Development of Machine Vision-based System for Iron Ore Grade Prediction using Gaussian Process Regression (GPR)

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Abstract: *India is one of the major iron ore producing country and requires quality monitoring of iron ore. An attempt has made to develop a vision-based system for continuous iron ore grade prediction during transportation of ores through conveyors. A Gaussian process regression (GPR) algorithm was used to develop the model. To design the system, a pilot conveyor belt setup was fabricated to replicate the mine conveyor system and consists of image capturing system to capture images during transportation of ores. The images were processed and GPR was calibrated using the grade values of 26-iron ore samples. A set of 18 features (9-colors and 9-textures) were extracted from each of the 26-captured images for model development. The performance results revealed that the predicted grade has closely agreement with the actual grade of the ores. The correlation coefficient (R2) between the observed and predicted grades was found to be 0.9569.*

***Keywords*:** Gaussian process regression, machine vision, iron ore grade prediction.

1. INTRODUCTION

In last few decade, the demand of steel increased many fold in all over the world. Due to increase in the demand of steel, the demand of iron ore is also increased as this is basic raw material for production of iron and steel. The steel producing industries also requires specific grade of iron ores for smooth running of the plants. On the other hand, the iron ore reserves found in wide varieties like hematite, magnetite, limonite, and siderite. This requires maintaining a quality control process in the mining industry. The quality of ore in terms of physical (size, shape, strength, etc.) and chemical (composition, grade, etc.) properties specifically defined for the extraction of valuable material through particular treatment process (Ivanov, 1986).

In India, the iron ore reserves are distributed in many parts of the country. The highest iron ore producing state is Odisha followed by Chhattisgarh, Jharkhand, and Karnataka (IBM annual report 2014-15). A little production of iron ore is also observed in Andhra Pradesh, Madhya Pradesh, Maharashtra, and Rajasthan. The quality of iron ores are varying in different reserves in India.

Thus, the present study attempts to develop an online machine vision-based system for iron ore grade prediction. The proposed system facilitates continuous ore grade prediction with a negotiated accuracy and operational cost.

The machine vision-based system is an approach to replace the human vision system. This technology is successfully implemented in many industries including mineral industries for various purposes. The machine vision technology was first introduced in mining industry with an automatic image analyzer installed in Mineralogy division of National Institute for Metallurgy in South Africa in 80's (Oosthuyzen, 1980). In early 90's at Tuscaloosa Research Center, the color-based vision system was introduced for mineral beneficiation (O'Kane et al., 1990). With the on-going development of advance image capturing and processing technology, the accuracy of the machine vision system has improved a lot in the last decade. Machine-vision system basically uses the image-based features like color, texture, and shape etc. (Chatterjee et al., 2010; Patel and Chatterjee; 2016; Perez et al., 2011; Singh and Rao, 2006; Tessier et al., 2007) for identification of the objects.

In the mineral industry, machine vision system are used for size distribution analysis (Koh et al., 2009; Thurley and Ng, 2008), ore classification (Chatterjee, 2013; Patel and Chatterjee, 2016; Perez et al., 2015; Singh and Rao, 2006; Tessier et al., 2007), material composition analysis of ore (Tessier et al., 2007; Chatterjee et al. 2010; Perez et al., 2011), and froth floatation analysis (Aldrich et al., 2010).

There are very few machine vision-based algorithms were developed for ore grade estimation. Oestreich et. al. (1995) analysed the correlation between color based features (color vector angle) and grade values using simple correlation analysis. In 2010, Chatterjee et. al. were suggested principal component analysis (PCA) based neural network (NN) model for quality monitoring system of limestone ores. In 2011, Chatterjee and Bhattacharjee were developed a genetic algorithm (GA)-based neural network (NN) model for iron ore grade estimation using color, texture, and morphological features. In all the past, the models for grade estimations were developed based on the images captured in offline condition. Thus, there is a question mark on the direct implementation of the technology in the industry. The present study aims to develop a machine vision-based system for iron ore grade prediction using the Gaussian process regression (GPR) algorithm in online mode. Gaussian processes are powerful, non-parametric tools for learning regression functions from sample data. The advantages of GPR-based system are its flexibility, ability to provide uncertainty estimates, and ability to learn noise and smoothness parameters from training data (MacKay, 1997).

2. METHODOLOGY

The iron ore samples were collected from TRB mine Tensa, of JSPL. It is situated on Tensa valley of Sundargarh District in Orissa (India). The location map is shown in Fig. 2. For the development of robust model, samples were collected from different parts of the mine to maintain the heterogenic condition. The stratified random sampling procedure was followed for sample collection.

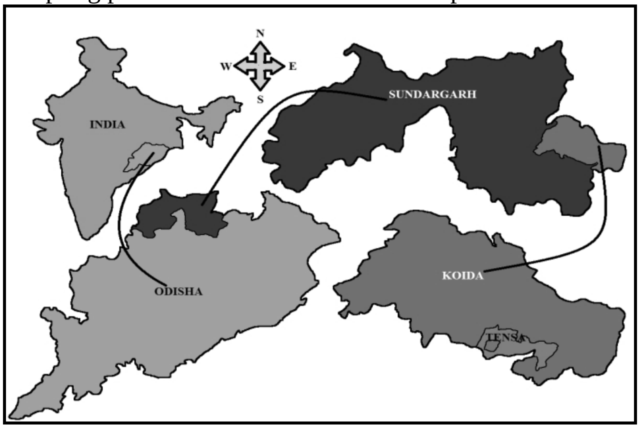

Fig.1 - Map showing the sample collection mine

A prototype of conveyor transportation system (shown in in Fig. 3) was fabricated in the laboratory for capturing the images during transportation of ores. The belt is run by a 0.5 horse power motor with 1400 rpm using electric power supply shown in the inner view of the image. For image capturing, a Logitech HD C310 webcam of 720 pixel quality and 30 fps was installed as shown in the outer view of the image. Light sources are mounted at an angle of 45º to minimize the reflectance and to get the better resolution image.

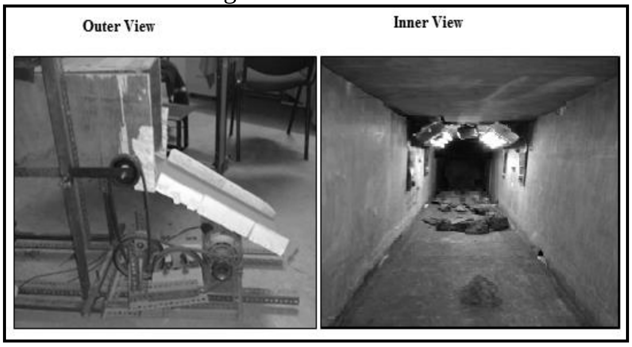

Fig.2 - Laboratory scale conveyor transportation system

The next step is image processing for extracting the image features. But, before extraction of features, image pre-processing is done for removing the noise in the images. In the past, a number of methods (median filter, Wiener filter, local pixel grouping, bilateral filter) were developed for noise removal. The present study uses adaptive median filter for noise removal. After noise removal, features were extracted from each of the captured images. These features were used for model development.

In the past, the Gaussian process was used for prediction in various domains of engineering and science (Archambeau et al., 2007; Atia et al, 2012; Chen et al., 2014; Bailer-Jones et al., 1997; Rasmussen & Williams, 2006).

Rasmussen and Williams (2006) has defined Gaussian process as a collection of random variables, any finite number of which has a joint Gaussian distribution. The Gaussian process can be represented with the mean and covariance functions as:

$$f \sim GP(m,k) \tag{1}$$

Where, m is the mean function and k is the covariance function.

The mean and covariance will be a vector and matrix respectively for the multivariate dataset. In most of the real problem mean are considered as zero, i.e., $m(x) = 0$.

If the training data set consist of N number of samples with d dimension as $x1, x2,\dots, xd$ and the scalar target t, then the training data can be represented as $D=\{(x_i, t_i), i=1,\dots,N\}$. The target value can be determined as $t_i = f(x_i)+\epsilon_i$, where ϵ_i is a Gaussian noise with zero mean and variance, σ_n^2.

If the testing data observation is represented by x^*, then its corresponding target, t^* can be estimated by the value of hypothesized Gaussian process f^* at the observation point (Raghavendra and Deka, 2016). This can be obtained as:

$$\begin{Bmatrix} t \\ f^* \end{Bmatrix} = GP\left(0, \begin{bmatrix} K(X,X)+\sigma_N^2 I_N & k(x^*) \\ k(x^*)^T & k(x^*,x^*) \end{bmatrix}\right) \tag{2}$$

where,

t is the joint normality of training target value and is given by $t = [t_i]_{i=1}^N$,

X is the joint normality of training observation and is given by $X = [x_i]_{i=1}^N$,

I_N is the identity matrix of size N×N,

$k(x^*)$ is the vector of covariance between testing observation and all training observation and is given by

$$k(x^*) \stackrel{\Delta}{=} \left[k(x_1,x^*),\dots,k(x_N,x^*)\right]^T,$$

$K(X, X)$ is the covariance matrix between the N training observation. This is given by

$$k(X,X) \stackrel{\Delta}{=} \begin{bmatrix} k(x_1,x_1) & k(x_1,x_2) & \dots & k(x_1,x_N) \\ k(x_2,x_1) & k(x_2,x_2) & \cdots & k(x_1,x_N) \\ \vdots & \vdots & \ddots & \vdots \\ k(x_N,x_1) & k(x_N,x_2) & \cdots & k(x_N,x_N) \end{bmatrix} \tag{3}$$

Thus, the predictive distribution model can be obtained by conditioning the training samples. This is given by

$$p\left(f^* \middle| x^*, D\right) = GP\left(f^* \middle| \mu^*, \sigma^{*2}\right) \tag{4}$$

where, $\mu*$ is the mean prediction. The mean prediction can be estimated as

$$\mu^* = k(x^*)^T \left(K(X,X) + \sigma_N^2 I_N\right)^{-1} \times t \tag{5}$$

$\sigma*$ is the variance prediction. The variance prediction can be estimated as:

$$\sigma^{*2} = \sigma_N^2 - k(x^*)^T (K(X,X) + \sigma_N^2 I_N)^{-1} k(x^*) + k(x^*, x^*) \tag{6}$$

From the above equations, it can be observed that the mean prediction is a linear combination of the observed target. Also, it was observed that the variance is depending only on the observed inputs and not on the observed target. This is one of the properties of Gaussian distribution.

3. RESULT AND DISCUSSION

The iron ore samples were collected from TRB iron ore mine, Tensa. These samples were feeded with a uniform rate at the inlet point of the pilot-scale conveyor system. The system were captured the images of the ores during transportation from inlet to outlet point of the conveyor set-up. A set of 26 images were captured and the corresponding samples were analysed in the laboratory for ore grade estimation. The captured images were further processed for feature extractions. A set of 18 features (9-colors and 9-textures) were extracted from each of the 26 images. The color features were extracted in RGB color space for all components (red, green, and blue). For each of the three color space, three features (histogram based weighted average, skewness, and kurtosis) were extracted. The intensity component of HSI color space was used for texture feature extraction. A set of nine textural features [one cumulative distribution function (CDF) based feature (Mustapha et al., 2014), four wavelet-based features (Murtagh and Starck, 2008), and four Gabor-based features (Perez et al., 2015)] were extracted.

These features were further used for the development of GPR-based iron ore grade prediction model. The extracted features along with the estimated grades were normalized in the range of 0 to 1. This is one of the pre-requisite for an efficient model development. The data set were divided into two parts (training and testing) approximately in the ratio of 3 to 1. That is, training data set consists of 19 samples and testing data set consists of 7 samples.

A Gaussian process toolbox GPML 3.5 (Gaussian process for machine learning) developed by Rasmussen and Nickisch (2015) were used for development of model. The toolbox is available free of cost in the website of Gaussian process organization (http://www.gaussianprocess.org). The model uses an isotropic squared exponential covariance function and zero mean function. The Gaussian likelihood function was used for likelihood operation. The Kullback-Leibler optimal approximation (KL) inference method was used in the model development.

The GPR based model was trained with the features data of 19 samples and tested with the features data of remaining 7 samples. The model performance results for the testing samples are shown in Fig. 4. A comparative values of GPS based regression result with the other two regression methods [tree based regression and radial basis function (RBF) based regression] and the actual grade of the iron ores are presented in Fig. 4. It can be easily inferred from Fig. 4 that the GPR-based prediction results for 7-testing samples are closely related with the actual iron ore grades. It is also observed that the deviations of GPR-based model results from the actual grades are less in comparison to the tree and RBF based regression.

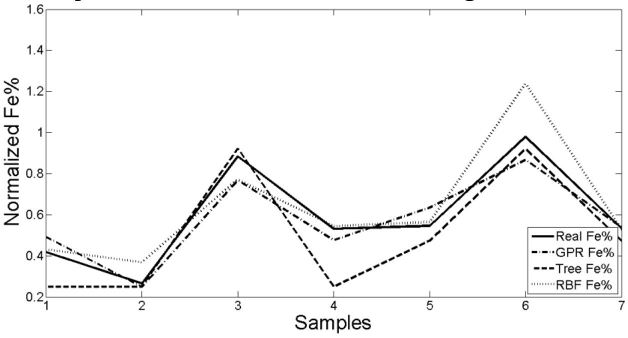

Fig.3 - Comparison of GPR model with TREE and RBF model

The correlation coefficient between the predicted and the actual grades of iron ores was calculated to check the accuracy of GPR model. The correlation coefficient was found to be 0.9569. The correlation coefficient value clearly indicates that the GPR-based regression model can predict the iron ore grade with good accuracy. On the other hand, the correlation coefficient between the predicted and the actual grades of iron ores of tree-based regression model and RBF regression models were found to be 0.9422 and 0.8998 respectively.

4. CONCLUSION

The machine vision-based iron ore grade prediction model was developed using the GPR techniques. The regression model were developed using the 18 image features (9-colors and 9-textures) and laboratory estimated grade values. The study was conducted in online mode for automatic image capturing, processing and grade prediction. The correlation coefficient between the predicted and the actual grades of iron ores was found to be 0.9569. The correlation coefficient value clearly indicates that the GPR-based regression model can predict the iron ore grade with good accuracy. The performance of the Gaussian process regression (GPR) model was found satisfactory and can be used for continuous grade prediction of iron ores during transportation in online mode.

5. REFERENCES

[1] A. K. Patel, S. Chatterjee. Computer vision-based limestone rock-type classification using probabilistic neural network. *Geoscience Frontiers*, 7(1) (2016). p.53-60.

[2] C. A. Perez, J. A. Saravia, C. F. Navarro, D. A. Schulz, C. M. Aravena, F. J. Galdames. Rock lithological classification using multi-scale Gabor features from sub-images, and voting with rock

contour information. *International Journal of Mineral Processing,* 144 (2015). P. 56–64.

[3] C. A. Perez, P. A. Estévez, P. A. Vera., L. E. Castillo, C. M. Aravena, D. A. Schulz, L. E. Medina. Ore grade estimation by feature selection and voting using boundary detection in digital image analysis. *International Journal of Mineral Processing,* 101(1) (2011). p. 28-36.

[4] C. Aldrich, C. Marais, B. J. Shean, J. J. Cilliers. Online monitoring and control of froth flotation systems with machine vision: A review. *International Journal of Mineral Processing,* 96(1) (2010). p. 1-13.

[5] E. J. Oosthuyzen. An Elementary Introduction to Image Analysis: a New Field of Interest at the National Institute for Metallurgy. *NIM Report No. 2058*, South Africa, (1980).

[6] F. Murtagh, J. L. Starck. Wavelet and curvelet moments for image classification: application to aggregate mixture grading. *Pattern Recognition Letters*, 29(10) (2008). p.1557-1564.

[7] H. Mustapha, S. Chatterjee, R. Dimitrakopoulos. CDFSIM: efficient stochastic simulation through decomposition of cumulative distribution functions of transformed spatial patterns. *Mathematical Geosciences,* 46(1) (2014). p. 95-123.

[8] J. M. Oestreich, W. K. Tolley, D. A. Rice. The development of a color sensor system to measure mineral compositions. *Minerals Engineering,* 8 (l/2) (1995). p. 31–39.

[9] J. Tessier, C. Duchesne, G. Bartolacci. A machine vision approach to on-line estimation of run-of-mine ore composition on conveyor belts. *Minerals Engineering,* 20(12) (2007). p.1129-1144.

[10] K. C. O'Kane, D. A. Stanley, D. L. Meredith, B. E. Davis (1990). Preliminary evaluation of a computer vision semm for analysis of phosphate tailings. *Proceedings of the Conference "119th Annual SME Meeting"*, Salt Lake City, Utah, 26 February - 1 March 1990, pp. 137-142.

[11] M. J. Thurley, K.C Ng. Identification and sizing of the entirely visible rocks from a 3D surface data segmentation of laboratory rock piles. *Computer Vision and Image Understanding,* 111 (2) (2008). p. 170–178.

[12] S. Chatterjee Vision-based rock-type classification of limestone using multi-class support vector machine. *Applied Intelligence,* 39(1) (2013). p. 14-27.

[13] S. Chatterjee, A. Bhattacherjee. Genetic Algorithms for feature selection of image analysis-based quality monitoring model: an application to an iron mine. *Engineering Applications of Artificial Intelligence,* 24(5) (2011). p. 786-795.

[14] S. Chatterjee, A. Bhattacherjee., B. Samanta, S. K. Pal. Image-based quality monitoring system of limestone ore grades. *Computer in Industry,* 16(5) (2010). p. 391-408.

[15] T. K. Koh, N. J. Miles, S. P. Morgan, B. R. Hayes-Gill. Improving particle size measurement using multi-flash imaging. *Minerals Engineering,* 22 (6) (2009). p. 537–543.

[16] V. Singh, S. Rao. Application of image processing in mineral industry: a case study of ferruginous manganese ores. *Mineral Processing and Extractive Metallurgy,* 115(3) (2006). p. 155-160.

[17] C. Williams, C. Rasmussen. Gaussian processes for regression. *Advances in Neural Information Processing Systems,* 8 (1996). p. 598–604.

[18] C. E. Rasmussen, C. Williams. Gaussian processes for machine learning. MIT Press, 2006. p. 248.

[19] O. P. Ivanov. Methodological aspects of ore quality control. *Soviet Mining Science,* 22(3) (1986). p. 207 - 212.

[20] D. J. MacKay. Gaussian processes-a replacement for supervised neural networks? *Proceeding of the workshop "Neural Information Processing Systems 1997 (NIPS'97)"*, Breckenridge, Colorado 5-6 December 1997, pp 1-37.

[21] N. S. Raghavendra, P. C. Deka. Multistep Ahead Groundwater Level Time-Series Forecasting Using Gaussian Process Regression and ANFIS. *Proceedings of the Conference "Second International Doctoral Symposium on Applied Computation and Security Systems (ACSS 2015)"*, Kolkata, India 23-25 May 2015, pp. 289-302.

[22] M. M. Atia, A. Noureldin, M. Korenberg. Enhanced Kalman filter for RISS/GPS integrated navigation using Gaussian process regression. *Proceedings of the Conference "Institute of Navigation International Technical Meeting 2012 (ITM 2012)"*, Newport Beach, California, USA 30 January - 1 February 2012, pp 1148–1156

[23] H. M. Chen, X. H. Cheng, H. P. Wang. Dealing with observation outages within navigation data using Gaussian process regression. *Journal of Navigation,* 67 (2014). p. 603–615.

[24] C. A. L. Bailer-Jones, T. J. Sabin, D. J. C. MacKay, and P. J. Withers. Prediction of deformed and annealed microstructures using Bayesian neural networks and Gaussian processes. *Proceedings of the "Australasia Pacific Forum on Intelligent Processing and Manufacturing of Materials (IPMM97)*", Sydney, Australia 14–16 July 1997, pp. 913-919.

[25] C. Archambeau, D. Cornford, M. Opper, J. Shawe-Taylor. Gaussian process approximations of stochastic differential equations. *Journal of Machine Learning Research,* 1 (2007). p. 1-16.

[26] H. Nickisch, C. E. Rasmussen C. E. Approximations for binary Gaussian process classification. *Journal of Machine Learning Research,* 9(10) (2008). p. 2035-2078.