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Development of Online Machine Vision System using Support Vector Regression (SVR) Algorithm for Grade Prediction of Iron Ores

Ashok Kumar Patel
Dept. of Mining Engg.
NIT Rourkela, India, 769008
ashokbecse2006@yahoo.com

Snehamoy Chatterjee
Dept. of Geological and Mining Engg. and Sci.
MTU, MI, USA, 49931
snehamoy@gmail.com

Amit Kumar Gorai
Dept. of Mining Engg.
NIT Rourkela, India, 769008
amit_gorai@yahoo.co.uk

Abstract

The present study attempts to develop a machine vision system for continuous monitoring of grades of iron ores during transportation through conveyor belts. The machine vision system was developed using the support vector regression (SVR) algorithm. A radial basis function (RBF) kernel was used for the development of optimised hyperplane by transforming input space into large dimensional feature space. A set of 39-image features (27-colour and 12-texture) were extracted from each of the 88- captured images of iron ore samples. The grade values of iron ore samples corresponding to the 88-captured images were analysed in the laboratory. The SVR model was developed using the optimised feature subset obtained using a genetic algorithm. The correlation coefficient between the actual grades and model predicted grades for testing samples was found to be 0.8244.

1. Introduction

The iron ore reserves in India are having of different types like hematite, magnetite, limonite, and siderite and their iron content also varies with lithology and geology. Thus, the mines should have a suitable quality system of ores to meet the customer's demand regarding grade values and ore types. The traditional method (laboratory analysis) of the quality monitoring system is time-consuming and costly operation. The grades of iron ore depend on the colour and texture of ores and thus can suitably be predicted using machine-vision-based system [1].

The machine vision technology was first introduced in the mining industry with an automatic image analyzer installed in Mineralogy Division of National Institute for Metallurgy in South Africa in 80's [2]. In early 90's, the colour-based vision system was introduced for mineral beneficiation at Tuscaloosa Research Center [3]. Recently, a number of machine vision-based algorithms were developed for ore classification [4,5,6], particle size analysis [7,8], froth flotation image analysis [9]. But, there are very few algorithms were developed for ore grade prediction. The grade estimation of ore was started by Oestreich using the colour based images (developed U.S. Bureau of Mines). The system was used to estimate the molybdenite percentage in the dry mixtures of chalcopyrite and molybdenite [10]. The study analysed the grades of molybdenite ores based on the colour features (red, green, blue) using multivariate regression analysis. It was observed that the colour-based features could not individually correlate with the grade values of the ores. Later in 2010, Chatterjee et al. were suggested principal component analysis (PCA)-based neural network (NN) model for grade estimations of limestone ores [1]. In 2011, Chatterjee and Bhattacharjee were developed a genetic algorithm (GA)-based neural network (NN) model for iron ore grade estimation using colour, texture, and morphological features [11]. In the past, all the models for grade estimations were developed based on the image analysis in offline mode. Thus, there is a question mark on the direct implementation of the technology in the industry for grade estimations. The present study to develop a machine-vision-based system for iron ore grade prediction using the support vector regression (SVR) algorithm in online mode. Iron ore grades are continuous value and thus can be suitably fitted with regression model for the prediction of grades based on image features.

2. Method

The proposed study was carried out in five major as image acquisition, image pre-processing, feature extractions, feature selection, and model development & evaluation. These steps are represented in a flowchart as shown in Figure 1.

2.1 Image acquisition system:

A laboratory scale flat conveyor system was fabricated to represent the replica of the belt conveyor material transportation system in mines. This high-speed motor coupled with idlers using pulley and belt setup. A Logitech HD Webcam c310 was used for image acquisition. The LED lights were installed on both the sides of the camera at an inclination of 45º to provide proper illumination with low reflectance.

The iron ore samples collected from mines has been for transportation from the inlet to outlet point of the conveyor setup for image acquisition in online mode. A total of 88 images were captured for model development. The iron ore samples corresponding to the 88-captured images were analysed in the laboratory for grade estimations. The results indicated that the grade values were ranged from 13.82% to 69.54 %. The results further in-

Figure 1. Flowchart of working methodology

dicate that the quality monitoring is highly desirable due to significant variation in grades in the same mine.

2.2 Image preprocessing:

Image preprocessing can significantly increase the reliability of an optical inspection [12,13]. Though in the current study, images were captured in a controlled environment, these may contain noises. Therefore, image preprocessing was done for removing the noise in the images before feature extractions. The present study used the adaptive median filter for noise removal [12]. Every image contains both the background (conveyor belt) and foreground (iron ore). Our interest was to extract the features of the foreground area of each image and thus background area was separated. A frame differencing method was used for background removal [14].

2.3 Feature extraction:

Feature extraction is a process of deriving the information of the specific details of texture, colour, morphology, etc. of the image. The characteristics of the image features have a significant role in the image processing [15]. A 5 × 5 sliding image window was chosen for calculating the feature value of each pixel. The sliding window method can reduce the illumination effect by considering a small global set of the pixel [16]. The value of each feature for each center pixel was calculated from the values of 24-neighbourood pixels along with the value of the centre pixel. The background was assigned a weight of '0' and foreground was assigned a weight of '1' for calculating the weighted mean value of the feature of a particular image. In machine learning, different image feature (colour, texture, and morphological) were used by different researchers [1], [5] in the past. In the present study, a set of 39 image features (colour and texture) were extracted for further analysis.

Colour Features. A colour image provides more detailed information about the object in contrast to the monochrome images [12]. The images of the ore samples were captured using the camera in RGB colour space. RGB is one of most widely used colour space for processing and storing the digital image data [17]. The disadvantage of RGB colour space is its sensitivity to illumination. To overcome this problem, Lab and HSI colour spaces were also used for feature extractions. Lab colour space image has a different component of luminance and chrominance [18]. It is considered as perceptual uniform colour space. The other advantage of Lab colour space is that it can represent as much as a human can percept. The HSI colour space helps in separating the image components into hue, saturation, and luminance or intensity [19]. The main advantage of HSI colour space is that it is unaffected by the illumination changes. Lab and HSI colour space image were derived from the original RGB colour space image. A total of 3- features (mean, skewness, and kurtosis) were calculated for each of the 9-colour component (R, G, B, H, S, I, L, a, and b) images. The flowchart of deriving a particular colour feature from the original image is shown in Figure 2. Thus, a total of 27 colour features (9X3) were derived from all the images.

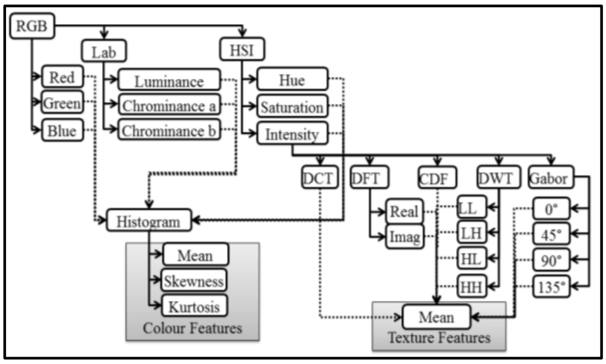

Figure 2. Flowchart of Feature Extraction

Texture Features. The textural property also helps in identification of the type of object [15, 20]. Thus, textural features of an image were also considered in the proposed model development. The intensity component of the HSI colour space image was used for extraction of texture feature of an image. For texture feature extraction, the intensity component of the image was transformed into five frequency domain viz. discrete cosine transform (DCT) [21], discrete Fourier transform (DFT) [22], discrete wavelet transform (DWT) [20], cumulative distribution function (CDF) [23], and Gabor filter transform [5]. The two texture components of DFT were obtained from the real and imaginary image component. The cumulative distribution plot was used for determining the CDF-based texture feature of the image. In the case of the wavelet transform, the features were extracted from 1 low-frequency image and 3 high-frequency images after one scale decomposition. For the Gabor filter frequency domain, the features were extracted in four different directions (0°, 45°, 90° and 135°). In the present study, the mean value of each component was considered as a feature value. Thus, a total of 12-texture features [1- CDF, 1- DCT, 2-DFT, 4-DWT, and 4-Gabor filter] were derived from each image. The flowchart of deriving the textural features from the original RGB image is shown in Fig. 2.

2.4 Feature selection:

After extracting the aforementioned features, a feature selection method was adopted to reduce the feature dimension [24]. A small set of features not only reduces the complexity of the machine vision system but also the effectiveness of the system [25]. The goal of the feature selection is to find the optimised feature subset that maximises the performance of the regression model. The present study used a genetic algorithm (GA) for optimising the feature set [4, 11]. A GA is an evolutionary algorithm used for best chromosomes (population of random solution) selection based on the criteria function. An SVR-based criteria function was used for the proposed model. The details about the SVR model is explained in Section 2.5. The new population was generated using the crossover and mutation process [11]. The optimised feature subset was derived using the GA technique. The optimised feature subset contains only 4 features (listed in Table 1) out of the 39 extracted features. These are the Kurtosis of Blue (B) components, Skewness of Green (G) component, Skewness of luminance (L) component, and, Gabor filter in180º direction. It was observed that the optimised feature set contains three colour features and one texture feature. The optimised feature subset is around 10 % of the total extracted features. Hence, the number of the selected features was significantly reduced and hence the computational time was also reduced.

Table 1: Optimised feature subset

Feature number	Feature details
F1	Mean of Gabor filter in the direction 90º
F2	Skewness of Green components
F3	Kurtosis of Blue components
F4	Skewness of Luminance components

2.5 Model development:

The present study attempts to develop a model for prediction of grades of iron ores using support vector machine algorithm. Support vector regression (SVR) is a supervised learning method [26], and thus, it requires a proper set of data for model development. SVR works on the principle of maximum margin algorithm. A non-linear function is leaned by linear learning machine mapping into high-dimensional kernel induced feature space. The capacity of the system is controlled by parameters that do not depend on the dimensionality of feature space. The objective of the SVR model was to optimise the generalization bounds given for regression. These depend on defining the loss function (often called epsilon (ε) -insensitive loss function) that ignores errors, which are situated within the certain distance of the true value. Figure 3 shown below represent one-dimensional linear regression function with – ε insensitive loss function. The variables measure the cost of the errors on the training points. These are zero for all points that are inside the band. The points situated outside the regression tube represent an error. The error level increases with the increase in the margin from the center of the tube. The goal of SVR is to identify a function for which all the training points have a maximum deviation, ε from the target values with a maximum margin.

Suppose a data set X has m patterns or samples with d+ 1 dimension. This can be represented as, $X = \{(x_{11}, x_{12},\dots,x_{1d}, y_1),\dots, (x_{m1}, x_{m2}, \dots, x_{md}, y_m)\}$, where $x_{id} \in R$ and $y_i \in R$. In the present case, $m=1, 2\dots 88$ (m is the number of samples) and $d=1, 2\dots, 4$ (d is the number of features). The data set was partitioned into training and testing for the model development and evaluation. Suppose the number of selected pattern for training the model is m_s. Then the linear regression function can be represented by, $y_i = w_{i1}\bullet x_{i1}+ \dots +w_{id}\bullet x_{id}+b_i$, where $w_{id} \in R$, $b_i \in R$, and $i=1, 2\dots, m_s$ $(m_s =62)$. The SVR model can be represented by

$$\text{Minimize } \frac{\|w_{id}\|^2}{2} \tag{1}$$

with the constraints

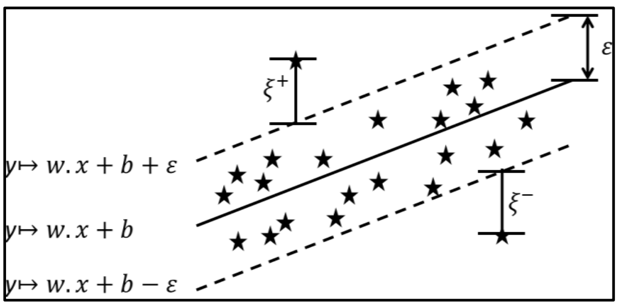

Figure 3. One-dimensional linear SVR

$$\begin{cases} w_{i1}\cdot x_{i1}+\cdots+w_{id}\cdot x_{id}+b_i-y_i\le \varepsilon, & i=1,\dots,m_s \\ y_i-w_{i1}\cdot x_{i1}-\cdots-w_{id}\cdot x_{id}-b_i\le \varepsilon, & i=1,\dots,m_s \end{cases} \tag{2}$$

However, we may not find a feasible solution for the above optimization problem, and thus we have to allow some error. Therefore, the support vector regression can be represented as

$$\text{Minimize } \frac{\|w_{id}\|^2}{2} + C\sum_{i=1}^{m_s}(\xi_i^+ + \xi_i^-) \tag{3}$$

with the constraints

$$\begin{cases} w_{i1}\cdot x_{i1}+\cdots+w_{id}\cdot x_{id}+b_i-y_i\le\varepsilon+\xi_i^+, & i=1,\dots,m_s \\ y_i-w_{i1}\cdot x_{i1}-\cdots-w_{id}\cdot x_{id}-b_i\le\varepsilon+\xi_i^-, & i=1,\dots,m_s \\ \xi_i^+\ge 0 \\ \xi_i^+\ge 0 \end{cases} \tag{4}$$

where, C (>0) controls the penalty associated with deviation larger than ε, and $\xi_i^+$and ξ_i^- are the respective slack variables associated with an overestimate and underestimate of calculated response. The slack variable is described as 0 if $|x_{id}| \le \varepsilon$ and $(|x_{id}|- \varepsilon)$ otherwise, where ε is an insensitive loss function.

The LIBSVM-3.20 library [27] was used for the ε-SVR model development.

3. Results and Discussions

In the present study, 88-image samples were captured during transportation of ores through the pilot conveyor system. The images were automatically captured using the camera with suitable code in MATLAB software. The grade values of the corresponding ore samples were analysed in the laboratory after image acquisition. The data set, X contains 88- image samples (m=88) with 4 feature dimensions (d=4) as input and one feature (iron ore grade value) as output. The input and output data were normalized in the range of 0 to 1.

Out of the 88-sample data, 62 samples (m_s = 62) were used for the training purpose, and the remaining 26 samples (m_r = 26) were used for the testing purposes or evaluation of the model. The datasets were partitioned for training and testing in the ratio of 70:30 respectively. The distribution of the training and testing datasets were examined using t-test statistics. The results indicated that both the training and testing dataset have a similar distribution. This is one of the pre-requirement for the developing a robust model.

The most important characteristics of an SVR is that the solution of the model can be obtained with a small subset of training points. Using the ε insensitive loss function the existence of the global minimum can be ensured and at the same time optimisation of reliable generalization bound. The optimal cost and gamma were obtained using RBF kernel function based on the minimum mean square error (MSE) of SVR model. An RBF kernel was chosen due to less number of hyper-parameter then polynomial kernel [28]. The range of gamma and cost were considered as 2^{-7} to 2^7 at 15 bins and 0.1 to 1 at 100 bins respectively. The range of ε was considered as 0 to 1 at 11 bins. The optimised value of cost, gamma and epsilon were found to be 1.2, 2^5 and 0 respectively. The performance of the model was examined with 26-testing samples. It was observed that the predicted grades and actual grades were closely matched. The correlation between the actual grades and predicted grades for testing samples was found to be 0.8244.

4. Conclusions

The present study attempts to develop a machine vision system for prediction of grades of iron ores in online mode. The performance of the proposed system was tested with a pilot plant study in the laboratory. A total of 39 image features were extracted from 88 image samples for examining the model performance. The number of features was optimised using GA techniques. The optimised feature subset contained only 4 features out of the total 39 extracted features. The images samples were partitioned in the ratio of 70:30 respectively for training and testing of the model. An optimal cost and gamma were obtained using RBF kernel function based on the minimum mean square error (MSE). The respective optimised value of cost, gamma and epsilon were observed as 1.2, 2^5 and 0. The correlation coefficient between the observed and predicted values of testing samples was found to be 0.8244. The results indicate that the proposed system can be used for online monitoring of iron ore grades. In the future, the model will be tested for the different mines with more number of samples for its robustness.

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