Powder Technology 261 (2014) 185–190

Contents lists available at ScienceDirect

Powder Technology

journal homepage: www.elsevier.com/locate/powtec

Estimation of particle size distribution on an industrial conveyor belt using image analysis and neural networks

E. Hamzeloo [a], M. Massinaei [a,*], N. Mehrshad [b]

[a] Mining Engineering Department, University of Birjand, P.O. Box 97175-376, Birjand, Iran
[b] Electrical Engineering Department, University of Birjand, P.O. Box 97175-376, Birjand, Iran

ARTICLE INFO

Article history:
Received 23 November 2013
Received in revised form 24 February 2014
Accepted 9 April 2014
Available online 18 April 2014

Keywords:
Particle size distribution
Sieving
Image processing
Neural network

ABSTRACT

Monitoring and controlling particle size distribution in crushing and grinding circuits are essential for improved energy efficiency and metallurgical performance. Machine vision is probably the most suitable approach for on-line particle size estimation because it is robust, cost-effective and non-intrusive. In the present study, size distribution of particles in crushing circuit of a copper concentrator was estimated using image processing and neural network techniques. Several images were taken from material on a conveyor belt and processed for particle identification and segmentation. A number of the most commonly used size features were extracted from the segmented images and their potential to estimate the actual particle size, represented by sieve size analysis, was evaluated. The results showed that there were substantial differences between size distributions obtained from various size measures. Maximum inscribed disk was found to be the most effective feature for particle size description. Finally, the particle size distribution of material on the conveyor belt was precisely estimated by Principal Component Analysis (PCA) and neural network techniques. The proposed soft sensors can be used for real time measurement of particle size distribution in the industrial operations instead of sophisticated and expensive instruments.

1. Introduction

On-line determination of particle size distribution in mineral processing industry is necessary for improved energy efficiency and crushing/grinding circuit performance [6,15]. However, owing to large size and high tonnage of the crushed materials, measurement of the particle size distribution by manual sampling and sieving is invasive, inconsistent and time consuming.

A machine vision-based control system is a fast, inexpensive, consistent and non-intrusive technique for particle size measurement in industrial operations. The main problem of this system is related to inherent overlapping and segregation of the particles and therefore not taking into account the small fragments located under the bigger ones [21]. In spite of extensive researches conducted, this problem has not been fully resolved yet.

In the last few years, a number of on-line optical sizing systems have been developed to measure the particle size distribution of coarse rocks [5,10,11,13,17] and iron pellets [16]. Williams et al. [19] investigated the feasibility of using an array of non-invasive tomographic sensors around a moving conveyor belt for on-line estimation of particle size distribution. Soft-sensors or model-based sensors have also been used for indirectly estimation of the particle size distribution [3,9]. In this approach a model, such as neural network, is developed to indirectly calculate variable of interest from easily measurable information. Kaartinen and Tolonen [8] introduced a new approach for the crushed ore analysis that was based on a combination of a belt weigher and a 3D laser scanner.

Thurley and Andersson [16] proposed an industrial prototype for sizing iron ore green pellets on conveyor belt using morphological image segmentation. Their findings showed that sizing of identified pellets gave promising results using the best-fit rectangle measure. Liao and Tarng [11] developed an automatic optical inspection system for coarse particle size distribution. The system was composed of four sub-modules (i.e. particle separation, image acquisition, image processing and electric control module) to improve the analysis error caused by overlapping particles. However, most of the above techniques have had limited or no industrial application so far.

In the present study, image processing and neural network techniques are integrated to estimate the particle size distribution of material on an industrial conveyor belt.

2. Experimental details

2.1. Image acquisition and sampling

Industrial images were collected from a conveyor belt in the crushing circuit at Qaleh-Zari copper concentrator in Iran. In this plant, the crushing circuit consists of a jaw crusher followed by two parallel cone crushers in closed circuit with vibrating screens. The material output from the jaw crusher was targeted for imaging and sizing. For that

* Corresponding author. Tel./fax: +98 561 2502301.
E-mail address: mmassinaei@birjand.ac.ir (M. Massinaei).

http://dx.doi.org/10.1016/j.powtec.2014.04.038
0032-5910/

purpose, the selected conveyor belt was stopped and a specified section of the materials (i.e. 1 m in length of the belt) was firstly imaged and then completely swept for the sieve sizing. The imaging system consisted of a Canon digital camera, with a 14.1 megapixels resolution, mounted on a metal structure above the conveyor belt. Images were captured under uncontrolled lighting conditions. Overall, 21 manual samples were collected and analyzed for particle size determination. Actual size distribution of the samples was determined using the sieve analysis technique. The sieves with square apertures and sizes of 110, 84, 53, 42, 30, 25, 15, 10, 5 mm were used.

2.2. Image processing

It should be pointed out that the main objective of this work was to investigate the potential of neural networks to estimate the particle size distribution not to introduce a new image segmentation algorithm. Hence, in order to eliminate the effect of erroneous segmentation on the results obtained from applying the proposed approach, images were segmented manually. In order to segment the particles manually, images to be segmented required preparations. This included image sharpening, edge extraction, converting RGB to gray level image, and image thresholding and segmentation (see Figs. 1, 2).

In order to quantify the proportion of fines between the coarse particles, the whole region occupied by the particles on the segmented image was determined using a closing operator (i.e. morphological dilation followed by erosion) with a disk structuring element (Fig. 2e) [4]. Then, the segmented image was subtracted from the above image to identify the fines (Fig. 2f). It should be noted that the proportion of fine particles detected by this approach was considered as −5 mm fraction.

2.3. Different size measures extracted from images

In this section a number of the most commonly used size measures including particle area and *circumference*, equivalent area circle, equivalent area ellipse (major axis, minor axes), best-fit rectangle (length, width), Feret diameter (Feret's length, Feret's width, Feret's average), and maximum inscribed disk are introduced. The above employed equivalent diameters are depicted in Fig. 3 and their definitions are as follows:

2.3.1. Particle area and circumference

Particle area and circumference were defined as the sum of all pixels forming each particle and the sum of all boundary pixels of any particle, respectively (Fig. 3c).

2.3.2. Equivalent area circle

Equivalent area circle is the circle with the same area as the particle (Fig. 3d). Equivalent area of any particle is the number of pixels in the binary image. The diameter of the equivalent area circle describes the size of the particle [18].

2.3.3. Equivalent area ellipse

Equivalent area ellipse is the ellipse that has the same area and orientation as the particle, where the center of the ellipse equals the center of the particle (Fig. 3e). Similarly, equivalent area of any particle is the number of pixels in the binary image. To describe the size and shape of the particle of interest, the major and minor axes are extracted from the equivalent ellipse [2].

2.3.4. Best-fit rectangle

Best-fit rectangle is defined as the rectangle with smallest area that fits around the region of interest at any rotation (Fig. 3f). The best-fit rectangle is calculated by simply determining the area of a rectangle that fits around the region for every one-degree rotation and finding the rectangle with the smallest area [18]. The best-fit rectangle length and width are measured and reported in this research.

2.3.5. Feret diameter

Feret diameter is the distance between two tangents on opposite sides of the particle (Fig. 3g). For each particle Feret diameter in different directions with one-degree steps is calculated. Thus, 180 Feret diameters are obtained for any particle. Finally, Feret length (maximum Feret), Feret width (minimum Feret) and Feret average are calculated [1].

2.3.6. Maximum inscribed disk

Maximum inscribed disk is the diameter of the largest disk that fits inside a particle (Fig. 3h). It is calculated using a simple brute force method using the mathematical morphology operator opening [2]. That is, erosion followed by dilation using flat disk-shaped structuring elements with increasing radius. Implementation starts with a disk of radius 1, and as long as the disk fits inside the particle, there is an image with at least one region larger than that disk. Any structuring element with a disk that does not fit inside the particle results in an empty image. This is when the iterative process stops.

2.4. Error evaluation

The goodness of fit of the estimated particle size distributions to the actual results (sieve sizing) was evaluated by the root mean square error (RMSE) from the following expression:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2} \qquad (1)$$

X_i cumulative passing % calculated by sieve sizing for the ith fraction
Y_i cumulative passing % estimated by image processing algorithm for the ith fraction
N number of fractions.

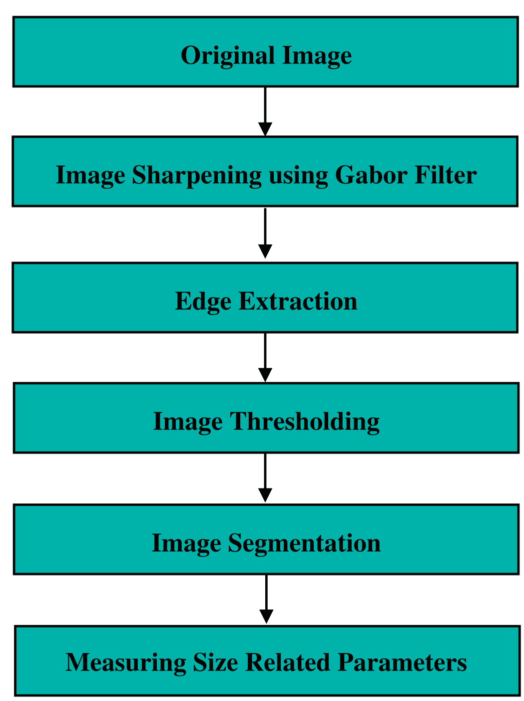

Fig. 1. Image processing routines used in present work.