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Spiral Concentrator Interface Monitoring through Image Processing: Optimization for Parameter Selection

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Abstract: Spiral concentrators are robust gravity separation devices that allow the concentration of slurry streams in terms of a desired mineral of interest. The optimal splitter position in a spiral concentrator is dependent on the interface position(s) between concentrate, middlings and/or gangue streams in the spiral trough. Image processing methods can be used to detect interface positions, which could be used in spiral concentrator operation monitoring and control. However, the algorithms required for interface monitoring by means of image processing involve a large number of parameters that must be specified. Such parameter specification can become onerous if done on a manual or ad hoc basis. The goal of this study is to investigate the potential of applying an optimization approach to determine optimal parameters for interface detection through image processing. Results are promising, indicating good interface detection, even for small training data set sizes (e.g. 50 images).

Keywords: Process Monitoring, Mineral Processing.

1. INTRODUCTION

Spiral concentrators represent one of many gravity separation units typically used to separate minerals. Spirals consist of a helical trough winding down a vertical support which receives feed from a flow correcting feed-box and dispenses product streams via splitters and a product-box (Burt, 1984).

As the mineral slurry flows down a spiral, smaller heavier particles tend to move to the inside edge of the trough and larger lighter material will move to the outer edge. The separation action of the spiral typically results in the formation of three mineral streams: concentrate, middlings and tailings (Burt, 1984). Mineral recoveries obtained from spiral concentrators are significantly influenced by the splitter position which is manually set by plant operators (Gold, 1991).

In industry, spirals are typically implemented in a compact manner with multiple spirals around single supports to maximize throughput. In plants with large amounts of spirals it becomes more difficult to ensure splitter settings are optimal, which will result in losses (Gold, 1991).

The problem of mineral losses due to inadequate splitter settings may be addressed by controlling splitters to track the mineral separation bands, given a suitable bias to achieve a desired recovery-grade trade-off. Such control can be automated (e.g. by splitter actuators), or manual (e.g. weekly adjustments by operators). Splitter control requires a robust monitoring framework capable of tracking the mineral separation bands in the spiral slurry. The interface tracker must be capable of isolating the desired interfaces with no spurious responses but should also be executable in real time with the simplest algorithms possible.

The purpose of this work is the development of such an interface monitor. In section 2.1, the general structure of the image processing algorithm is specified. In section 2.2, the various image processing functions that make up the algorithm are described. In section 2.3, the image processing algorithm is presented as an optimization problem. (The main focus of this paper is to find the optimal parameters of the proposed image processing algorithm and to determine whether it can only detect a desired mineral interface over a range of interfaces.) Section 3 presents results, while sections 4 and 5 give conclusions and future work.

2. Interface monitoring software framework

2.1 Required image processing algorithm

The overall objective is to prepare an algorithm that produces a binary image where the pixels labelled with 1 represent a desired mineral interface from an image of a spiral in operation. Figure 1 illustrates an example of the desired output imposed on an image of separating slurry.

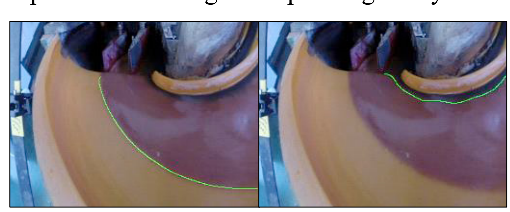

Fig. 1. Examples of desired output from the image processing algorithm.

In many mineral separation operations there is distinct colour differences between light and heavy particles. When sharp light intensity changes occur across mineral separation bands

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edge detection will become critical in the identification of interfaces which will show up in gradient maps of slurry images (Gold, 1991). Vermaak, Visser, Bosman and Krebs (2008) showed that these colour differences can be used to measure concentrate bandwidth from intensity images.

Edge detection; however, will not be able to produce robust and accurate interface detections on its own. This necessitates several pre-processing and post-processing (or higher-level image processing) steps and evaluation of detection results against reference images (Zhang, 1996).

2.2 Image processing functions

2.2.1 Pre-processing

Images are generally captured in RGB format and can be converted to intensity, or grayscale, images using Eq.1 (Gonzalez, Woods and Eddins, 2009).

$$I = rR + gG + bB \qquad \text{(Eq.1)}$$

R, G and B are matrices containing the intensity values for each of the different colour representations. The r, g and b scalars weigh the values of each of the colour matrices to control their contribution to the final intensity image.

Image enhancement algorithms are principally used to make images more suitable for certain applications (Maini and Aggarwal, 2010). Pre-processing (referring to spatial domain manipulation) can emphasize certain features while suppressing others, depending on what is to be done downstream. Two categories included in spatial domain manipulation are intensity transformations and spatial filtering (Gonzalez, Woods and Eddins, 2009).

A commonly used intensity transformation is histogram equalization. This method seeks to produce an image with a uniform histogram of intensities (Maini and Aggarwal, 2010; Gonzalez, Woods and Eddins, 2009). Equalization to different histogram profiles can also be implemented (Maini and Aggarwal, 2010) along with intensity binning. Figure 2 illustrates the effect of global histogram equalization.

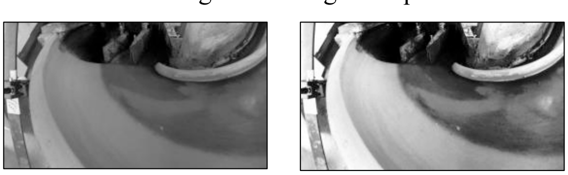

Fig. 2. Histogram equalization example.

Spatial filtering refers to the convolution of an image with some filter (kernel) known as linear filtering. Non-linear spatial filtering's implementation is similar to convolution and is performed as neighbourhood or local operations (Gonzalez, Woods and Eddins, 2009). Gaussian smoothing kernels form part of the linear spatial filters and is frequently used in noise suppression (Canny, 1986; Gonzalez, Woods and Eddins, 2009).

A well-known non-linear image filter is the median filter which is also known as an order-statistic filter (Gonzalez, Woods and Eddins, 2009). A median filter algorithm sets a pixel's intensity (on which a neighbourhood is centered on) to the median intensity value in a surrounding n-by-n neighbourhood. Median filters are especially effective at suppressing so-called salt-and-pepper noise but also maintains edge information within images (Gonzalez, Woods and Eddins, 2009; Narenda, 1981).

2.2.2 Edge detection

Object analysis can be greatly simplified when structural information is maintained and the balance is discarded. Edge detectors are used to obtain object boundaries from the gradient and orientation of gradients in an image (Canny, 1986).

Canny (1986) developed the foundations for optimal edge detection and his detector became a well-established benchmark by 1991 (Petrou and Kittler, 1991).

The Canny edge detector finds edges in local maxima of the gradient of an image which are also in the direction of the edge (Canny, 1986; Gonzalez, Woods and Eddins, 2009). An input image f(x,y) = I, where x and y denote row and column location of a pixel, is firstly convolved with a Gaussian filter, obtained using Eq.2, to reduce noise.

$$G = \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \qquad \text{(Eq. 2)}$$

The gradient of the smoothed image is then obtained with Eq. 3 which can then be used to estimate edge orientation n with Eq. 4 (Gonzalez, Woods and Eddins, 2009).

$$grad(I_{smoothed}) = \nabla(G * f) \qquad \text{(Eq. 3)}$$

$$n = \frac{\nabla(G * f)}{|\nabla(G * f)|} \qquad \text{(Eq. 4)}$$

Image gradient and gradient orientation estimation is followed by non-maximal suppression, hysteresis thresholding and edge linking to obtain a final binary edge map of f(x,y) (Gonzalez, Woods and Eddins, 2009).

Edge detectors typically produce a binary image with several responses to what a particular algorithm might perceive as an edge. Extraction of more specific patterns or features can be accomplished using the Hough transform (Illingworth and Kittler, 1988). However, investigations (not reported here), revealed that the mineral interface will not always exhibit a well behaved shape. This reduces the relevance of the application of Hough transforms and rather highlights the use a more optimized edge detector.

2.2.3 Connected components

Since edge detectors produce binary images with wanted and unwanted features, additional filtering can be performed to refine results. Edges in binary images can be considered as connected components which can be filtered to remove spurious responses.

If S represents a subset of pixels within an image I then two pixels p and q in S are connected if there is a path between them in S. The connected pixels in S then also form a connected component and in general these constructs have various descriptive properties including their perimeter, orientation, area and so forth (Gonzalez, Woods and Eddins, 2009).