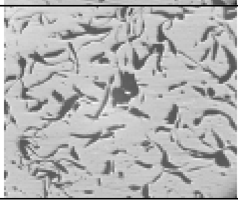
Algorithm 2: Classification and quantification
Step 1: Input gray scale microstructure image (training image).
Step 2: Apply active contours method to the input image and obtain segmented binary image.
Step 3: Construct the GLCM1 through GLCM8 with G=2 each in eight angles (00, 450, 900, 1350, 1800, 2250, 2700, and 3150) at a distance of 1 unit.
Step 4: Compute the Haralic texture features, f1,f2, f3 and f4 for each GLCM.
Step 5: Compute the mean values, µ_1,µ_2,µ_(3)and µ_4 and standard deviation values, SD1, SD2,SD3 and SD4 of features f1,f2,f3 and f4, respectively.
Step 6. Simulate the ANFIS with feature values computed in the Step 5.
Step 7: The output of ANFIS is the constant membership function value, which indicates the grain class to which the microstructure in the image belongs.
Step 8: (Quantification) Compute the stereological parameter, graphite percent area of each microstructure image.

8. RESULTS AND DISCUSSIONS

The belowtable shows the results for microstructures fed into the programmed system it has provided the type of flake present in the grey cast iron, total number of flake, percentage area of graphite flakes in microstructures present.

Table 1.Result of microstructures fed into system

Sl.No.	Gray Cast Iron Microstructure Test Images	Tot.Flakes	Type of flake	Percentage area of graphite flakes (%)
1		**133**	**A**	**27**

2		**132**	**A**	**30**
3		**131**	**A**	**23**
4		**169**	**A**	**22**

9. CONCLUSION

In this paper we had fed many number of microstructure images of grey cast specimens into the programmed system which has identified the type A flake as per ASTM A 247 standard and also provided the result of number of flakes present in microstructure and percentage area graphite flakes covers in microstructure which is very essential since it has direct effect on mechanical properties like tensile strength, hardness and frictional properties.

We also compared the obtained results with the manual computation the manual identification needed much time and skills and the results also varied from person to person based on skills. Manual counting of number of flakes present in microstructure is hectic process to achieve. Therefore we conclude that the programmed system is very accurate, high speed and also economical in mass production system.one can easily apply this programmed system for better manufacturing process in industries. Further one can develop the system for identification of Type B, C, D and E type of flake as per ASTM A 247 standard.

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