

Feature Descriptors Applied to Slag Characterization on Casting Process



Julio-Alejandro Romero-González, Ana M. Herrera-Navarro, Hugo Jiménez-Hernández

Abstract: Vision systems are increasingly entering the field of metallurgy, carrying out operations where a human operator is not possible due to the process conditions. The purpose of these systems is the monitoring and control of the process to improve the quality and manufacturing of the products. Nevertheless, the amount of slag, the presence of gases and high temperatures are the main problems that make this task difficult. In this proposal the characterization of the slag is treated, through the analysis of the light changes with the functions of Fourier and Gabor, which allow to identify or locate the location of the slag in the material, so that, in future works the slag It can be segmented, measured or used to detect the level of the metal in the refractory. In addition, results obtained when evaluating sensitivity and precision curves are presented, with which the information recovered by the algorithms is evaluated.

Keywords: Features detection, Fourier Transform, Gabor Filter, Image Processing, Vision Computing.

I. INTRODUCTION

In recent years, computer vision has had an important role in human visual perception, which in general refers to a basic ability of the visual system to derive clusters and corresponding structures from an image without prior knowledge of its content [1]. At present, the developments made for scene recognition have mainly focused on robotic applications [2], detection and monitoring of people [3], and obstacle detection [4] to name a few. Nevertheless, in recent years, a lot of vision systems have focused on inspection [5], monitoring [6] and control of industrial processes [7], such as metallurgy. Metallurgical processes have evolved significantly, of which 90% is constituted by continuous casting, where the speed to pour the liquid metal influences the temperature of this process, when the emptying is slow the temperature decreases generating crystallized or granulated slag [8], the amount of slag on the surface influences the degree of purity and undesirable cracks of the material. Therefore, to ensure the quality of the material, the casting process must be carried out at an adequate speed and with the least amount of slag possible. Some approaches have been made to solve both problems, which are described in the related works section.

II. RELATED WORK

Usually, the detection of slag has been carried out by a human operator, but due to hard process conditions, methods have been developed to carry out this task automatically. Mainly the use of accelerometers [9] has been used to measure the vibration generated by the flow of molten steel, in the method proposed in [10] the frequency domain and time domain analysis of the vibration signal acquired by accelerometers and sensors electromagnetic. Similarly, in [11] the analysis of the frequency spectrum is proposed by means of the discrete wavelet transform, in addition, experimentation based on probabilistic methods has been carried out, such as the proposal made in [12], where the authors measure vibration due to the Density difference between steel and slag, the vibrations caused by this effect, are evaluated with the Markov hidden model statistical method. Other studies such as those proposed in [13-15] measure the amount of slag, analyzing the difference in emissions between molten steel and slag.

In [16], artificial neural networks are used to characterize the slag, in which some products are used to mimic the slag on surface. Similarly, competitive neural networks are used to analyze conditions and influence of disturbances [17]. Also, a radar created by a HATCH enterprise is being used for measuring of slags on the refractory [18]. However, the build-up of the product and high temperatures produced damage in the units. The damage in the units and their cost of repair are not easy for the companies at all because the measurement requires high requirements due to the hard conditions of the process, on the other hand, an interferometer of radio waves has been implemented [19], it was placed behind of a protection window of the smelting furnace for measurement of the spatter generated by the fall of the melted metal. Also, the radiated heat of the hot material is used in [20] to measure the slag, where authors use temperature sensors in a cooling pipe to detect changes in the water temperature and the slag foaming.

Moreover, other methods were developed based on acoustic, as [21] and [22] present a method that employed signals of an audiometer. These signals were registered and analyzed for their measurement of slag levels, on having raised levels, the signal starts to be reduced in a gradual form. Finally, they got a model to estimate the level slag in the smelting furnace.

The reduction of the slag improves the performance and quality of the production in casting operations, in method proposed by [23] and [24] spectrometry, diffraction and morphological analysis were used to analyze surface area properties. In the same way, in [25] properties of mold slags were measured to observed the behavior between crystalline layers of slag and steel surface quality.

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Correspondingly researches in the literature focus on level measurement [26], slag detection, slag measurement [27] and others [28-29] to improve the quality materials.

III. FOUNDATIONS

There is a wide variety of parametric and non-parametric methods used to analyze texture, whereby they describe the changes of intensities to quantify the texture of an object, surface or scene, within these methods are the Fourier Transform and Gabor Filters. Both methods are used in this manuscript to characterize and detect slag in casting processes, these methods are described below.

A. Discrete Fourier Transform

The Fourier transform is defined in terms of sinus and cosine functions that at a certain frequency represent the distribution of the frequency spectrum of a particular function, which is defined by [30] as equation (1).

$$F(x(t)) = \int_{-\infty}^{\infty} x(t) e^{-2i\pi ft} dt \quad (1)$$

Where x represents a function in the time domain, f are the frequencies and F is the transformation of the spatial domain to the frequency domain, expressed in a centered way. That is, both positive and negative values are included.

Now, the generalization of the Fourier transform is expressed in a single form and is known as the Discrete Fourier Transform (DFT), where now a continuous function over time is discretized with and represented as a sample of N points. The definition of the Fourier transform is shown below in equation (2).

$$X[k] = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} f_{i,j} \cdot e^{-i2\pi \left(\frac{k_i+i_j}{N}\right)} \quad (2)$$

Where f is the grayscale image, ki and lj are the samples of the 2-D function, i and j are the position in the image, N the number of points sampled and X represents the DFT of the image.

While the Discrete Inverse Fourier Transform is defined in equation (3).

$$f_{i,j} = \frac{1}{N} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} X_{k,l} \cdot e^{i2\pi \left(\frac{k_a+l_b}{N}\right)} \quad (3)$$

Where N is the number of points sampled, Xk,l represents the DFT of the image, ka and lb are the samples of the 2-D function, i and j are the position in the image.

B. Gabor Filter

The Gabor function was developed by [31], and is widely used in the literature, since it is sensitive to subtle changes in texture, the method consists in convolute a Gaussian function with a sine and cosine function, the real part of the function defines the structure of objects and the imaginary part its texture. The Gabor function is defined as shown in equation (4).

$$G_{\beta} = \frac{f}{2\pi\sigma} \cdot e^{\left(-\frac{u^2+vy^2}{2\sigma}\right)} \cdot e^{j2\pi fu+\varphi} \quad (4)$$

Where f represents the frequency of the function, σ is the standard deviation of the Gaussian function, γ is the spatial aspect ratio and φ is the phase offset. Now, u and v are the cartesian coordinates of the spatial and they are defined in equations (5) and (6).

$$u = x \cos(\theta) + y \sin(\theta) \quad (5)$$

$$v = y \sin(\theta) - x \cos(\theta) \quad (6)$$

Where θ is the orientation of Gabor function.

IV. FEATURE DESCRIPTORS

The Fourier and Gabor transforms are functions widely used to describe changes in intensity in an image. When these changes are distinctive in an object, these represent features that are used to identify, segment or define the properties of an object. The way in which these features are obtained is different for both methods. In fig. 1 the frequency spectrum obtained by applying the DFT is shown. When a low pass filter is applied to attenuate these frequencies, pixel values have higher intensity are highlighted in the image after of apply the IDFT.

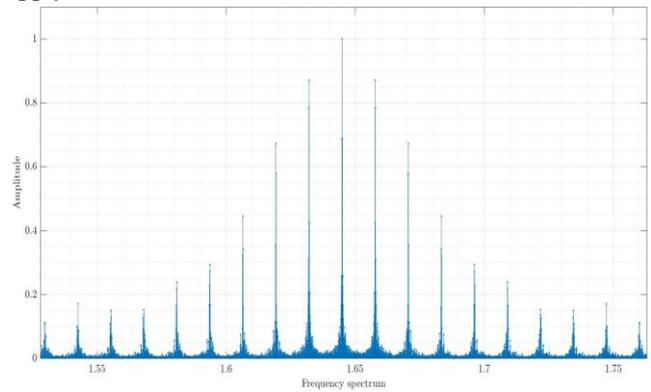


Fig. 1. Frequency spectrum. (source: own elaboration)

Unlike to DFT, the Gabor function employs the convolution of a sine wave with a Gaussian function, the result of this convolution is shown in fig. 2, when the lambda value is increased or decremented, different frequencies can be obtained, which allow characterizing the intensity changes in the image to detect thin or thick edges, which represent features.

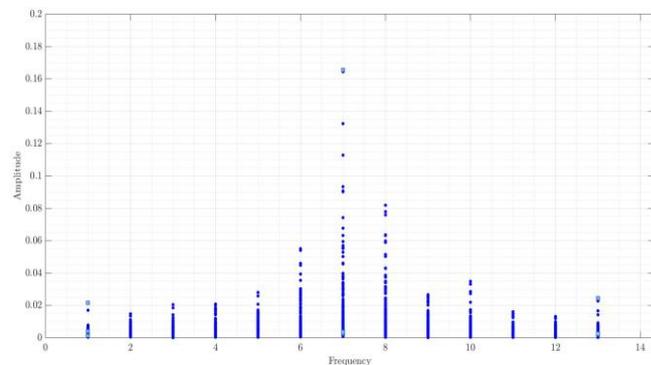


Fig. 2. Gabor frequencies. (source: own elaboration)

V. EXPERIMENTAL DESIGN

The analysis of the slag in casting process is a hard task, mainly due to the gas produced by the slag, when this occurs, the visibility of the camera is reduced, losing sight of the slag in the metal, whereby the characterization was not carried in real-time; this reason is one of the limitations of this proposal. Nevertheless, in the experimental design of this proposal, the application of two texture descriptor algorithms is suggested, which by analyzing the intensity changes due to high temperatures, allow segmentation and spatial location of the slag position based on their features. In this section, the experimental design proposed consists of the analysis of sequences of images of 640 x 480 pixels, of which their characteristics were obtained by applying the Fourier and Gabor transforms, results obtained are shown in fig. 3.

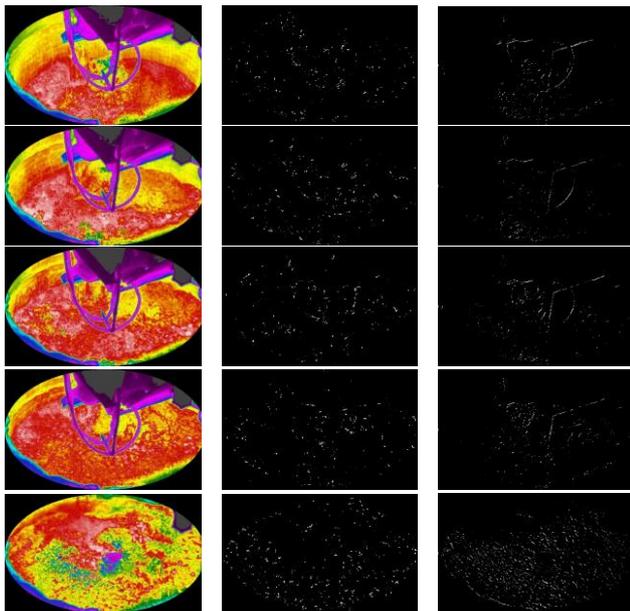


Fig. 3. Features extracted. In the left column are shown the original images, in the middle column DFT features and the right column Gabor features are shown. (source: own elaboration)

The procedure applied to obtain Fourier features is described below.

- 1) Apply DFT to move from the time domain to frequency domain.
- 2) Apply a low pass filter to highlight higher intensity pixels.
- 3) Apply IDFT to return to the time domain.
- 4) Apply a threshold to segment the image and obtain the characteristics

The process to extract the Gabor features is simpler, since only the convolution between the grayscale image and G_{β} is required, the difficulty of this method lies in choosing the appropriate frequency value to detect greater or lesser details. Parameters used to carry out this experiment are shown in table I.

Table- I: Name of the Table that justify the values

| | Gabor | Fourier | |
|-----------|----------|-----------|--------------|
| f | 2.22 Hz | Attenuate | 5% |
| φ | 0 ° | N | 307,200 |
| θ | 0° – 90° | W | 32x32 pixels |
| σ | 2.5 | σ | 0.2 |
| γ | 0.5 | | |

VI. RESULT AND DISCUSSION

To validate the data on the characteristics obtained by the algorithms, tests were carried out with 500 images, the tests consisted of obtaining the true positives, false positives, true negatives, and false negatives, with the results obtained from this analysis, the ROC curve was determined (Receiver Operating Characteristic), with which the accuracy and sensitivity of the algorithms have been evaluated. The ROC curve obtained is shown in fig. 4.

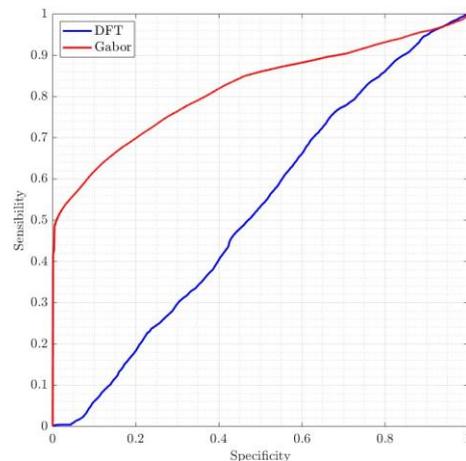


Fig. 4. Roc curve

According to the results shown in fig. 4, the Gabor filter shows greater precision, obtaining about 80% of the slag characteristic points, while with the DFT it is not possible to discriminate the sensitivity of the algorithm since the value of this method in the ROC curve is around about 50% With this data, it can be inferred that the Gabor method is a better texture descriptor, this means,

The Gabor function has better information retrieval in terms of the number of images evaluated. And with this method it is possible to segment and characterize most of the slag as long as the parameters are adjusted properly.

In addition, in fig. 5, one of the possible applications of the slag characterization is shown, where the modification of the position of the liquid metal in a smelting furnace is shown, the red line shows the modification of the position, while the blue lines show the standard deviation of level estimation.

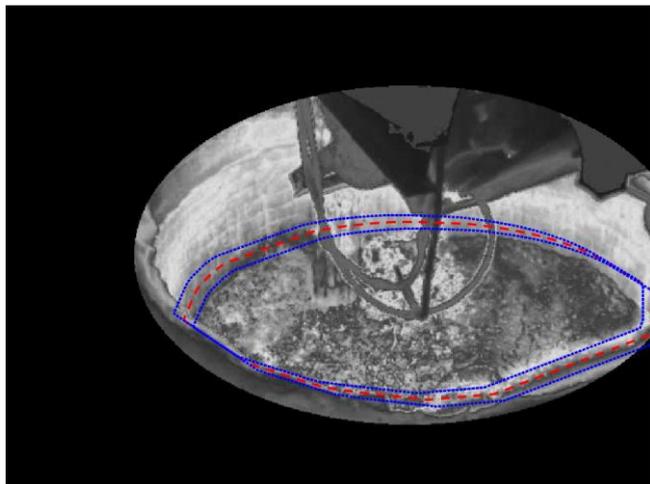


Fig. 5. Location of molten steel level in a smelting furnace.

VII. CONCLUSION

This paper proposes a way to characterize the slag of liquid metal in casting processes, the motivation of this work is based on the fact that, in the casting processes, tasks become difficult for human operators to do, due to hard conditions that the process demands, such as high temperatures; the generation of gases caused by the fall of slag in the metal, which hinder visibility and can cause health problems in human operators; or damage to refractories caused by turbulence and metal overflows.

Although research is reported in the literature to deal with some of the aforementioned points, these focus on the measurement of chemical properties of the material, measurements by mechanical elements, obtaining shape for slag segmentation or measuring the percentage of slag in the metal, The latter is one of the most important that defines the quality of the material. Based on these observations, a vision algorithm that analyzes the characteristics of the slag and that allows them to identify, segment or locate the location of the slag in the material has not yet been reported, so that it can then be segmented, measured or obtained the level of the metal.

According to the results presented in this paper, the Gabor and Fourier function allow to extract distinctive characteristics, but the Gabor function shows invariance to intensity changes, thus reducing noise and erroneous detection of characteristics. As it could be observed, the sensitivity-precision curves are more favorable for the Gabor transform in terms of positive predictions, in addition to offering better information retrieval.

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