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Classification of ductile cast iron specimens based on image analysis and support vector machine

Francesco Iacoviello[a], Daniela Iacoviello[b]*, Vittorio Di Cocco[a], Alberto De Santis[b], Laura D'Agostino[a]

[a] *Università di Cassino e del Lazio Meridionale, DICeM, via G. Di Biasio 43, 03043, Cassino (FR) Italy*
[b] *Università di Roma "La Sapienza", DIAG, via Ariosto 25, 00185 Roma, Italy*

Abstract

The ductile irons discovery in 1948 gave a new lease on life to the cast iron family. In fact, these cast irons are characterized both by a high castability and by high toughness values, combining cast irons and steel good properties. The high mechanical properties (especially ductility) are mainly due to the peculiar graphite elements shape: thanks to the addition of some elements like Mg, Ca, Ce, graphite elements shape can be near to spheres (nodules) instead to lamellae as in "normal" grey cast irons. In this work, the problem of classification of ductile cast irons specimens is addressed; first the nodules present in each specimen are identified determining their morphological shapes. These characteristics are suitable used to extract global features of the specimen. Then it is outlined a procedure to train a classifier based of these properties.

Keywords: Ductile Cast Irons; Image analysis; Artificial Neural Networs.

1. Introduction

In the first half of the last century, the goals of a combination of good castability and high toughness values were fulfilled by malleable iron by means of an extended annealing treatment of white iron. During this heat treatment, cementite decomposes to graphite that precipitates as aggregates in a matrix whose composition (ferrite or pearlite)

* Corresponding author. Tel.: +39-677274061
E-mail address: iacoviello@dis.uniroma1.it

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depending on the cooling cycle from the annealing temperature. The high costs related to the extended annealing treatment and the difficulty to cast sound white iron components limited its utilization. In 1943, in the International Nickel Company Research Laboratory, a magnesium addition allowed to obtain a cast iron containing not flakes but nearly perfect graphite spheres. In 1948, a small amount of cerium allowed to obtain the same result. These cast irons are characterized by a very good combination of overall properties: high ductility (up to more than 18%), high strength (up to 850 MPa and, considering austempered ductile iron, up to 1600 MPa) and good wear resistance. The matrix controls these good mechanical properties and the spheroidal cast iron types are designated by the matrix names. The ferritic ductile irons are characterized by good ductility and a tensile strength that is equivalent to a low carbon steel; the pearlitic ductile irons shows high strength, good wear resistance and moderate ductility, whereas the ferritic-pearlitic grades properties are intermediate between the ferritic and the pearlitic ones. The martensitic ductile irons show very high strength, but low levels of toughness and ductility; the bainitic grades are characterized by a high hardness. The austenitic ductile irons show good corrosion resistance, good strength and dimensional stability at high temperature. The austempered grades show a very high wear resistance and fatigue strength, as shown in Ward (1962) and Labrecque (1998). Nowadays, ductile cast irons are widely used in a number of industries, e.g. wheels, gears, crankshafts in cars and trucks etc.

During solidification, usually graphite elements nucleate corresponding to different inclusions (e.g., MgS, CaS, SrS, MgO etc.) e they grow by means of carbon atoms solid diffusion through the austenite shield that solidify around the graphite nucleolus, Morrogh (1967). Considering a stressed cast iron manufacts, graphite elements can act as “stress raisers” or as “crack arresters” depending on their morphology, strongly influencing the macroscopical mechanical behavior, Fig.1.

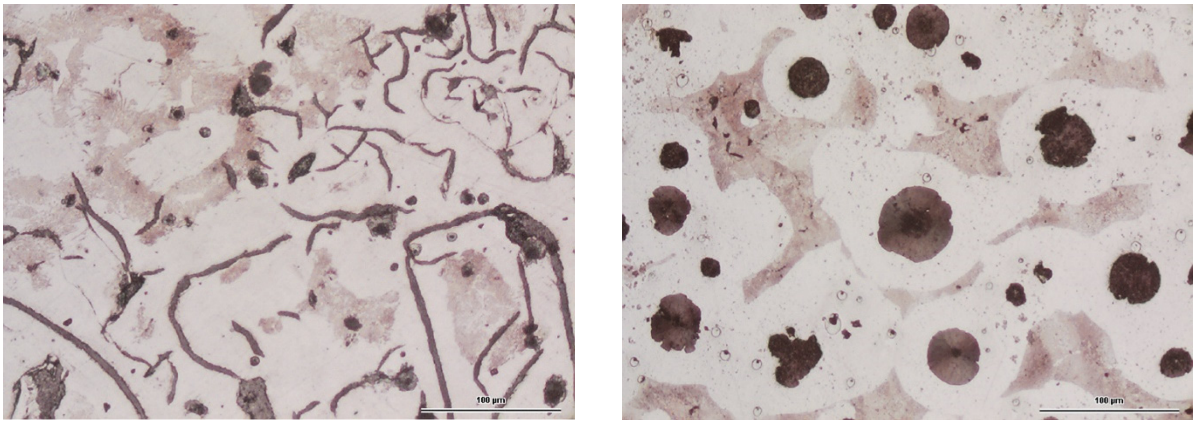


Fig. 1. Ferritic-pearlitic DCIs with different graphite elements: lamellae (left) and nodules (right)

The ASTM standard, A247-16a (2016), covers the classification of graphite elements in cast irons in term of type, distribution and size by visual comparison to reference photomicrographs.

In this work, the problem of classification of the specimens of ductile cast irons (DCIs) on the basis of the morphological properties of the graphite nodules is investigated. First the nodules are identified by image segmentation analysis; their morphological properties are identified, yielding a set of features for each nodule present in the specimen. The information of each nodules in the specimen are collected together, in order to provide a global description of the specimen, yielding global features.

A suitable classifier can be trained in order to assign each specimen to a class of the international classification regulation, A247-16a (2016). The aim is to determine a signature of each kind of specimen in order to be able to classify a data with an automatic and objective procedure. In Fig. 2 the total procedure is outlined. It is divided into two steps: the offline one in which the classifier is trained and the online step in which a test over new images (not used in the training phase) is proposed.

As a preliminary work, a binary classification is proposed, aiming at separating metallographically prepared (not etched) DCI specimen to specimens with abnormal nodules.

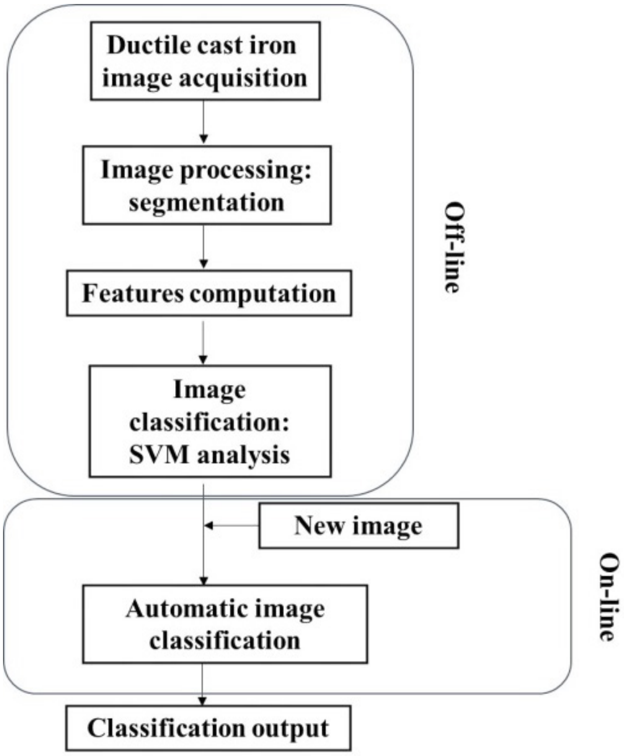


Fig.2. Block diagram of the classification procedure.

2. Materials and methods

In this section the procedure to obtain a classification of the LOM images is proposed; first the images are segmented thus allowing the determination of useful features, i.e. characteristics that univocally identifies the data. These features are then suitably collected together in order to provide a global description of the specimen. Then a classifier based on the support vector machines (SVM) is trained.

2.1 Image analysis and identification of nodules morphological properties

Light Optical microscope (LOM) observations of metallographically prepared DCIs specimens (not etched) allowed to obtain images like Fig. 3. Graphite elements (black) are embedded in the metal matrix (white) with some artifacts (e.g. scratches) that are the consequence of a non-perfect metallographic preparation of the specimen and that should be considered in the quantitative analysis.

From a mathematical point of view, a digital image obtained by the LOM is a matrix Y of dimension $M \times N$ of natural numbers in the scale $[0 \;\; 255]$ (8 bits) that represents the quantized gray levels of the analyzed specimen. The first step is the segmentation of the data into regions homogeneous with respect to some properties, for example their gray level, their shape or their texture, in order to quantitatively characterize the deformation.

The considered images appear of good quality but the presence of dust or oxidation degrades the signal. The objects of interest are not well separated from the background, therefore they cannot be directly analyzed, as can be noted in Fig.4 where the gray level of line 300 of the data of Fig.3 is represented.

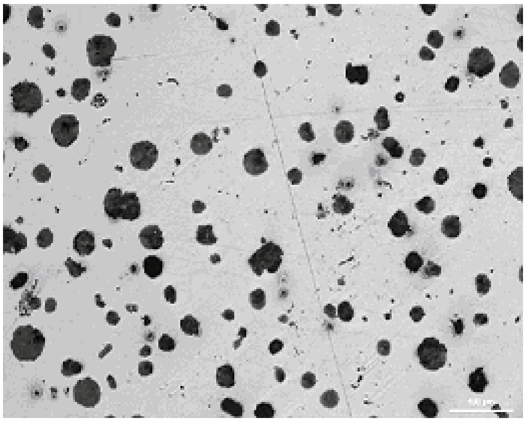


Fig. 3. Example of a metallographically prepared (not etched) DCI specimen.

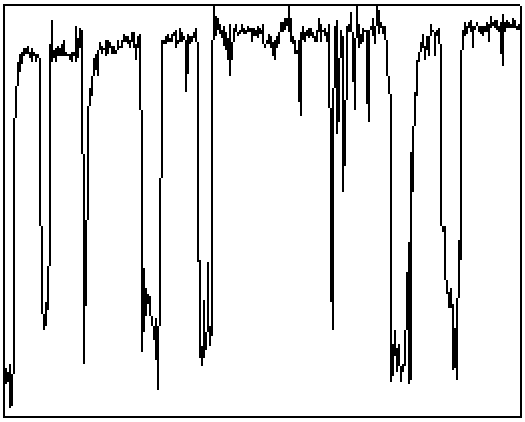


Fig. 4. Gray level of line 300 of the data of Fig.3

To segment the metallographic images different methods have been studied, implemented and adapted to the specific application of interest for this paper, Filho et al. 2015, Gacsi 2003, De Santis et al. 2008a, De Santis et al. 2007a, De Santis et al. 2008b, De Santis et al. 2014, Freitas et al, 2010, De Santis et al. 2007b, For the present application the level set theory adapted to a discrete description of the data is considered (De Santis et al.2007). The segmentation of the specimen provides a simplified version of the image yielding the identification of each nodule.

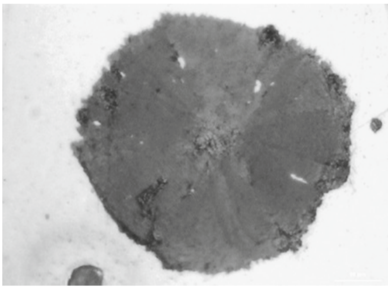


Fig. 5: Graphite nodule.

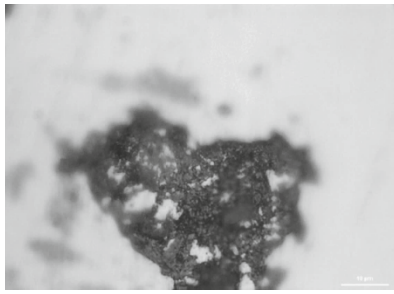


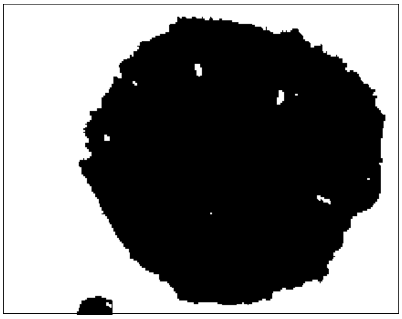
Fig. 6: Exploded graphite

When the image is segmented, each nodule can be well identified and useful morphological properties can be easily identified. In Fig. 5 and Fig. 6 examples of nodules with different morphology are presented; more precisely, Fig. 5 shows a nodular graphite element with a regular profile, whereas Fig. 6 represents an irregular graphite element: its shape is quite far from a nodule, with some matrix particles embedded in the graphite. These peculiarities are usually semi-quantitatively evaluated by means a mere visual comparison with figures available in the AST standard. In Fig.7 and 8 the binarization of the images of Fig.5 and 6 respectively is proposed: here the nodules are identified as black objects over the background, and some their useful morphological properties are evaluated, such as:

- the area: the number of pixel of the identified object;
- the centroid: the position of the nodule in the specimen;
- the Euler number: it specifies the number of objects in the analyzed region minus the number of holes in those objects;
- the filled area: it is the number of pixels in the object in which the holes are filled in;
- the convex area: it is the number of pixel of the object convex hull;
- the solidity: the ratio between the area and the nodule convex area;
- the extent: it is the ratio between the object area and the area of its bounding box.

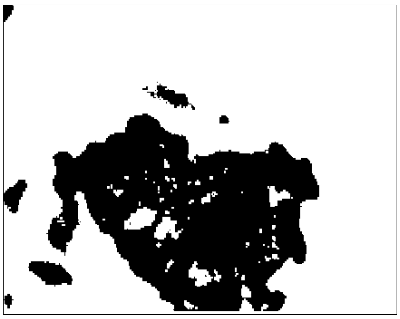
Some properties are evaluated on the ellipse with the same normalized central moments of the identified object:

the major and minor axis length, the eccentricity and the orientation.
All these properties can be easily determined, once a binarization is obtained, with the @Matlab command "regionprops".



Area: 203190
Centroid: [414.3902 270.3934]
MajorAxisLength: 528.4243
MinorAxisLength: 494.1898
Eccentricity: 0.3541
Orientation: 0.5322
ConvexArea: 213406
FilledArea: 204011
EulerNumber: -7
EquivDiameter: 508.6350
Solidity: 0.9521
Extent: 0.7331

Fig.7: Binarization of the image of Fig.5.



Area: 106718
Centroid: [358.4913 368.6075]
MajorAxisLength: 519.3000
MinorAxisLength: 314.1605
Eccentricity: 0.7962
Orientation: -13.5768
ConvexArea: 142508
FilledArea: 114637
EulerNumber: -60
EquivDiameter: 368.6158
Solidity: 0.7489
Extent: 0.5869

Fig.8: Binarization of the image of Fig.6.

It could be easily noted that there are some characteristics that help in distinguishing these two kind of nodules, for example the solidity and the eccentricity.

In Fig.9 an image of a specimen with some nodules is shown with its binarization represented in Fig.10. By analyzing all the nodules and determining their morphological properties, it is possible to extract some characteristics that could help in classifying the specimen.

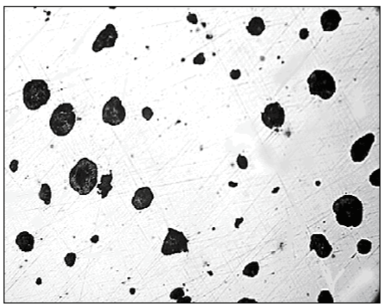


Fig. 9: LOM image.

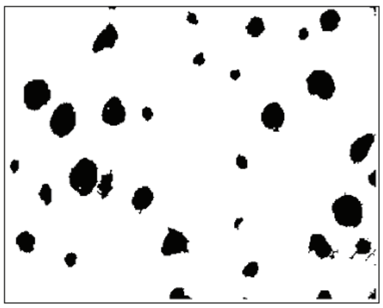


Fig. 10: binarization of the image of Fig.9.

The identified parameters may be evaluated for each nodule present in the specimen and, adequately collected together, could allow an overall description of the specimen.

Some global features that could be considered for each specimen are: the percentage of area occupied by the nodules and their number, the mean value and the standard deviation of the area, the solidity, the eccentricity and the Euler number of the nodules present in the specimen. Obviously, depending on the specific kind of specimen, a different modality of collecting the data should be advisable; for example, it could be useful to stress the influence of the number of nodules with area in specific intervals along with their properties (solidity and eccentricity), as is considered in this paper.

2.2 Classification of the specimens by the support vector machines

The features determined are classified by Support Vector Machines; they may be considered as points to be separated in two (or more) classes. In general, the SVM separates the data into two groups, aiming at determining the optimal hyperplane as a trade-off between the requirement of maximizing the Euclidean distance between the closest points and the requirement of minimizing the error on misclassified points, Chang et al. (2011), Hsu et al. (2003), see Fig.11.

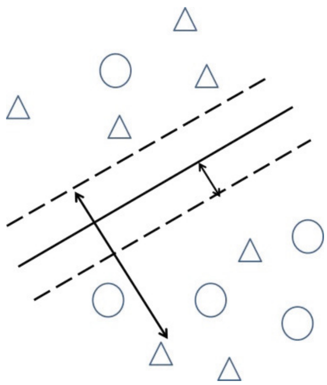


Fig.11. Graphical representation of the classification method adopted

The SVM classifier may be determined as a binary one, thus allowing the classification of an object (in the present application the object is a specimen) into one of two possible classes #Class1 and #Class2; if more than two classes are present, for example three classes, more than one classifier is determined allowing the final allocation of the object by a poll system.
Therefore to test possibility of introducing SVM as a classifier for metallographic specimens, the first step is to check its capability in discriminating the "normal" graphite set (from now on #Class 1) versus the set of "abnormal" one (from now on #Class2).

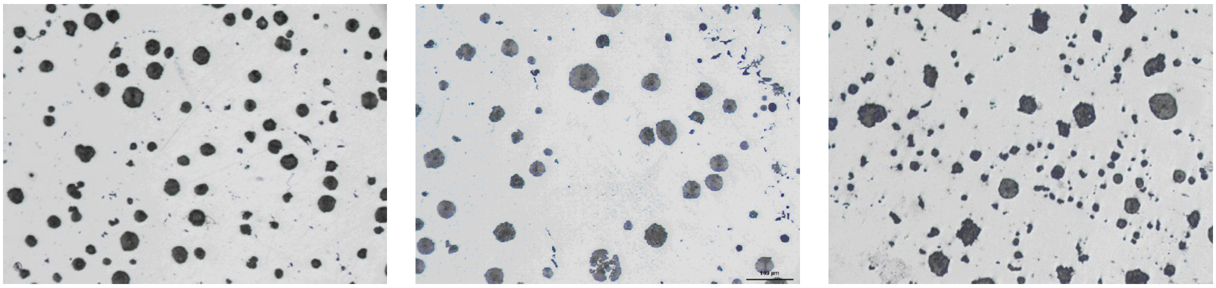
3. Numerical Results

For a first preliminary analysis, a set of 75 images are considered: 25 whose nodules are well formed, 25 with irregular nodules and 25 with deteriorated nodules. The classifier we are going to describe must be able to distinguish a nodule well formed from one of the other two kind. In Fig.12 examples of the data that we are going to classify are proposed.

As previously said, for a first attempt to train a classifier the following features are considered:

i. the number of nodules with area (in pixels) between 25 and 125 (elements with areas less than 25 pixels are considered as connected to defects like powder or scratches);
ii. the number of nodules with area (in pixels) between 126 and 500;
iii. the number of nodules with area (in pixels) between 501 and 900;
iv. the mean value of the solidity and of the eccentricity of each set of points i)-iii);

v. the granularity of the specimen defined as a property describing the total number of pixel with significant area (more than 25 pixels) normalized with respect to the total area of the specimen.



a) b) c)

Fig.12. Example of the images considered to train the classifier: a) specimen with well-formed nodules; b) specimen with irregular nodules; c) specimen with deteriorated nodules.

Therefore 10 features have been identified for each of the 25 images of the three classes. Some of these features could be more important for the classification in two classes and therefore an analysis with Principal Component Analysis (PCA) aiming at determining the best data representation is performed (Jolliffe et al. 2016) and implemented by @Matlab.
An SVM is trained (Chang et al. 2011) in order to separate the set of images of specimen classified by experts as “normal” and the set of images of specimens with different kind of irregularities.
The first preliminary tests provide results with success over 95%.
Future work will be mainly devoted in the following directions:

- obtain a more robust classifier by considering other features;
- implement a multi class classifier in order to replicate, as much as possible, the classification of the international standard.

4. Conclusions

Considering that the characterization procedure of the graphite elements in a cast iron is still based on a visual observation of metallographically prepared specimens and comparison with “standard” images, and considering that the graphite nodules morphological peculiarities (shape, dimension and distribution) are extremely important to define the macroscopical mechanical properties of cast irons. In this work a preliminary automatic classification procedure is implemented; it is based on the evaluation, by image processing, of global characteristics of the specimens (the features). A support vector machine classifier is trained and a binary classification is obtained separating the class of specimens with well-formed nodules from the class of specimens with irregular nodules.

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