STATISTICAL DESIGN OF EXPERIMENTS APPLIED TO THE IMAGE ANALYSIS OF CAST IRON MICROSTRUCTURES

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Abstract

A factorial design is applied to assess the influence of the processing and experimental parameters on digital image analysis results. Microstructures of cast iron with nodular, vermicular and lamelar graphite were evaluated with different luminosity, minimum particle and different operator. We conclude that some parameters can significantly influence the final results of quantitative metallography and the statistical design of experiments technique is highly effective for this type of evaluation.

INTRODUCTION

The quantitative image analysis has increasing importance in the field of materials science and engineering, were the principal interest is to obtain quantitative data of microstructures. Rapid analysis, easiness of application, high precision, richness of details are some of the competitive factors which motivates the use of digital image analysis. The systems to perform image analysis (hardware and software) have rapidly became sophisticated and cost effective in the last years contributing to the popularisation of the technique.

In the process of acquisition and processing of micrographies, various parameters are adopted and their influences in the results are not always clear. A frequent question for a materials engineer is 'how much can I trust in the quantitative result of my microstructure image analysis in terms of physical reality and experimental reproducibility?'. The analysis of the influence of a particular parameter must be evaluated statistically in various experimental situations to be consistent. Although the facility and rapidity that the image analysis is performed, the analysis of the numerous parameters (variables) and their interactions can become very complex and fatiguing. The statistical design of experiments (DOE) [1,2] is a rational way of analysis of the influence of parameters in the final results with a minimum effort. The main objective of this paper is to show 'in job' how the statistical design of

experiments can be applied to the evaluation of the influence of experimental and processing parameters in the final results of image analysis.
The following section is a short review of the process of digital image analysis with the aim of emphasises the most important associated parameters. A short introduction to the design of experiments is composed and followed by the application for the given example.

DIGITAL IMAGE ANALYSIS

The digital image analysis is a powerful tool to the quantitative description of visual data. In the materials science field the main application of this tool is the quantification of microstructures. The process of image analysis of microstructures has distinct steps as illustrated in figure 1.

The image acquisition can be done directly on the microscopes (optical or electronic) by digital cameras or using 'scanners' to digitise micrographies. A typical image acquisition system is shown in figure 2.
A digital image can be represented by a matrix, where each element has a value that corresponds to the grey level of a point in the image. Some important parameters in the image acquisition process are the light intensity, contrast, focus, shadow, amplification and digitalisation resolution. In the image enhancement some different processing procedures can be applied like operation in the histograms (normalisation, linerarisation, etc.), linear and non linear filters (various). To extract quantitative information of the images is normally necessary their segmentation (or binarisation) to separate the 'objects' of the image. In the segmentation process various algorithms (and parameters) can be used. The measured results can be global (density, dispersion, anisotropy, etc.) or specific features (diameter, area, position, sphericity, etc.). Table 1 presents concisely the main parameters that can be involved in the image analysis process.

STATISTICAL DESIGN OF EXPERIMENTS

Design of experiments (DOE) are methodologies that applies statistics to develop a 'planning' of experiments which gives a minimum experimental effort to a determined significance level of the results. The DOE assumes that the system is composed of a set of principal variables (or parameters/factors) as inputs and as the output the response (or results) for each input configuration. The objective is to analyse how the changes in the inputs alter the response. There are various DOE techniques known as 'factorial' (complete or fractionated), 'Taguch', Placktt-Burmam, among others, but whenever possible a complete factorial is used. This method allows the experimental search of the influence of N variables and their interactions, changing them in two levels (low and high). The statistical analysis of the results allows the determination of the significance of the results and to obtain a experimental equation that relates the variables and the results. In the case of the image analysis, the inputs are the parameters used in the acquisition and processing (see table 1) and the outputs are the results. More details of the application of the DOE to the image analysis will be given in its application to an example.

APPLICATION OF DOE TO MICROSTRUCTURE CHARACTERISATION OF CAST IRONS

The measurement of precise quantitative parameters of cast iron microstructures is very important for a number of reasons like the determination of metallurgical parameters influence [3,4], the development of alternative techniques of microstructural characterisation [5,6], correlation of microstructure and the mechanical properties [6] etc. Some of the most important microstructural element of cast irons is the precipitated graphite and their different size, form and densities. Figure 3 illustrates typical graphite forms in cast irons.
The main parameters to be measured are the number of particles (or density), the size (diameter, area, etc.) and the geometry (sphericity, axis ratio, etc.). The application of the image analysis for measurements of graphite parameters in cast irons is quite simple, because the particles are well defined (have a quite different grey level) when the images have a good quality. Three experimental and processing parameters were chosen to be analysed in this research:

- Variable A: **minimum size** of the particle (in area) to be counted. This parameter is in general present in the image analysers and the objective is reduce the effect of the small particles that can be noise in many cases. The levels of 10 and 50 area pixels (1.6-4 x $10^{-5}$$mm^2$) were adopted.
- Variable B: **Luminosity** of the optical microscope. The levels 7 and 10 of the microscope were used.
- Variable C: **Operator**. Some of the variables have direct influence of the operator like the focalisation, the threshold for the grey level in the segmentation, etc. Two operators of the same training level repeated the experiment.

The experiment is therefore of two levels and three variables (2^3). Table 2 shows the eight possible configurations of the experimental system.
The complete factorial design of experiments can analyse the effect of each variable (A, B, C) and also their interactions (AB, AC, BC and ABC). To have the effect of a variable, we must compare the results for the configuration were it has high values with the configuration were it has low values. For the variable A we have,

$$\text{Effect}_A = (Y_a + Y_{ab} + Y_{ac} + Y_{abc})/4 - (Y_{(1)} + Y_b + Y_c + Y_{bc})/4 \qquad (1)$$

The interaction effects are obtained in a similar way. For example the interaction AB can be expressed by,

$$\text{Effect}_{AB} = (Y_a + Y_{ab} + Y_{ac} + Y_{abc})/4 - (Y_{(1)} + Y_b + Y_c + Y_{bc})/4 \qquad (2)$$

Two graphite characteristics were taken as results. They are the 'axis ratio' and the 'major axis' of the graphite. Table 3 shows the results obtained for the axis ratio of a lamellar graphite cast iron with the calculations of the effects by an algorithm know as Yates (it is a alternative way to the use of equations like (1) or (2)).
The second column (R) of table 3 is the results of the configuration given in the first column (see also table 2). These results are the average of five analysis in the same

experimental conditions, but of images of different regions (random) of the metalographic sample. The columns 4, 5 and 6 (Y-1, Y-2, Y-3) is the application of the Yates algorithm for the calculation of the effects (as shown in equations 1 and 2). The effect for each experimental configuration is presented in column 7 (DM) that must be compared with a parameter of experimental error for the significance determination. The statistical error associated with the experiment is obtained by the composition of the variances of the results for each configuration (column 2), disregarding, for the moment, significant figures for their computing. Equation 3 presents the calculation of the standard deviation of the average difference, that is, the statistical error associated with the calculated effect.

$$\mathrm{SDAD}^2 = \mathrm{SDAD}^2_{+} + \mathrm{SDAD}^2_{-} = \frac{S^2{}_D}{DF.N/2} + \frac{S^2{}_D}{DF.N/2} = \frac{1}{N}\frac{\sum S^2{}_I}{DF} \qquad (3)$$

Where: SDAD = Standard deviation of the mean difference (+ and – are related to the high and low values for each configuration);

S_D = Variance associated with the average value of the high and low configuration;

S_I = Variance associated with each mean value R (column 3 of table 3);

N = Number of experiments;

DF = Degree of freedom associated with each R (column 2 of table 3).

For our case we have $\Sigma S^2{}_I = 0.0171$, N =8, DF =4 resulting in SDAD = 0.023, with 32 degrees of freedom.

The relationship between SDAD and DM must be evaluated by a statistical distribution with a desired reliability level. The variance was estimated (no previous knowledge) from the results, so the adequate statistical distribution is the ‘student (or t-distribution). For a confidence level of 95% and a degree of freedom of 32, from N*DF, we have the t-student parameter $t_{tab} = 2.04$, which multiplied by the SDAD results in the calculated DM value to be compared with the experimental DM values.

$$DM_{calc} = t_{tab} * SDAD = 2.04 * 0.023 = 0{,}047 \qquad (4)$$

Comparing the DM_{calc} with the values of column 7 (DM) of table 3 we can see that the configuration C is significant, that is, the influence of the operator in the results is greater than the estimated error of a confidence level of 95%, being therefore significant. The other parameters (A, B, and their interactions) showed to be not significant. The same procedure of table 3 was used to calculate the significance for the other cast iron microstructure (figure 3) and the table 4 presents the results.

It can be seen that most of the variables and their interactions did not significantly affect the results. The variable A (minimum particle size) showed to be important for the measurement of the major axis for the three microstructural types. The variable C (operator) showed to be significant for the lamellar and nodular microstructure, but without significant influence on vermicular microstructure. The interactions AB (minimum particle size + luminosity) and AC (minimum particle size + operator) showed to be significant in the results for the axis ratio of the nodular graphite.

DISCUSSION

The statistical design of experiments technique applied to the present case provides very important conclusions about the influence of some variables in the accuracy of the results. An example is the influence of the operator that showed to be significant in majority of the situations experimented. The method seems to be a very good alternative to the evaluation of accuracy of the image analysis technique and the evaluation of the influence of experimental parameters as it can be easily adapted to different applications, contrary to other possible methods like chart ratings. The statistical design of experiments allows the identification of the parameters/factors that are more influent in the results and the quantification of this influence. The influence of the luminosity (variable B), for example, have not been significant as an isolated variable. This may be explained by the fact that the operator can correct this parameter in the segmentation process. But the influence of the operator showed to be significant for the analysis of the lamellar and nodular microstructures. The significance of a parameter determined by the statistical design of experiment technique depends on the influence of this parameter but also on the variance (or noise level) related to this result. So the significance observed for the nodular microstructure are more related with the low variability associated with their results and not with the influence itself. This cannot be said for the others microstructures.

CONCLUSIONS

The application of the digital image analysis technique can present results that are quantitatively inaccurate due to numerous variables that can affect the results. The statistical analysis of experiments, presented by an example, showed to be highly efficient tool to evaluate the influence of the experimental and image processing parameters in the final results. This method gives easily and statistically consistent the significance of each parameter and their combination, providing good insight of the accuracy level associated with the image analysis results.

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Figure 1

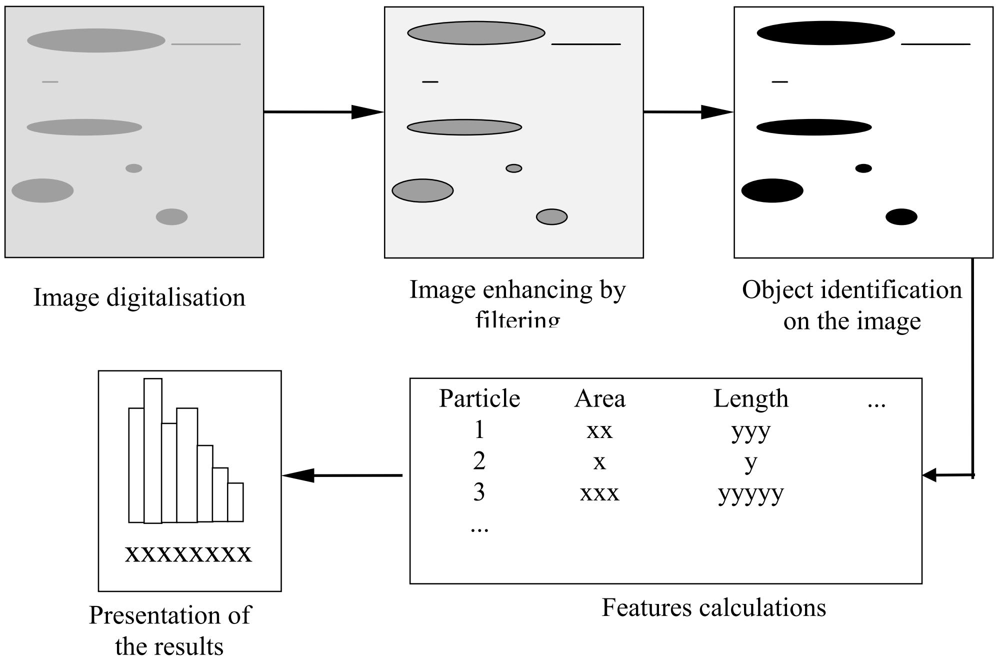

Figure 1 - Process of image analysis applied to microstructure evaluation.

Figure 2

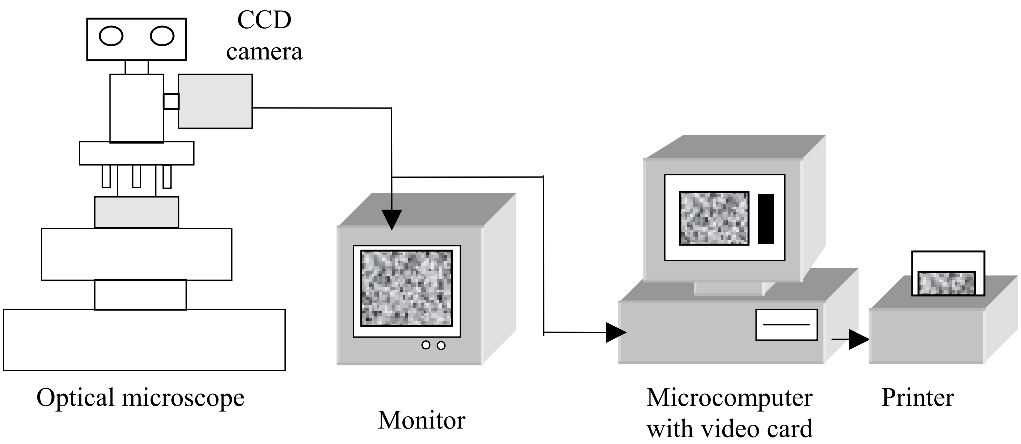

Figure 2 – Image acquisition system connected to a optical microscope.

Figure 3

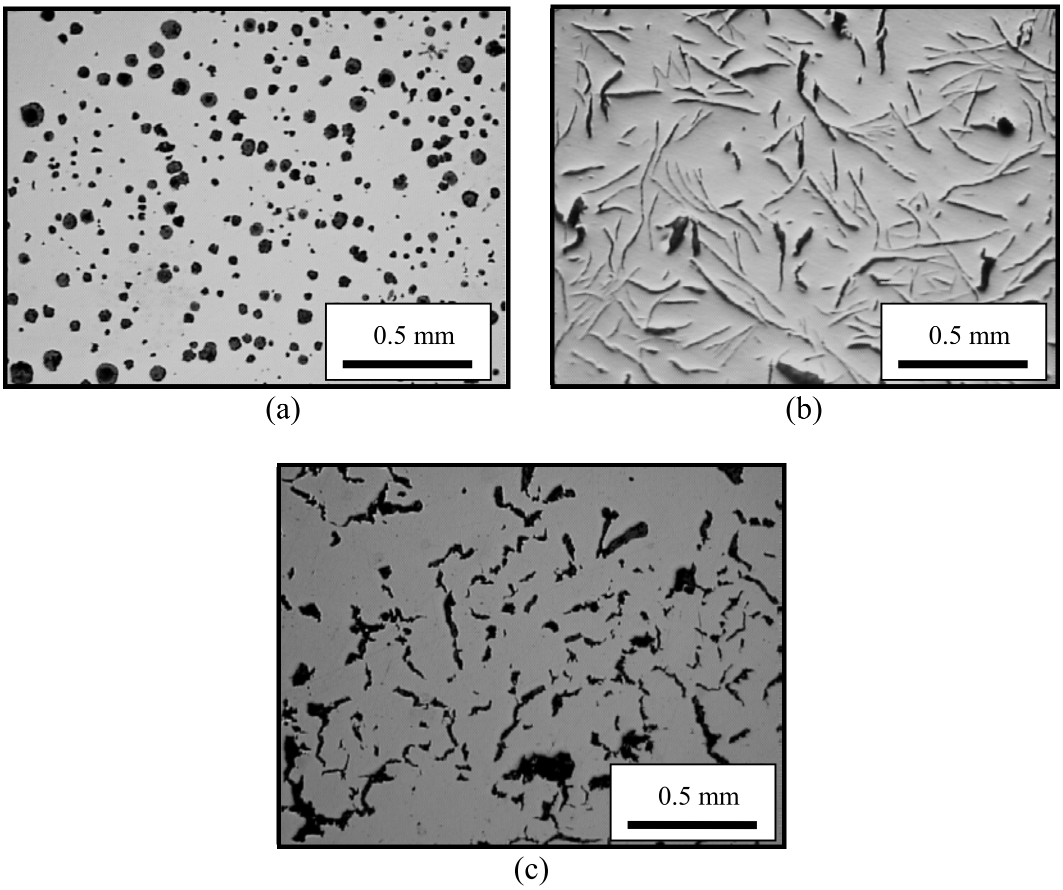

Figure 3 – Typical microstructures of cast irons (a) spheroidal (nodular) graphite (b) Vermicular (compact) graphite and (c) lamellar (flake) graphite. Optical micrography without etching.

Tables 1 and 2

Step	Parameters (or variables)
Acquisiton	Contrast, light intensity, focus, shadow, amplification, digitalization resolution.
Image enhancement	• Histogram operations: normalisation, linearisation, ... • Linear filters: low pass (mean, Gausian, etc.) and high pass (subtraction of low pass, maximum gradient, Sobel, Roberts, Laplacian, etc.) • Non linear filters: low pass (median, sigma, etc.) high pass (gradient, hall correction, etc.) • Fourier transforms
Segmentation	• Fix or adaptive threshold • Gradient • Local maximum and waterfall technique • Heuristic search • Binary processing operations
Object identification	• Elimination of objects that cut the image borders • Elimination of particles of particular size or form.

Table 1 – Some techniques (and parameters) that can influence the image analysis results

Notation	Variable A	Variable B	Variable C	Result
(1)	10	7	operator 1	$Y_{(1)}$
a	50	7	operator 1	Y_a
b	10	10	operator 1	Y_b
ab	50	10	operator 1	Y_{ab}
c	10	7	operator 2	Y_c
ac	50	7	operator 2	Y_{ac}
bc	10	10	operator 2	Y_{bc}
abc	50	10	operator 2	Y_{abc}

Table 2 – Possible combinations for the factorial design of experiments in our example.

Tables 3 and 4

	R	$S_I^{\ 2}$	Y-1	Y-2	Y-3	DM	Significance
(1)	0.35	0.00155	0.68	1.29	2.45	-	-
a	0.33	0.00237	0.61	1.16	-0.11	-0.0275	NS
b	0.32	0.00285	0.58	-0.05	-0.17	-0.0425	NS
ab	0.29	0.00413	0.48	-0.06	0.01	0.0025	NS
c	0.31	0.00310	-0.02	-0.07	-0.23	-0.0575	S
ac	0.27	0.00162	-0.03	-0.10	-0.01	-0.0025	NS
bc	0.25	0.00065	-0.04	-0.01	-0.03	-0.0075	NS
abc	0.23	0.00083	-0.02	0.02	0.03	0.0075	NS

Table 3 – Results and the calculation of the effects by the 'Yates' algorithm of the axis ratio of the lamellar graphite sample.

Var.	Axis ratio			Major Axis		
	Lamellar	Nodular	Vermicular	Lamellar	Nodular	Vermicular
a	NS	NS	NS	S	S	S
b	NS	NS	NS	NS	NS	NS
ab	NS	S	NS	NS	NS	NS
c	S	S	NS	S	S	NS
ac	NS	S	NS	NS	NS	NS
bc	NS	NS	NS	NS	NS	NS
abc	NS	NS	NS	NS	NS	NS

Table 4 – Significance results obtained for the tested variables: (S) significant (NS) not significant. The graphite characteristcs analysed was the axis ratio and the major axis for the lamellar, nodular and vermicular cast iron microstructures.