The application of hyperspectral image processing to the steel foundry process.

Authors:
José A. Gutiérrez Olabarria. Engineer, Tecnalia- Infotech
josea@robotiker.es
Artzai Picón Ruiz. Ph.D. in Industrial Engineering, Tecnalia-Infotech, apicon@robotiker.es
Sergio Rodriguez Vaamonde, Engineer, Tecnalia-Infotech
srodriguez@robotiker.es
Robotiker- Tecnalia
Parque Tecnológico Edif. 202
48170 Zamudio (Biscay) Spain

Ignacio Girbau, Engineer, Arcelor – Mittal Olaberria
ignacio.girbau@perfiles.arcelor.com
Arcelor – Mittal Olaberria
Ctra. Madrid-Irún, KM. 417.
20212 Olaberria (Gipuzkoa) Spain

1. Summary

In the steel industry many technologies are applied in order to optimise the cost of the production process and to improve the quality of the final product. Despite these efforts, there are still areas where the parameters of the process are established by subjective evaluations. More specifically, this is the case in the slag characterisation processes in the Electrical Arc Furnace (EAF) and in the Ladle Furnace (LF).

In the EAF process, to be precise, the chemical composition of slag is not known during the process as the samples must be analysed in special spectrometers and this requires a previous treatment and preparation. In this process, the knowledge of both the basicity of the slag as well as the oxidation level of steel would be valuable in order to know the chemical composition of slag. At present, both of these characteristics are only known after laboratory tests. During the LF process, the estimation of the degree of deoxidation and desulfuration of steel is based on the visual evaluation (Figure 1) of the slag samples and on the chemical composition of the steel. In this process, although spectroscopes have been used for years, they are used after the process is finished, thus requiring additional time for the samples to be prepared. However, hyperspectral image-based technology provides information on the spectral response of the elements of the process (slag) in a wide range of wavelengths, from infrared to ultraviolet. This

provides the characteristics of the chemical properties of these slag.

Unlike spectroscopy, these techniques, though less precise, can provide an automatic online analysis. This allows for the estimation of the chemical composition of the elements that form part of the process and enables the optimisation of the parameters during the process in order to achieve the desired properties of the steel.

A sample of each type of slag is obtained and is spectrally and spatially processed in order to achieve this purpose. From this processing, a feature vector is extracted containing the spectral information (which provides the chemical composition of the sample), as well as its spatial information. Spatially, the slag is composed of various elements that can have a non-uniform distribution. This means that each pixel of the hyperspectral image of the slag has a different chemical composition. Thanks to spatial processing, we can provide the general characteristics of a particular type of slag. This provides a better identification of the slag than by only using spectral information. After calculating this spectral-spatial descriptor, a specific multivariate Gaussian classifier is built to properly characterise the slag. This trained classifier is able to distinguish between the chemical compositions of different types of slag and, therefore, will be able to predict desired steel properties.

This promising study is being carried out at Robotiker - Tecnalia in collaboration with Arcelor Mittal Olaberria. The final system will be located close to the Electric Arc Furnace (deslaging door) and in the Ladle Furnace and will automatically provide reliable and robust on-line data from the slag samples coming from the melting and refining processes.

2. Key Words

Hyperspectral, Machine vision, EAF process, LF process, Image processing, Colourimetry, Automation

3. Introduction

In the modern iron and steel industry, certain tasks are still being performed based on the subjective appraisal of an expert. An example of this approach is that many of these tasks continue to rely on the visual appearance of the production elements. The refining process is a case in point. Although having available means such as a spectroscope in the laboratory for the later analysis of samples and despite having available the information on the chemical composition of steel, the visual appearance of cooled down slag is still used in the process. Thus, the adding of ferro alloys and other additives to the batch still has a human component that is prone both to the subjectivity as well as the expertise of the worker. The addition of ferro alloys and other additives could be optimised by knowing with greater precision the chemical composition of slag, thereby reducing the total cost of the productive process.

Fig. 1 Manual taking of samples

In the case of the Electric Arc Furnace (EAF), the "on-line" knowledge of the chemical composition of slag is more complex as the differences in the oxide content cannot be noticed by visual inspection. At present, this composition can only be known once the samples have been processed in the laboratory. The production process would be better controlled if one had knowledge of the amount of iron oxide in slag as it would be easier to minimise the waste while at the same time it would provide the worker with the knowledge of the basicity of slag and thus be able to regulate the additives based on it. The "on-line" knowledge of these two characteristics of slag would help to optimise the regulation of the process, provide cost savings in refractory and increase productivity.

Image analysis by means of machine vision is an alternative in order to automate this type of data entry. Within this field, colour processing seems to provide a good solution.

These conventional methods have their limitations, as in a large number of cases the response to either colour or intensity is very similar in classes and these models are very difficult to create.

However, hyperspectral image processing technologies, by providing the emission spectra of the different elements of the process in real time, allow obtaining very valuable information that can even provide information beforehand on the chemical composition of the observed element.

Hyperspectral systems, unlike colour cameras, can see multiple bands, from the ultraviolet to the infrared with very high spectral resolution, (up to 2,5 nm within bands). An example is the AISA camera of the Finnish company SPECIM. This versatility allows the systems to detect, classify and identify different materials, thus overcoming some of the limitations of the colour cameras which operate in the range of visibility.

In any case, powerful processing software is necessary in order to both have an efficient and robust analysis of such a great volume of data as well as to adapt the spectral characterisation algorithms to the requisites of the application. To be precise, these algorithms must meet certain conditions of robustness, must be able to adapt to different types of samples while at the same time bearing an adequate computational cost that permits compliance with the required times in production. The following sections provide the technical solution details:

4. Description of the proposed system

a. Hyperspectral Image acquisition and correction

The employed methodology for the acquisition of hyperspectral images allows the simultaneous capture of all spectral bands. In order to do so, the variability of the angle of refraction in relation to the wavelength is used. This way, starting with the capture of a line of an image similar to a line scan camera, the spectral information is extracted through a prism that refracts the incident beam in each of the wavelengths in the image. Thus, the obtained image contains, in abscissas, the position of the captured line and, in ordinates, each of the spectral frequencies. In order to obtain the entire image, several snapshots are combined in which each snapshot has a line of the entire image.

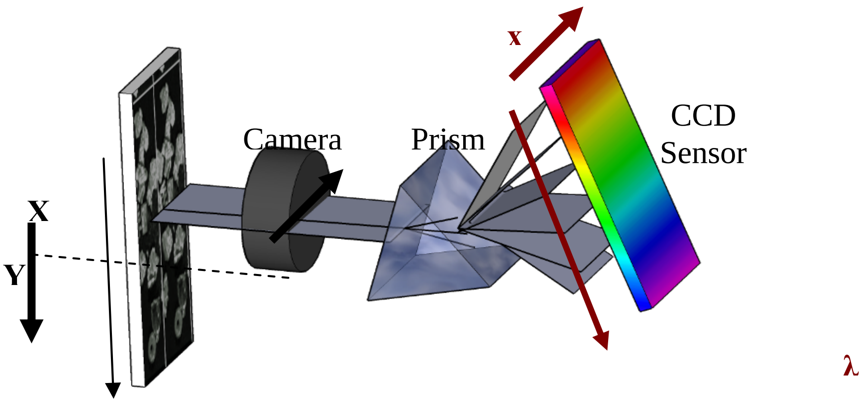


Fig. 2 Principle of hyperspectral image capture.

Figure 2 shows this principle. First, a line of the image is captured and the light of each of those points in that line is spread vertically by the prism based on its wavelength. This way, each line is captured in the CCD sensor as a twodimensional image in which the horizontal axis represents the pixel position in that line (X axis) and the λ axis represents the different wavelengths spread by the prism.

Synchronising the capture by the camera with the Y movement produced between the camera and the object, one obtains the different lines of the object and creating the associated hyperspectral image (Figure 4).

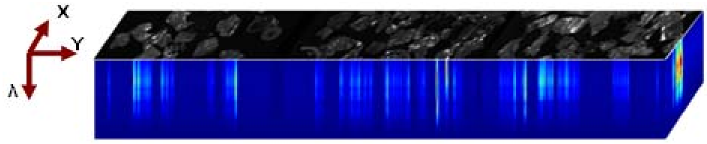


Fig. 4 Hyperspectral Image

A hyperspectral image, as shown in Figure 4, is represented by a cube in which each layer corresponds with a certain wavelength. In this manner, each image pixel is characterised by a vector which represents the luminous spectrum reflected by the material. One of the advantages that hyperspectral images have over traditional spectroscopy, which can only provide spectral information in a point, is that each of the image pixels is associated with its electromagnetic spectrum, thus allowing for greater information.

Fig. 5 Different hyperspectral camera models (Robotiker- Tecnalia)

Specifically, each point (x,y) of the image (Figure 4) is represented by a vector L(x,y), whose components correspond with each of the K responses in intensity of the wavelengths in which the spectrum is discretised, that is, the quantity of light reflected in that (x,y) pixel based on its wavelength. This way, each image point is represented by vector L(x, y), that is associated with the spectral response to that point, as defined in equation (1)

$$\mathbf{L} = \{L_1, L_2, ..., L_K\}^T \quad (1)$$

This vector, in theoretical conditions, is dependant of the physical and chemical nature of the material as well as its structural properties. Performing treatments (Picón A. 2009), it can be used for its characterisation.

Each of the hyperspectral images contains a great amount of information about the molecular properties of the elements in each image. However, this great amount of raw data makes more difficult the creation of automatic classifiers that will allow associating each element of the image with the material to which they belong. This is due to the Hughes Phenomenon (Hughes GF. 1968) which causes that the existence of a greater number of variables which allow defining a material in turn makes necessary a greater number of samples in order to create a model that will allow to automatically associate a set of variables to the material to which they belong. Likewise, a greater number of unknowns imply a greater number of equations in order to resolve it, thus being necessary to reduce the dimensionality of available data in order to obtain a spectral signature of reduced dimensions.

Due to the aforementioned, the **decreasing of the information** is necessary based on two reasons:

- Avoid the redundant information present in the spectrum.

- Transform the data in order to have available a vectorial representation where the separation of the material is highest.

Earlier studies undertaken with materials to be classified show that given their great spectral dispersion, the use of only spectral information was insufficient to undertake their robust classification, with obtained results of 56% (Picón A et al. 2010). The use of techniques to reduce characteristics allowed to increase the classification rate up to 71% through the use of an innovative technique for the reduction of characteristics that is bioinspired in the behaviour of the human eye. This technique imitates the functioning of human visual cones and extends it throughout the non visible spectrum as a hyperspectral eye that is capable of emulating the process of extraction of information, in the same manner that the human eye does it in the visible spectrum, thus creating 8 hyperspectral cones which are sensitive to different wavelengths.

The precision obtained through these techniques for the reduction of characteristics is not enough for the correct description of the materials. Therefore, the authors developed methodologies which permit the integration of the spectral features of each element of the image with their variation in close neighbourhoods, that is, we include information of the **"texture"** of the material within the spectral information. This approach provided very positive results and achieved a correct classification rate of 98% (Picón et al. 2009). This approach is based on the calculation of a histogram associated to each of the spectral pixels of an image and has the variation of each of the characteristics of the neighbourhood associated to each pixel. A detailed definition of this algorithm of spectral-spatial description can be found in (Picón et al. 2009).

In this manner, each spectral pixel is not only defined by its spectral characteristics, but rather is defined by the diffuse neighbourhood histogram of each of its spectral characteristics in a neighbourhood associated to the pixel,.

b. Particle classification

This signature, which bears the spectral and spatial features of the particle, is used as an input vector of a classifier based in the multivariate Gaussian distributions. The use of this classifier is due to the adequate interpretability as well as the good generalisation obtained with this type of classifiers.

$$\mathrm{N}(\mathbf{H} \mid \boldsymbol{\mu}_{C_i}, \Sigma_{C_i}) = \frac{1}{(2\cdot\pi)^{D/2}} \frac{1}{\left|\Sigma_{C_i}\right|^{1/2}} e^{\left\{-\frac{1}{2}(\mathbf{H}-\boldsymbol{\mu}_{C_i})^T \Sigma^-\right.} \tag{2}$$

In this way, the spectral signature of each of the previously segmented particles is labelled as that class to which its membership probability is greatest (maximum likelihood), thus obtaining a relation between each image point and its most probable membership class.

5. Results of the slag tests

The tests that have been performed consist of a reasonable sampling, both in the EAF as well as in the LF, in different moments in time and with different states of composition. The object is to be able to differentiate them so as to identify when the adequate chemical composition has been achieved A model of each state of the group has been created and then each model has been tested with new samples in order to see if its differentiation is possible.

The need to use hyperspectral vision technology can be seen in the following image which captures the grey levels in different moments of the sample:

As can be seen, the differences in grey are difficult to detect, therefore, the sample classification can have a probability of error.

However, if one uses a system of hyperspectral capture in near-infrared (NIR), ranging in wavelength between 900 nm and 2600 nm, one can notice that its classification is simpler.

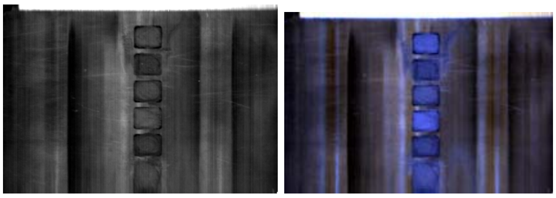


Fig. 5 Images captured in grey levels (left) and hyperspectral NIR (right)

The tests that have been performed have analysed the slag samples for each of its composition characteristics. With a group of samples at different times in the production line, a model has been created and another sample group has been used to test this model. The classification method mentioned in section 4 has been used.

As figure 6 shows, the identification of the three existing classes, at first glance, is simpler. However, we are working to find a better description of them.

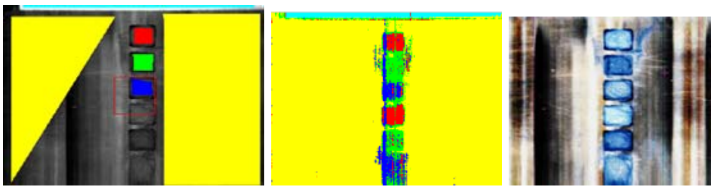


Fig. 6 Classes created, classified sample and with pseudocolored balanced lighting. The chosen wavelengths for colouring have been 1121 nm, 1494 nm and 2319 nm.

Analysing the results, a more or less clear differentiation is possible, though the rate of mistakes is quite high with conventional methods. Therefore, the aforementioned algorithm has been used. The first necessary step is to correct the lighting. The need for this correction is due to the imperfections both in light and in the lenses of the equipment, as they can substantially vary the wavelengths of the samples.

The right hand image in figure more clearly shows the difference between classes. This difference is also noticeable in spectral space, as shown in figure 7.

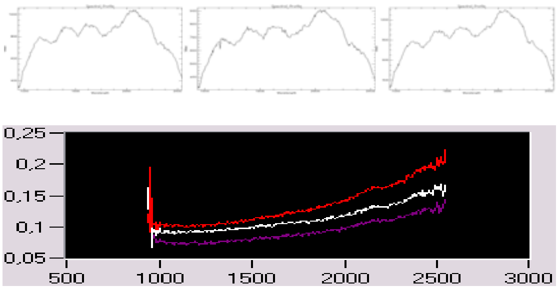
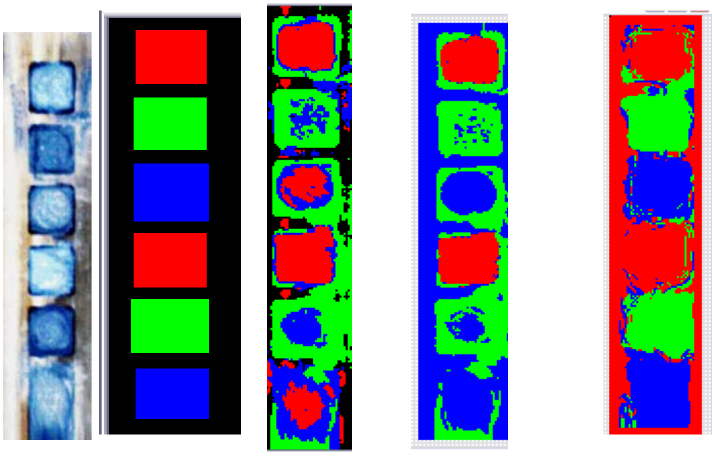


Fig7 (above) medium wavelengths of each class without lighting balancing. (below) after the correction

One can notice that there are minimal differences. However, with lighting correction, the differences between spectral signatures of each sample become more apparent, as shown in figure above.



Classical Gaussian model	FuzzySets + Gaussian model	Fuzzysets+spectro-spatial model
56%	67%	97%

The performed tests show that slag characterization is better performed using our Spectro-spatial model approach with an accuracy of 97%. The use of the undecorrelated spectra or just the spectral information without including the spatial information deals to a great increment in the classification rate.

Once the correction is made, the difference between the slag classes is a difference between the slopes of their spectra.

6. Future Works

This study is promising, but the project still needs further important work previous to the implementation of the solution.

- Decision: Cold or hot analysis. Current state of tests, if additional bands (far from NIR) allow the direct classification for hot samples, then we will avoid having to wait for the cooling down of the sample.

- Work is being carried out regarding the creation of classification libraries as a commercial product. In contact with important suppliers

- Design of the final system

    - Automated capture of the sample that is simultaneous to the taking of the spectrometer sample.

    - Automated submittal of the sample to a hyperspectral system for its analysis.

    - Report of the results to the automated line control.

7. Conclusions

This work has shown a new methodology inspired in the human visual system which allows for the classification through the incorporation of spectral information (spectroscopy) and spatial information (machine vision) without increasing the computational cost required for the their classification and notably increasing its classification rate.

Though at first, this study is very promising in its application for use with slag, this methodology can also be applicable in diverse fields of iron and steel production and other fields. At this time, work is being done to detect (metals, plastic) composition on line, to include spectral-spatial descriptors for the description of tumours in magnetic resonance imaging and for the description of real estate in multispectral airborne images, allowing a segmentation and characterisation that is much more precise, thus showing this method´s cross-disciplinary polyvalence.

8. References

[1] *Perkins S. "Genie Pro: Robust image classification using shape, texture and spectral information", Algorithms and Technologies for Multispectral, Hyperspectral and Ultraspectral Imagery XI, SPIE, 2005.*

[2] *Picón A. et al. "Bio-inspired Data Decorrelation Methodology for Hyperspectral Imaging",Pattern Analysis and Applications*, to be published (2010).

[3] Picón A. et al. "Spectral and Spatial Feature Integration for Classification of Non-ferrous Materials in Hyper-spectral Data*", IEEE Transactions on Industrial Informatics*, 2009.

[4] Panner, "Industrial application for inline material sorting using hyperspectral imaging in the NIR range", Real-Time Imaging, *vol. 11, no. 2, Spectral Imaging II,* pp. 99-107, 2005.

[5] Chang, "Independent component analysis-based dimensionality reduction with applications in hyperspectral image analysis", IEEE Transactions on Geoscience and Remote Sensing, vol. *44, no. 6, pp. 1586-1600, 2006.*

[6] *William L. G, Zissis G J, The Infrared Handbook*. 1978 Publisher:Environmental Research Inst. Volumes: 1 1978

[7] Willis, "Hyperspectral image classification with limited training data samples using feature subspaces", Algorithms and Technologies for Multispectral, Hyperspectral and Ultraspectral Imagery X, SPIE, 2004.