Rock Grindability Estimation based on the Quaternion Color Extraction Model. Reference Number: 886

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Abstract

In mineral processing plants it is important to estimate rock composition, size and grindability to improve control of the grinding process. It is well known that variation in ore grindability and size distribution directly affects mills power consumption and throughput. This paper extends a general machine vision approach for on-line estimation of rock mixture composition using color information. Our proposed rock lithological recognition method requires the following steps: division of each image into sub-images, color feature extraction using the Binary Quaternion-Moment-Preserving thresholding technique (BQMP) and support vector machines (SVM) for classification. The BQMP thresholding technique splits the image in two and chooses representatives of each half using the histogram as features. The statistical parameters of the color data can be expressed using the quaternion moments into the representatives. This method can be recursively applied to the sub-images, obtaining 5x2n features in n iterations. Once the feature vector has been computed, each vector is assigned to one of three classes using a classifier. The method was tested on a database containing 20480 sub-images (64x43 pixels) of five ore types as follows: massive sulphide (MS), disseminated sulphide (DS), net textured (NT), gabbro (G), and peridotite (P). These ore types were assigned to three grindability classes: soft (MS), medium (DS and NT) and hard (G and P). The database was divided in 2 subsets: 15360 sub-images used for training and cross validation and 5120 sub-images used for test. The classification accuracy was compared with a method previously published based on a mixture of principal components analysis (PCA) for color, and wavelet texture analysis (WTA) for texture feature extraction. WTA-PCA approach reached a 76% accuracy in test while our BQMP method reached 90% of classification accuracy using only color features. Experimental results show that our proposed method yields excellent results compared to previously published results.

Keywords: rock classification, lithological classification, grindability estimation

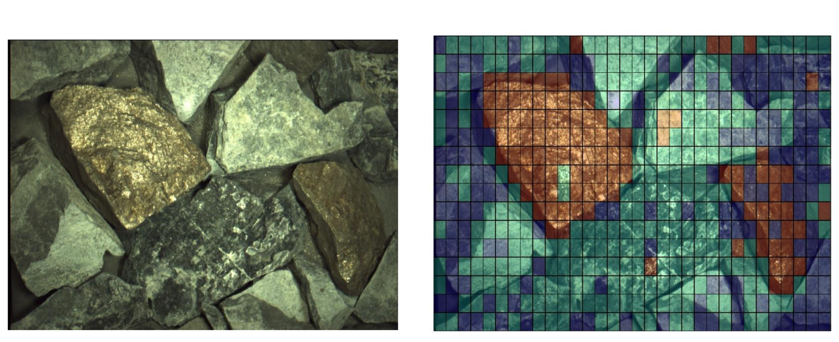
1. Introduction

In this paper we present a new approach using BQMP thresholding. A moment-preserving thresholding technique called binary quarternion-moment-preserving (BQMP) thresholding (Pei et al., 1999) can be used as a tool for color image processing by expressing the input color space as a quarternion-valued space. We tested our method using part of a database presented in Tessier et al., 2007. Results are compared to the previously proposed method WTA-PCA. We show significant results improvements.

2. Methods

The proposed method for rock classification includes the image acquisition, the image subdivision and background removal, the color feature extraction with the BQMP thresholding technique, and support vector machine (SVM) for classification.

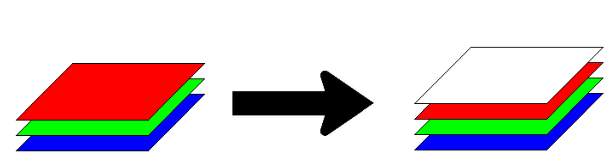
2.1 Image Subdivision



Images of 1024x1376 pixels are divided into 512 sub-images of 64x43 pixels. Each sub-image is considered the main processing unit.

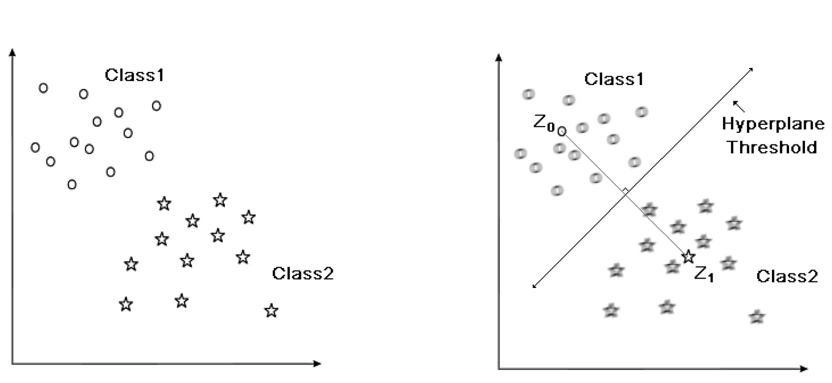
2.2 Color Feature Extraction

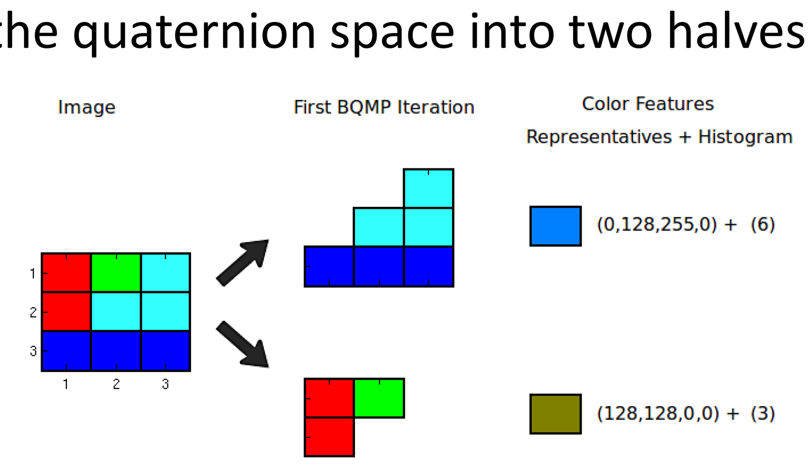
A color value {R, G, B } can be treated as a quaternion with $q_1 = R$, $q_2 = G$, $q_3 = B$ and $q_0 = 0$.



$$\hat{q} = q_0 + q_1 \cdot i + q_2 \cdot j + q_3 \cdot k$$

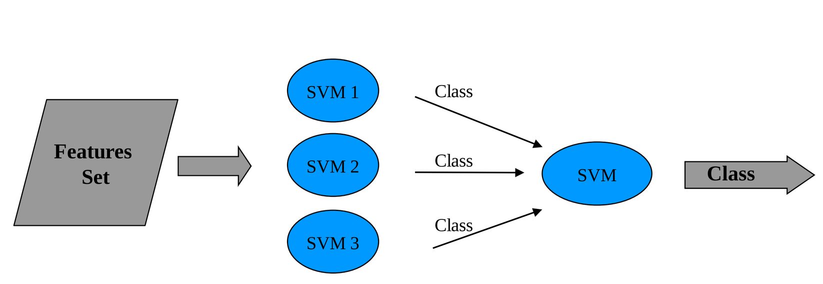
A hyperplane is selected as a threshold such that if all below-threshold data points and above-threshold data points in Q are replaced by the representative values z_0 and z_1 . To implement the BQMP thresholding, a hyperplane l is selected which is perpendicular to the line segment and splits the quaternion space into two halves





2.3 Classifier

Feature Vector of size forty is generated by using the BQMP Thresholding technique three times. The first eight features are the amount of pixels represented by each of the z, and the next thirty two features are each of the four scalars that compose those eight z representative values.



2.4 Database

- Images from five ore types of a nickel mine were obtained [Tessier, 2007].
- Each digital image of 1024 x 1376 pixels was divided into 512 sub-images of 64x43 pixels.
- Nine dry and nine wet databases were created, each one composed of two images (1024 samples) of each rock type (5120 samples).
- 5 subsets (dry or wet; 25,600 samples) were used for five fold cross-validation, in order to find best parameters for SVMs. The other 4 subsets were used for test the classification accuracy.

3. Results

- Results in Wet database for WavePCA and BQMP

Base	Features	D/W	Training	Test
1	WavePCA	Wet	69,86	69,26
2	WavePCA	Wet	69,34	69,39
3	WavePCA	Wet	71,00	69,12
Average	WavePCA	Wet	70,07	69,26
Std Dev	WavePCA	Wet	0,85	0,14

base	Features	D/W	Training	Test
1	BQMP	Wet	95,37	89,35
2	BQMP	Wet	95,33	89,17
3	BQMP	Wet	94,63	89,21
4	BQMP	Wet	94,92	89,27
5	BQMP	Wet	95,25	89.08
Average	BQMP		95,10	89,22
Std Dev	BQMP		0,32	0,10

- Results in Dry database for WavePCA and BQMP

Base	Features	D/W	Training	Test
1	WavePCA	Dry	79,49	78,84
2	WavePCA	Dry	78,63	78,90
3	WavePCA	Dry	77,85	78,75
Average	WavePCA	Dry	78,66	78,83
Std Dev	WavePCA	Dry	0,82	0,08

base	Features	D/W	Training	Test
1	BQMP	Dry	95,25	91,62
2	BQMP	Dry	95,16	91,82
3	BQMP	Dry	95,14	91,73
4	BQMP	Dry	95,41	91,76
5	BQMP	Dry	95,61	92.03
Average	BQMP	Dry	95,31	91,79
Std Dev	BQMP	Dry	0,19	0,15

4. Conclusions

- A new rock classification method using the BQMP thresholding technique for extracting color features was presented and tested on a rock database.
- The performance of the method using a SVM multiclass classifier reach over 90% accuracy which is higher than previously published results.
- The method was tested on an image database with three classes of different rock hardness with good results.
- Many applications in rock sorting or in optimizing the throughput of mills within a mine could be performed using the proposed method.

5. Selected References

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