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Monitoring of mineral processing systems by using textural image analysis

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ABSTRACT

In the last few decades, developments in machine vision technology have led to innovative approaches to the control and monitoring of mineral processing systems. Image representation plays an important role in the performance of the recognition systems used in these approaches, where the use of feature representations based on second-order statistics of the image pixels have predominated. However, these representations may not adequately capture or express the visual textural structure associated with the observed patterns in images. In this study, the use of texton and complex multiscale wavelet representations (steerable pyramids) that exploit higher-order statistical regularities, is investigated. These techniques are applied to two image data sets: industrial platinum group metals froth flotation, and coal particles on a conveyor belt. Compared to grey level co-occurrence matrix and classical wavelet representations, these are observed to improve performance when used as input in the pattern recognition phase.

1. Introduction

The application of machine vision technology in mineral processing has grown steadily over the last few decades. This includes application in statistical process monitoring, regulatory control and automated inspection for product quality assurance (Duchesne et al., 2012). Key factors driving this interest include the nonintrusive nature of machine vision systems and improved data acquisition capacity. In addition, these systems can be easily integrated within SCADA configurations, and are particularly critical in unsafe or hazardous operating conditions. Recent applications include ore sorting and ore grade estimation (Singh and Rao, 2005; Tessier et al., 2007; Perez et al., 2011), particle size analysis in conveyor belt feed systems (Ko and Shang, 2011; Jemwa and Aldrich, 2012), froth flotation image analysis (Aldrich et al., 2010b), multivariate image analysis of flames in kilns and combustion systems (Yu and MacGregor, 2004; Szatvanyi et al., 2006; Hernández and Ballester, 2008; Lin and Jørgensen, 2011; Chen et al., 2012), use of gray level co-occurrence matrices and wavelet techniques to predict the alumina content of anode cover materials used in primary aluminum smelters (Tessier et al., 2008), etc.

Generally speaking, a raw pixel representation of image content is inefficiently structured for handling computational tasks aimed at interpretation of images. This includes signal-based approaches, where pixels are not sufficiently expressive of the statistical dependencies associated with the visual imprint of an image to be exploited in recognition and segmentation applications.

Therefore, until recently, a lot of effort has been expended in hand crafting high-level feature representations tuned to specific applications. For example, a number of commercial image analysis systems used in the monitoring of froth flotation in concentrator circuits evaluate the physical properties of the froth, such as bubble size, froth velocity and froth stability, for froth characterisation (Marais and Aldrich, 2011). Likewise, different systems designed for particle size analysis might attempt to exploit the geometrical characteristics of the particles (compactness, sphericity, etc.) to better identify them as individual objects that can be analysed.

Depending on the application, these approaches may not capture all the information embedded in the image, and an alternative approach to image analysis is to characterise the texture or spectral characteristics of images, instead of focusing on specific physical or geometrical features of the image. In this respect, two popular approaches process applications are based on statistical features computed from gray-level co-occurrence matrices or GLCMs (Haralick et al., 1973), and energy signatures obtained from the wavelet decomposition of images (Mallat, 1989). However, these algorithms may not be able to automatically discover all the statistical properties of the signal, and in theory, higher order approaches should provide better results when dealing with complex image data in line with the notion that what humans recognise as salient structures in images, arises from what are called

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higher order spatial correlations in images (Awate and Whitaker, 2005).

Therefore, in this paper, the use of a number of such higher order textural features to characterise categories of images associated with different process conditions is investigated, following the basic outline illustrated schematically in Fig. 1. The images on the left belong to different categories. A suitably defined tranform is applied to each image to obtain a set of descriptive (compact) features. Projection of these in the feature space (in this case a two-dimensional plane, as indicated on the right of Fig. 1) illustrates the discriminative capacity retained by the features. A pattern classifier can be used to learn the decision boundary separating the classes.

The discriminative capacity of the various textural feature sets is assessed by comparing the classification performance obtained when these features are used as input in classification learning tasks. Data obtained from two important applications in mineral processing are used in the evaluation, viz. (a) characterising froth surface conditions associated with different metal concentrations in platinum bearing ore, and (b) discriminating between aggregates of coal ore particles containing different proportions of fine material.

The paper is organised as follows. In the next section, an overview of texture feature extraction is presented, including an outline of the various methods investigated. This is followed by a brief discussion of the algorithms used for classification based on the extracted features in Section 3. In Section 4, a description of each data set used in the evaluation is given, followed by a discussion of the results in Section 5.

2. Texture modelling

In image analysis, it is widely recognised that texture provides cues regarding the physical surface properties of a captured scene, which are important in image processing tasks such as object recognition, classification and segmentation images. Intuitively, the notion of texture encapsulates repetitive, short-range patterns in an image, particularly those with non-smooth intensity variations, probably reflecting some underlying generative model or spatial organisation (Tuceryan and Jain, 1998). It is this so-called *visual texture* that is considered amenable to statistical modelling (Portilla and Simoncelli, 2000). Statistical and transform-based approaches to texture analysis have been investigated the most, because of their close relation to perception models in neuroscience (Tuceryan and Jain, 1998). In this study, textural features are considered based on the following:

- gray level co-occurrence matrices (GLCMs);
- classical wavelet decomposition;
- overcomplete complex wavelet decomposition (steerable pyramids); and,
- texton representations.

A brief discussion of each approach follows.

2.1. Grey level co-occurrence matrices (GLCMs)

The GLCM of an image summarises the spatial interrelationships among the image pixels (Haralick et al., 1973) and is defined as follows: Each (i,j)-th entry in the GLCM is an estimate of the joint probability of co-occurrence of pixel pairs having intensity values i and j at two arbitrary positions. From this matrix a set of 14 GLCM features (or Haralick set) may be calculated, of which the most popular are energy, contrast, homogeneity, correlation and entropy. GCLM features have been successfully used in process control and monitoring applications in mineral processing, e.g. Moolman et al. (1994) and Kaartinen et al. (2006).

2.2. Wavelets

The wavelet transform is a powerful signal and image processing tool that has been used in various applications such as image denoising, segmentation and classification (Pichler et al., 1996). Wavelet transforms possess desirable properties for real-world signal analysis, namely space-scale localisation, multiresolution, sparse representation and an efficient computation algorithm.

In wavelet analysis, a signal is decomposed into multiple levels based on frequency and time or space localisation, using suitably defined basis functions called wavelets. For discrete signals (as all real-world signals are), an efficient implementation based on subband coding techniques was proposed by Mallat (1989). Unfortunately, the use of discrete wavelet transforms compromises the quality of information retained in the resulting transformation, thus affecting the quality of the extracted features (Pichler et al., 1996). Moreover, wavelets are not rotation or translation invariant and, therefore, not always ideal particularly in image classification tasks.

2.3. Steerable pyramids

To circumvent limitations imposed by wavelets, steerable pyramids were introduced as alternative transform in multiresolution image analysis (Simoncelli et al., 1992). The basis functions of the steerable pyramid are a set of directional derivative operators with different sizes and with a number of orientations based on the order of the derivative. The resultant representation has the advantages of being both translation- and rotation-invariant, but on the downside it is overcomplete by a large factor of $4n/3$, where n is the number of orientation bands.

Based on this steerable pyramid representation, Portilla and Simoncelli (2000) proposed a set of visually meaningful statistics that capture independent textural features. Specifically, using the redundant multi-scale complex wavelet representation obtained from the use of steerable pyramids, they defined the following groups of Markov statistical descriptors, which are evaluated using pairs of wavelet coefficients at adjacent spatial locations, orientations, and scales, i.e. (i) marginal statistics, (ii) raw coefficient cor-

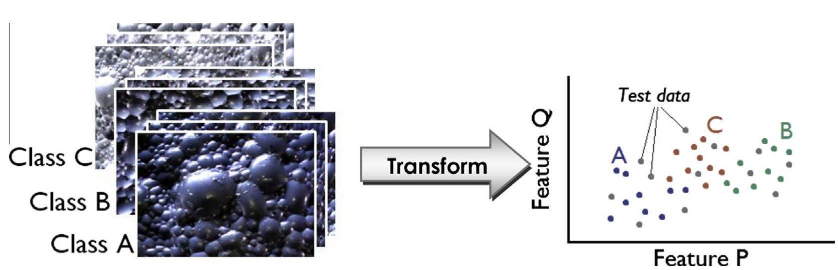

Fig. 1. Basic flow of the image representation and classification framework used in thispaper.