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Automated cement fragment image segmentation and distribution estimation via a holistically-nested convolutional network and morphological analysis

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ABSTRACT

The distance between two rollers in a ball grinding mill is determined by the size of cement fragments. As such, automated detection of fragment size distribution is of great importance to the cement production industry. Therefore, we propose a holistically-nested convolutional network (HCN) and corresponding morphological analysis to estimate cement fragment distributions. This procedure can be divided into three stages. First, a cement fragment image training set was input to the HCN, helping the algorithm distinguish between fragments and the background. A series of morphological operations including morphological clean and opening operation were then employed to improve segmentation performance and the accuracy of fragment size calculation. Finally, the 'open' operation was employed to obtain the fragment distribution from a segmented image. Experimental results demonstrated that the segmentation and size calculation achieved using our algorithm were superior to those using comparable conventional techniques. The precision,F_1-measure, PRI and VI using proposed method are improved at least 1.3%, 3.3%, 9.5% and 36.5% respectively.

1. Introduction

Grinding processes used in ball mills are the most effective way to produce cement, which has become indispensable in modern construction, on a large scale. The distance between any two rollers in the grinding apparatus, a critical operational parameter, is determined by the size of cement fragments. As such, cement fragment distribution has a significant effect on grinding efficiency. Currently, cement fragment distributions are measured via manual sampling, which is time consuming and does not provide real-time feedback for automated control purposes. Segmentation of cement fragment image is the key to automatically estimate cement fragment distributions. However, automated cement segmentation images have few complications: (1) cement fragments are often in contact with each other and overlap, (2) stains are often present in the images, and (3) cement fragments vary widely in size, shape, appearance, and texture.

In this study, we propose a novel hybrid strategy to overcome these challenges. We first review conventional segmentation methods and introduce their application to actual object segmentation. Then, we discuss the similarity of rock fragment and cement fragment image segmentation. Finally, the motivation for developing a novel approach which overcomes current limitations is presented.

1.1. Related work

Segmentation is a common image processing technique used in a wide variety of fields. Various algorithms have been proposed, studied, and applied to increasingly diverse applications [1–4]. For example, Otsu [5] presented a nonparametric and unsupervised method of automatic threshold selection for picture segmentation, in which an optimal threshold was selected by discriminant criteria. Juraj Horváth [6] applied fuzzy c-means clustering to classify pixels into appropriate segments. Beucher [7] established an intuitive definition of the watershed transform and applied it to image segmentation. Chen et al. [8] proposed an application of Otsu's method to segment nuclei in a background and deployed a watershed technique to further separate overlapping nuclei. Salinas et al. [9] developed a watershed-based algorithm capable of segmenting rock fragment images automatically.

Despite these developments, there are currently few applications of traditional segmentation methods to cement. This is because analysis of such images becomes significantly more difficult for the three reasons. First, fragments are in contact with each other and often overlap. Second, stains are commonly present in these images. Finally, the size,

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shape, appearance, and texture of fragments vary significantly. In this study, we found the segmentation of cement fragments to be highly similar to segmentation of rock fragments. Each includes challenges such as object overlap and texture noise. All these methods [9–11] employed in rock fragment segmentation can be used to segment cement fragments, but their segmentation accuracy is not enough to calculate the cement fragment size accurately.

Recently, there has been a growing interest in the application of convolutional neural networks for the analysis of image segmentation. In [12], deep convolutional neural networks (DCNNs) were applied to image segmentation, which achieved a great performance in high level vision tasks. In [13], conditional random fields (CRFs) were used to learn CNN features, in order to produce a more accurate segmentation. In [14], fully convolutional networks (FCNs) were proposed to segment objects against a background. However, these methods perform poor segmentation in case of complicated images of cement fragment. To attain good performance, modification and post-processing is required in these methods for effective application to cement fragment fields. Based on this, we propose a holistically-nested convolutional network (HCN), combined with morphological analysis, to process cement fragment images. The HCN was developed from the literature [15] by modifying the loss function. In this study, we apply it to the cement fragment segmentation because the pixels distribution in cement fragment segmentation is similar to the image edge detection. One type of the pixels (cement pixels or backgrounds pixels) is account for more than 90%. Additional, morphological operations are also employed to improve the performance of segmentation and calculate the cement fragment distributions. Experimental results demonstrate that the proposed method can effectively suppress noise, avoid over segmentation and calculate cement fragment size accurately.

1.2. Contributions of our work

In this study, we applied the HCN to cement segmentation because the pixel distribution in cement fragments is similar to edge detection. A single pixel type (cement pixels or backgrounds pixels) accounts for more than 90% of the image. The primary contributions of this work include three points.

First, a dataset was built for cement fragment segmentation and a holistically-nested convolutional network developed from literature [15], which alters the loss function, was applied to the segmentation of cement fragments. Morphological operations were introduced in the post-processing step to improve segmentation performance and calculation accuracy for cement fragment distributions.

Second, cement fragment size detection, based on the morphological ‘open’ operation, was employed to obtain the cement fragment distribution. We first increased the size of this morphological structural element. The cement fragment was filtered when the radius of maximum circle contained in the cement fragment was smaller than the morphological structural element's radius. Then, the corresponding unfiltered cement fragment pixel values were then added in each opening operation. Each value represented the cumulative area of cement fragments larger than a certain size, which represented by the size of morphological structural element.

Finally, extensive experimental results (and comparisons with common methods) demonstrated that the proposed method can effectively suppress noise, avoid over segmentation, and accurately calculate cement fragment size. As such, the proposed method is a promising new tool for segmentation of industrial cement images.

In the following sections, we develop and demonstrate this technique. Section 2 presents our methodology in detail, while Section 3 describes the experimental setup and several comparisons made with other methods. Section 4 provides a discussion and section 5 concludes the paper.

2. Methodology

We propose an efficient strategy for automatic segmentation of cement fragment images and calculate cement fragment distributions. An overview of the proposed method is shown in Fig. 1. First, the HCN, a convolutional neural network developed using previous studies [15] was trained to efficiently segment cement fragments from the background. This process is explained in detail in the following sections.

A series of morphological operations were then introduced during post-processing to improve segmentation performance and the accuracy of cement fragment size calculations. Finally, cement fragment size detection, based on the morphological ‘open’ operation, was employed to obtain the fragment distribution and the cumulative area distribution.

2.1. Holistically-nested convolutional network

The HCN was developed from a trimmed VGG net which is produced by cutting the last stage, including all fully-connected layers and the fifth pooling layer. As shown in Fig. 2, an additional deep supervision step was added to the trimmed VGG net. Additional deep supervision was established by connecting the side output layer to the last convolutional layer in each stage, conv1_2, conv2_2, conv3_3, conv4_3, and conv5_3, respectively. The side output layer was implemented as a convolutional layer with a kernel size of 1 and a single output. In addition, the HCN added a fusion layer to the network which can link all side output layer predictions and learn fusion weights during training. As a result, the overall loss function L can be written as:

$$L(I,G,W,w) = L_{side}(I,G,W,w) + L_{fuse}(I,G,W,w) \quad (1)$$

where L_{fuse} denotes the fusion layer loss function, L_{side} denotes the side output layer loss function, I denotes the raw input image, and G denotes the corresponding ground truth binary segmentation map. The term $w = (w(1),\ldots,w(M))$denotes the corresponding weights for each side output layer. W denotes the collection of all other network layer parameters.

The loss function for this HCN has been modified from the network in [15] because most of the pixels in a cement image are positive (fragment pixels), in contrast to edge detection where 90% of pixels are negative (background pixels). The class-balancing weight β_j can then be described as:

$$\beta_{\mathrm{j}} = \frac{I_+}{I} \quad (2)$$

where the index j is over spatial image dimensions of I. The terms I_+ and I denote the number of cement fragment (positive) pixels and the total number of pixels, respectively.

2.1.1. Training workflow with HCN

The HCN was trained using the image-to-image approach. When an image was input to the HCN, as shown in Fig. 1, the result is five side output maps and one fusion output map. The five side-output layer loss, fusion layer loss, and overall loss were then calculated. Afterwards, a back-propagation strategy was used to adjust network weights according to these losses (L_{side},L_{fuse},L). This produced the HCN model used for cement fragment segmentation.

2.2. Post-processing

A series of morphological operations were employed to improve segmentation performance and fragment size calculation accuracy. First, a large threshold was selected to produce a binary image. This threshold degrades segmentation performance, but improves size calculation accuracy by reducing the probability of fragments overlapping