Lithological classification based on Gabor texture image analysis

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Abstract

Lithological classification is important to improve control of the grinding process in a mining plant. Based on the lithological classification the hardness of the mineral can be estimated and mill operation can be optimized. In this paper we proposed a method for rock lithological classification based on Gabor texture analysis and support vector machine classification. We use images from a database formed using rocks extracted from a typical mining plant in Chile. Six different lithological classes were used. Ten images for each lithological class were used for each class for training and another ten images for each class were used for testing. Results on the testing database were measured using 5 cross-validations for the six classes. Our results show that extracting texture features with Gabor filters and rock segmentation based on the Watershed transform reached over 80% accuracy on the testing database.

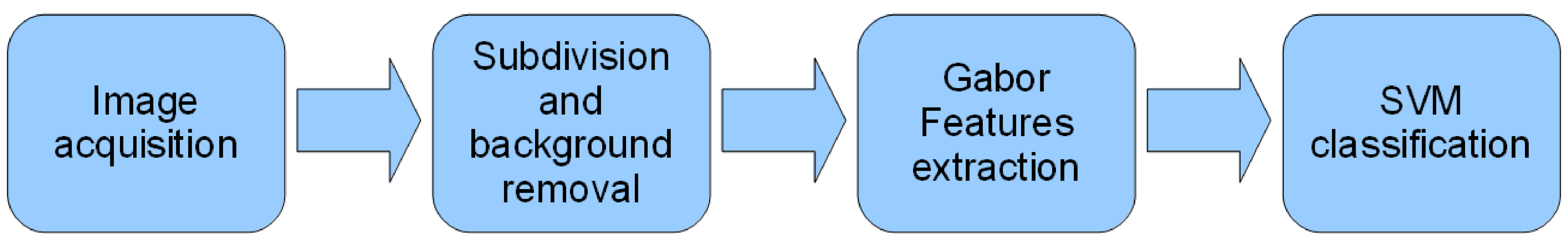
Keywords: Lithological classification, rock type estimation, Gabor feature extraction, rock grindability.

1. Introduction

In this paper we propose a method for lithological classification based on Gabor texture analysis and support vector machine classification. The feature extraction process includes five different spatial scales and eight orientations for the Gabor filters. These features are used as inputs to a support vector machine (SVM) classifier to estimate rock lithology. The method is applied on a database from a mining plant considering six different rock lithologies.

1. Methods

The proposed method for rock classification consists of several steps:



2.1 Image Subdivision

Images of 640x480 pixels from six rock types, divided into 128 sub-images of 60x40 pixels. Each sub-image is considered the main processing unit.

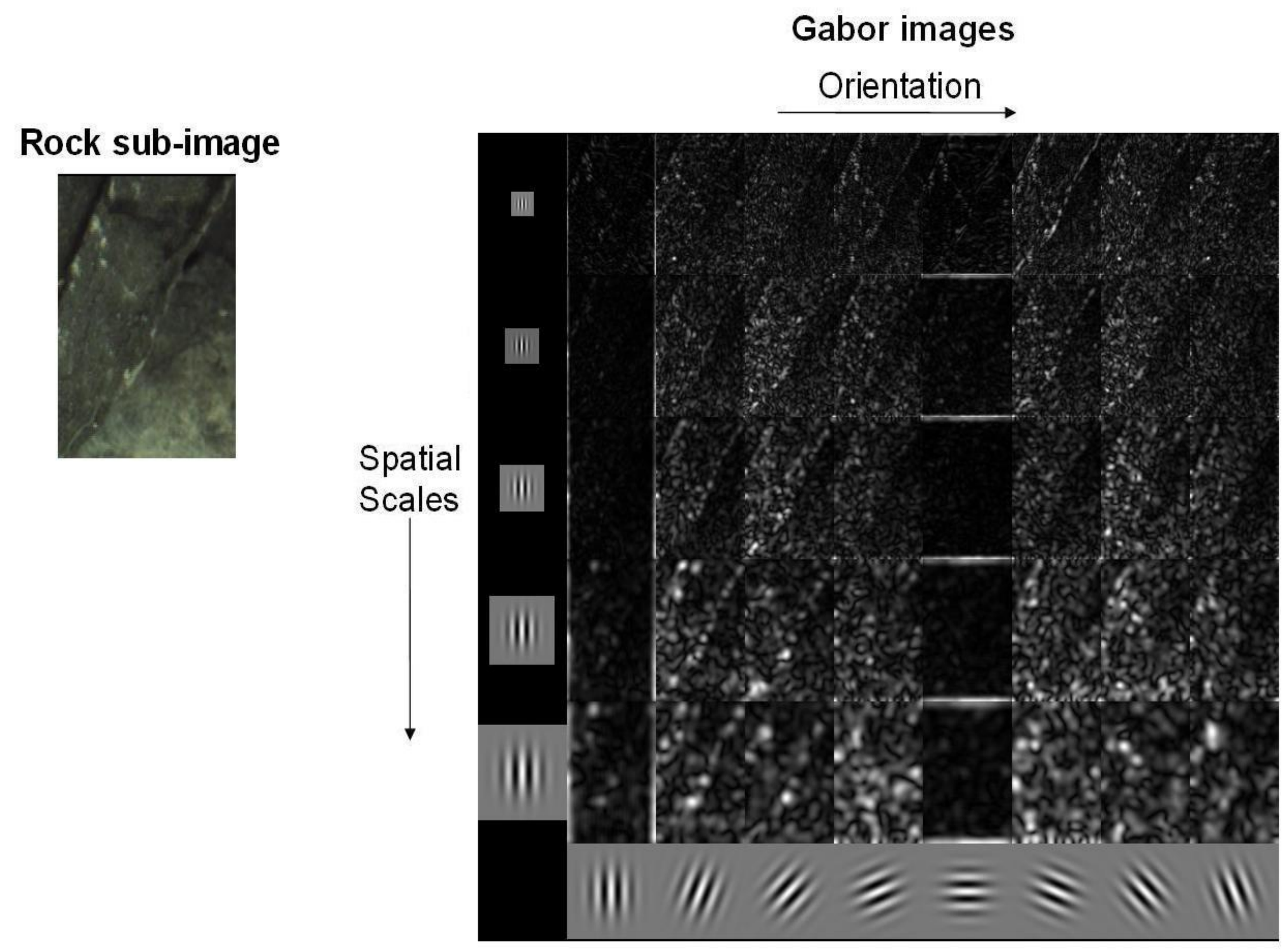
2.2 Gabor Features Extraction

Texture features extraction is made using Gabor filters. A Gabor filter in 2D is a sinusoidal function modulated by a Gaussian envelope, with orientation *u* and spatial scale *v*.

$$\Psi_{u,v}(x,y) = \frac{\left|\vec{k}\right|^2}{\sigma^2} exp\left(-\frac{\left|\vec{k}\right|^2 \left|\vec{r}\right|^2}{2\sigma^2}\right)\left[e^{i\vec{k}\cdot\vec{r}} - e^{-\sigma^2/2}\right] \quad \text{where} \quad \vec{r} = (x,y)^T \quad \vec{k} = \frac{k_{max}}{f^v} e^{i\pi u/8}$$

In this paper we use 8 orientations and 5 spatial scales. The feature vectors were built using the average and variance of the magnitude from the 40 Gabor images (5 scales and 8 orientations) in each of the three channels HSV (80 features per channel). Features were concatenated forming a feature vector of length 240.

Example of a Gabor filter bank applied on a sub-image:



2.3. Classification

We used an SVM multiclass classifier with an RBF kernel. The database contains images of six different rock lithologies with 120 images in total. The database was partitioned in two subsets for training and testing leaving 10 images of each class for training and 10 for testing. The testing was performed using five groups for cross-validation.

3. Results

The results for the six lithological classes show a classification accuracy of 80.7% on the testing database. The method includes a post-processing step after sub-image classification employing information from the rock segmentation. A voting scheme was implemented among all sub-images within each segmented rock allowing assignment of the same class to all sub-images within the same rock. Rock segmentation was performed using the Watershed transform reaching a significant improvement of around 10%.

Method	Accuracy
Wavelet-PCA (Tessier et al.)	40.8%
Wavelet-PCA + Post processing	65.1%
Our method	80.7%

4. Conclusions

A new method for rock lithological classification has been presented with encouraging results on a real database containing rock lithologies from six different classes, outperforming previously published results. Further improvements will include color information in the future.

5. Selected References

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