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Research paper

Computer vision-based limestone rock-type classification using probabilistic neural network

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A B S T R A C T

Proper quality planning of limestone raw materials is an essential job of maintaining desired feed in cement plant. Rock-type identification is an integrated part of quality planning for limestone mine. In this paper, a computer vision-based rock-type classification algorithm is proposed for fast and reliable identification without human intervention. A laboratory scale vision-based model was developed using probabilistic neural network (PNN) where color histogram features are used as input. The color image histogram-based features that include weighted mean, skewness and kurtosis features are extracted for all three color space red, green, and blue. A total nine features are used as input for the PNN classification model. The smoothing parameter for PNN model is selected judicially to develop an optimal or close to the optimum classification model. The developed PPN is validated using the test data set and results reveal that the proposed vision-based model can perform satisfactorily for classifying limestone rock-types. Overall the error of mis-classification is below 6%. When compared with other three classification algorithms, it is observed that the proposed method performs substantially better than all three classification algorithms.

1. Introduction

The cement industry provides the main building material for infrastructure and limestone is the main raw material for the cement industry (Ingram and Daugherty, 1991). To meet the increasing cement demands, cement kilns must have consistent and reliable raw material feed. The consequences of poorly prepared raw meal are two folds. First, high lime causes meal to be burned hotter and refractory life drops. Second, high alkaline may cause cyclone blockage and restrict the use of the cement produced. Therefore, before feeding the raw material limestone to the cement plant, a proper quality planning is necessary to control the lime and the alkaline proportion in the limestone to the smooth working of the cement plant (Lea, 1971).

Cement industries are taking different measures to maintain the raw material feed quality. Even though all possible measures are taken to control the quality of feed, the final quality of limestone may not respect with the requirements of cement plant (Mayfield, 1988). To deal with this situation, a suitable quality monitoring should be done at mine before sending the limestone at the stockyard for blending process to maintain feed quality for cement plant.

Monitoring the quality of limestone at mine is always a difficult task due to non-availability of fast, reliable and inexpensive on-line sensors. Generally, the limestone quality is determined by manually collecting samples from mine and analyzing chemically in a laboratory and that is tedious and time-consuming operations. However, the quality parameters of the limestone depend largely upon the constituent rock-type; therefore, information about the rock-type provides valuable information for quality monitoring purpose (Tessier et al., 2007).

Although, rock-type information about limestone is valuable for quality monitoring; however, the information about the rock-type at mine can be gathered by visual observation in naked eye by experience geologist or mining engineers. The accuracy of the identification of rock-types varies from person to person and it requires human intervention. Nonetheless, identification of

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accurate rock-type is a challenging task because of heterogeneity of rock properties. However, with the advancement of the computer vision, rock-type information can be gathered by capturing the rock image. It is frequently experienced that the rock images are non-homogeneous in their shape, texture, and color; and computer vision techniques can analyze complex rock images for rock-type classification purpose.

Although the study of computer vision-based rock-type classification is limited; however, some distinguished results have been reported by researchers (Murtagh and Starck, 2008; Mukherjee et al., 2009; Chatterjee et al., 2010). Computer vision-based system is introduced in mining industry in the early 90's by Oestriech et al. (1995) when the U.S. Bureau of Mines has developed a sensor system that uses color to instantaneously measure mineral concentrations in flotation froths and other process streams. Later, lithological composition sensor and ore grindability soft-sensor are developed by Casali et al. (2000) using image analysis. Lepisto et al. (2005) investigated bedrock properties by analyzing the images collected from the bedrock. Different rock layers can be recognized from the borehole images based on the color and texture properties of rock (Lepisto et al., 2005). Tessier et al. (2007) developed an on-line estimation of run-of-mine ore composition on conveyor belts. An application for aggregate mixture grading using image classification is designed by Murtagh and Starck (2008). Mukherjee et al. (2009) designed an image segmentation system specifically targeted for oil sand ore size estimation. Chatterjee et al. (2010) developed a quality monitoring system of limestone ore grades. Ore grade estimation by feature selection and voting is proposed by Perez et al. (2011). Khorram et al. (2012) developed a limestone chemical components estimation using pattern recognition.

In vision based technology, data are presented as images. Various information (color, texture and morphological) could be extracted from images. Different researchers have demonstrated the importance of different image features. Khorram et al. (2012) have used color components, namely r, g, b, H, S, I, and gray for color feature extraction. Perez et al. (2011) have used color and texture feature of a sub image for ore grade estimation. Morphological, color and textural features were used by Chatterjee et al. (2010) for quality monitoring system of limestone ore. Mukherjee et al. (2009) used color and morphological features for image segmentation for oil sand ore size estimation. Murtagh and Starck (2008) used texture feature, 2nd, 3rd and 4th order moments of multi-resolution transform coefficients as features. Tessier et al. (2007) used color features using multi-way principal component analysis (MPCA) and textural feature using two-dimensional discrete wavelet transform analysis (WTA). Singh and Rao (2006) studied ferruginous manganese ores with histogram analysis in the RGB color space, combined with textural features based on the gray level co-occurrence matrix and edge detection. Lepisto et al. (2005) used Gabor filtering in Red-Green-Blue (RGB) and Hue-Saturation-Intensity (HIS) color space with different scales to incorporate color in texture features.

Since, it is not known beforehand that which image features have considerable impacts on the rock-type classification; therefore, these algorithms involve extraction of the significant number of features. Thus, the computational time associated with these algorithms is significantly larger due to more numbers of parameters associated with the classification model. Nevertheless, the extra image features may sometime lead to a poor model performance (Steppe et al., 1996; Micheletti et al., 2014). Also, the number of training samples necessary for model development grows exponentially as the number of features grows (Duda and Hart, 1973).

Therefore, reduction of the dimensionality or selection of some features is necessary for valid models (Narendra and Fukunaga, 1977; Chatterjee and Bhattacherjee, 2011). The limitations of these approaches are multifolds; especially, feature extraction time is still significantly very large and sometimes requires huge computational time. This limitation can be overcome by generating limited number significant features; therefore, the computation time for feature extraction and training of the classification model can be significantly reduced.

In this paper, a computer vision-based model was developed for limestone rock-type classification. A new set of significant image features was extracted from limestone rock images and probabilistic neural network (PNN) was applied for classification purpose. The parameter of PNN model is selected by cross-validation study.

2. Methodology

The methodology of the present work can be categorized into three different parts: image acquisition, feature extraction, and classification. The images of limestone rock samples were captured in an isolated setup made for image acquisition. Color histogram based features were extracted in true color images. A probability based neural network model was used for classification of images into different rock types.

2.1. Image acquisition

The images of the limestone rock samples were collected in an isolated setup made for image acquisition. The illumination and temperature are continuously monitored and maintained throughout the experiment to ensure that all images are captured exactly in the same environment. All precautions were taken to ensure that the experimental setup has a uniform and diffused illumination, and reduced glair and specular reflections. More description about the experimental setup can be found elsewhere (Chatterjee, 2013).

2.2. Feature extraction

Many features can be extracted from an image that includes color, morphology, and textural features; however, it is not necessary that all features are significant for the specific classification purpose. Those redundant features increase the computational time exponentially for classification algorithms. Therefore, it is always necessary to extract limited features which could be helpful for classification. In this paper, color image histogram-based features were extracted. The reason for a color image histogram is that the content based image retrieval (Jadhav et al., 2012; Malik and Baharudin, 2013) and medical image analysis (Wiltgen et al., 2003), color image histogram feature plays an important role for classification. Medical image classification is considered to be a difficult task as it has a rich pattern in color and structure (Wiltgen et al., 2003). In the same way as medical image classification, limestone classification has a different pattern in color and structure; so it is expected that histogram based features will capable to classify the limestone with better accuracy. The feature extraction method is shown in the Fig. 1.

The color histogram of an image has the ability to describe the frequency of the presence of a particular level of color. An image has mainly color feature; however, other features such as edges, textural, and morphological features can be derived from image color.

In this paper, three different histograms were calculated for each color space, red, green, and blue. The histogram was generated by scanning the red, green, and blue components of each pixel of the image.

Let, an image I of size $p \times q$, has a pixel intensity $f(x, y)$, where $x = 1, 2, \ldots, p$ and $y = 1, 2, \ldots, q$ and the pixel intensity values $f(x,$