Online Monitoring of Dynamic Slag Behavior in Ladle Metallurgy

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(Received on September 24, 2002; accepted in final form on February 6, 2003)

1. Introduction

The lack of real time sensors for ladle metallurgy stations means that current process control systems are dominated by manual procedures. This shortage of real time sensors is attributed to the harsh operating environment of ladle metallurgy especially the high temperatures and corrosive slags associated with the process. The present operating practices are usually focused on achieving certain quality requirements for the downstream process in a consistent fashion (“stable operation”) rather than on optimizing the ladle process. The availability of online sensors should allow improvements in both product quality and the potential of optimizing the process to achieve these quality requirements.

One key operational parameter of ladle metallurgy is the dynamic behavior of the molten slag. It is well known that gas injection into a ladle will cause disturbances to the surface of the ladle slag, such as “spout eye” formation, that can adversely affect the steel quality. The presence of “crusty” or solid phases in the slag is an important operating parameter. In this paper, a new real time instrument for slag monitoring using a multivariate image processing approach is proposed. The discussion will start with a brief description of the mathematical procedure of on line multivariate image analysis followed by application of this approach for identification and quantification of molten slag behavior in an operating ladle.

2. Mathematical Procedure

A digitized image may be viewed as a data matrix and when collected in multiple spectral bands produce a stack of congruent matrices. This shortage of real time sensors is attributed to the harsh operating environment of ladle metallurgy especially the high temperatures and corrosive slags associated with the process. The present operating practices are usually focused on achieving certain quality requirements for the downstream process in a consistent fashion (“stable operation”) rather than on optimizing the ladle process. The availability of online sensors should allow improvements in both product quality and the potential of optimizing the process to achieve these quality requirements.

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A digitized image may be viewed as a data matrix and when collected in multiple spectral bands produce a stack of congruent matrices. Figure 1 illustrates the image data matrices of an RGB (Red-Green-Blue) format. The RGB format is a common way to represent high-resolution color images, in which each pixel is specified by three values—one each for the red, green, and blue components of the pixel’s color. This image is a stack of three congruent n x m pixel images and mathematically, the image can be viewed as a matrix, Im, with dimension n x m x 3 or for simplification can be written as Im(n x m x 3). This matrix can be unfolded into an extended two-way matrix X(n x m x 3) using procedure presented in Fig. 2.

Figure 1. A schematic diagram of RGB image structure.

Multivariate statistical methods, such as principal component analysis (PCA) and partial least squares (PLS), have been successfully used for multivariate image analysis. Using these approaches, a set of highly dimension and highly correlated data can be projected into a set of un-correlated data with a reduction in dimensionality. In this paper, the PCA approach will be used to develop a procedure for online monitoring of molten slag. The chose of the PCA approach is based on its simplicity and reliability of the method, which allows developing a fast method of image processing. Discussion about processing speed will be presented later in this paper.

PCA is often used for finding structure in a highly correlated data tables. Using this method, a set of multivariate data is transformed into a set of uncorrelated parameters, its principal components, in which all information in original data is retained in the principal components. Furthermore, usually the number of principal components can be considerably reduced without any significant losses of useful information from the original data.

For simplifying the problem, consider a set of RGB image data with data structure as illustrated in Fig. 1. The image data can be viewed as a three-way matrix, Im, with dimension n x m x 3 or for simplification can be written as Im(n x m x 3). This matrix can be unfolded into an extended two-way matrix X(n x m x 3) using procedure presented in Fig. 2.

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The unfolded image matrix, $X$, can be decomposed by performing principal component analysis. The relation between the original matrix and its principal component is given by the following equation:

$$X = \sum_{i=1}^{n} t_i p_i^T + E = TP^T + E$$

where: $X$ is an unfolded version of $I_f$; $T$ is score matrix; $P$ is loading matrix; and $E$ is residual matrix.

By assuming that all information in the image is retained in the first two principal components, i.e. $t_1$ and $t_2$, the $X$ matrix can be approximated by:

$$\hat{X} = \sum_{i=1}^{2} t_i p_i^T$$

The score vectors, $t_i$, are linear combinations of the variables (columns) in the data matrix $X$ that explain the greatest variation in the multivariate data. These vectors have a property of orthogonality with respect each other. Loading vectors, $p_i$, are the eigenvectors—in descending order—of the variance–covariance structure ($X^TX$) in the data matrix. These vectors have a property of orthonormality with respect to each other (i.e. $P^TP = I$; where $I$ is the identity matrix). Based on the property of the score and loading vectors, the value of score matrix, $T$, can be obtained by multiplying $X$ by $P$:

$$T = XP$$

Following the assumption that all information in the image is retained in the first two principal components, the combination of the first two score vectors ($t_1$ and $t_2$) would be almost identical with these pixels, as shown mathematically in Eq. (3). Therefore, the combination of these principal components can be used to extract information from (or to discriminate materials in) the considered image. In addition, the value of the first principal component, $t_1$, represents the average of the pixel intensities at each wavelength whilst the second principal component, $t_2$, represents the contrast or difference among the pixel intensities at various wavelengths.

### 3. Example

To provide data for developing the procedure, two set images have been taken from an industrial ladle metallurgy station. The ladle diameter and ladle capacity were 4.4 m and 315 tonnes, respectively, and the slag height was approximately 60 to 80 mm. The images were taken from a camera positioned directly above the surface of the ladle. Each set of image data consisted of eight to ten images. To generate the spout eye or bare metal and provide stirring to the ladle, argon gas was injected through a bottom porous plug with the flow rate varied from 10 to 40 Nm³/hr. The images were taken using a standard digital camera (Kodak DC4800 3.1 Megapixel) in RGB format with size of 2 160×1 440 pixels/image. After preprocessing to minimize the perspective (shooting view angle) effect, by stretching and cropping, the size of the image is of 1 720×2 010 pixels/image.

Figure 3 shows an example of image taken from the ladle, which was taken at gas flowrate of 20 Nm³/hr and slag height of 60 mm. This image has size of 408×520 pixels. The figure depicts a bare metal (white), thin slag (yellow), fluid slag (brown), and crusty-slag (black).

The data from the image presented in Fig. 3 is unfolded by using the procedure given in Fig. 2 to give matrix $X$. All computation for this report is performed in a high-level computer language, i.e. MATLAB Version 6 and MATLAB Image Processing Toolbox Version 3. Analyzing the principal component of matrix $X$ using a standard procedure of PCA gives values of loading vector, $p$, and eigenvalues presented in Table 1.

As shown in Table 1, the cumulative variance of the first two principal components totals 96.76% (81.61% and 15.15%, respectively). Therefore, it is reasonable to assume that the majority of information in the considered image is retained in first two principal components; the combination of these principal components can be used to extract information from (or to discriminate materials in) the image and then, only the first two principal components will be used in the subsequent analyzes. The loading vectors for these two principal components are $p_1 = [0.5405 0.6754 0.5017]$ and $p_2 = [0.6265 0.0749 -0.7758]$.

A scatter plot of the first two score vectors ($t_1$ versus $t_2$) is presented in Fig. 4. The figure has 253 440 score combinations plotted, one for each of the 528×480 pixel loca-

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**Table 1.** Loading vectors and eigenvalues of the image presented in Fig. 3.

| Score | 1     | 2     | 3     |
|-------|-------|-------|-------|
| Loading vector | 0.5405 | 0.66265 | 0.5615 |
| 0.6754 | 0.6749 | -0.7336 |
| 0.5017 | -0.7758 | 0.3827 |
| Eigenvalue | 0.3324 | 0.0617 | 0.0132 |
| Total variance, % | 81.61 | 15.15 | 3.24 |
A multivariate image analysis procedure has been developed for identifying and quantifying the dynamics of slag behavior in a ladle based on image data taken above the ladle. Since the computation time of this procedure is relatively fast, it can be used for real-time monitoring of the process and offers the potential of improved process control.

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