Ore image edge detection using HOG-index dictionary learning approach

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Abstract: A new edge detection method based on histogram of oriented gradient (HOG)-index dictionary learning is proposed. The HOG-index dictionary includes HOG feature bases of various granularity ore image and its corresponding ground-truth binary image bases. For each pending image, its HOG feature is extracted to compare with the HOG feature bases in the dictionary. The binary image bases of the closest matched HOG bases will be chosen as a reconstruction of the original pending image. Compared to bi-neighbourhood Otsu thresholding method, experimental results show that the proposed algorithm improves both precision and noise immunity performance efficiently, especially for small particle size and large-complex ore images.

1 Introduction

Ore image edge detection is a key step procedure of Ore particle size detection, aiming at finding out the object and edge parts of target ore image. Thresholding methods have been widely used in image edge detection task. Bi-neighbourhood Otsu [1] combines the bi-neighbour technique with Otsu’s method. It has a good performance on multi-scale objects and non-uniform illumination images, as it can overcome the misdetection of lower brightness objects which exist in many global thresholding methods. However, the experiment results of bi-neighbourhood Otsu show that some small objects are missed in high light image area and more noise areas are detected in large-complex ore image. Apart from thresholding methods, histogram of oriented gradient (HOG) feature has been applied in edge detection task as well [2]. As gradient information is mainly on the edge, HOG feature can well describe the appearance and shape of an object. In Başa’s method [2], HOG was directly used for edge detection on field programmable gate array (FPGA). However, it is applied on characteristic objects such as pedestrian in Institut National de Recherche en Informatique et en Automatique (INRIA). It is not suitable for ore edge detection. Inspired by dictionary learning on super-resolution work [3], the edge detection (from natural image to binary image) could be considered as image reconstruction.

In this paper, we propose an edge detection algorithm based on HOG feature and coupled dictionary learning. The edge detection work is considered as an image reconstruction. First, for each pending image, its HOG feature is extracted to compare with the HOG bases in the dictionary. Then, the binary image bases of the closest matched HOG bases will be chosen as a reconstruction of the original pending image. The dictionary learning problem was optimised with sparse coding work [4]. The proposed method shows a satisfactory performance as it can overcome some drawbacks of bi-neighbourhood Otsu such as small objects misdetect on the high light area and more noise in the large-complex objects. Also, some future advice will be mentioned at the end of this paper.

2 Related work

HOG feature represents the local shape and appearance of targets as gradient statistics mainly on the edge and contour [2]. Since the process of HOG feature extraction including colour and gamma normalisation, derivation operation of gradient calculation and gradient strength normalisation, HOG feature efficiently weaken illumination and shadow effect of the target image.

Sparse coding is widely used in machine learning which models data vectors as sparse linear combinations of (dictionary) basis elements. It provides efficient stochastic approximations for dictionary learning on signal reconstruction and classification. Mairal et al. [4] optimised the dictionary learning problem as a smooth non-convex objective function over a convex set. Also, an iterative online algorithm is provided to efficiently minimise quadratic surrogate function of the empirical cost over the set of constraints. Liang [3] presented a pair of dictionaries and a mapping function for super-resolution and cross-style task. This work forwards a joint optimisation of the dictionary pair and the mapping function in the sparse domain.

3 Proposed method

In this paper, the edge detection of ore image is considered as an image reconstruction work. The edge and contour feature of pending image is collected by HOG feature extraction. Then, a coupled dictionary is defined including HOG bases and binary image bases. The binary image bases are collected from ground-truth binary image patches of various kinds of ore images and the HOG bases are the corresponding HOG features. The pending image and the defined dictionary are compared on the HOG feature space to seek a ground-truth binary image set which closely match on HOG space. The result shows that the proposed method provides a competitive performance (Fig. 1). The detail of the algorithm is described as follows.

Assuming \( x_i \in G^{\nu} \) is the pending ore image and \( \theta = f(x_i) \in G^{\nu} \) is its corresponding HOG descriptor. As \( f(\bullet) \) is a one-to-many function, we need to seek a binary image set \( \delta \) which closely match \( x_i \in G^{\nu} \) on the HOG feature space \( \theta = f(x_i) \in G^{\nu} \), so

\[
\delta = \arg \min_{x_i \in G^{\nu}} \sum_{i=1}^{N} \| f(x_i) - \theta \|_2^2
\]  

(1)

Inspired by sparse coding, we propose a coupled dictionary leaning approach to optimise (1). Suppose \( x_i \) and \( \theta \), respectively, represented by binary image bases \( I \in G^{K \times K} \) and HOG feature bases \( F \in G^{D \times K} \) with a shared coefficient \( c \in G^K \)

\[
x = cI, \quad \theta = cF
\]  

(2)

\( K \) represents the size of dictionary. As mentioned before, the reconstruction work is mapping \( \theta \) to \( F \) set. Then seek the binary image
is the sparsity regularisation parameter. As shown in Fig. 1, the coupled dictionary learning approach and our method are illustrated in Figs. 1d–i.

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5 Conclusion

We introduced a new HOG-index dictionary approach to segment ore images. This method presents a coupled dictionary learning approach with HOG feature space comparison. The edge detection performance of the proposed method is better than bi-neighbourhood Otsu thresholding method. We hope the future work could focus on post-processing of denoising to refine the result.

6 Acknowledgment

The method in this paper is evaluated by crude ore images (as shown in Fig. 1). Fig. 1a is small particle size ore image with uneven illumination. Fig. 1b contains different sizes of ore objects in low luminance. Fig. 1c is a normal illumination image of large-complex objects. The results of bi-neighbourhood Otsu’s approach and our method are illustrated in Figs. 1d–i.

We optimise the sparse coding work using \( \mathbf{Y} \). We optimise \( I \) and \( F \) with dictionary size \( K = 1024 \) and experiment verification parameter \( \Lambda = 0.02 \). About 29 k image patches including gold, copper and iron ore images are selected as training set.

4 Experimental results

We introduced a new HOG-index dictionary approach to segment ore images. This method presents a coupled dictionary learning approach with HOG feature space comparison. The edge detection performance of the proposed method is better than bi-neighbourhood Otsu thresholding method. We hope the future work could focus on post-processing of denoising to refine the result.

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7 References

| Image | Fig. 1a | Fig. 1b | Fig. 1c |
|-------|---------|---------|---------|
| Size   | 1032 \( \times \) 778 | 408 \( \times \) 289 | 293 \( \times \) 214 |
| time, \( \text{s} \) | bi-neighbour Otsu | proposed | 46.315 | 20.637 | 10.951 |
| PSNR, dB | bi-neighbour Otsu | proposed | 6.39 | 7.09 | 6.63 |

| \( \text{PSNR} \) values of bi-neighbourhood Otsu and proposed method will be shown in Table 1. The proposed method shows an average 1.05 dB improvement of PSNR. The appearance and quantitative results of the proposed method are obviously better. | 7.61 | 8.16 | 7.49 |

We optimise the sparse coding work using [4]. As HOG is sensitive to noise, there is an annular noise in the largest object of Fig. 1f. Finally, the running time and the peak signal-to-noise ratio (PSNR) values of bi-neighbourhood Otsu and proposed method will be shown in Table 1. The proposed method shows an average 1.05 dB improvement of PSNR. The appearance and quantitative results of the proposed method are obviously better.

Fig. 1 Original image and binarisation processed image

c–f: Binarisation processed image using bi-neighbourhood Otsu method
d: Binarisation processed image using HOG-index dictionary method

Fig. 2 Edge detection using HOG-index dictionary learning. First, we compute HOG vector on pending image and HOG basis. The coupled dictionary is defined by joint learning HOG feature and ground-truth binary image of ore images. We can transfer the coefficients after comparing the HOG vector of pending image and \( \mathbf{I} \), then find the corresponding patches from \( \mathbf{I} \) to reconstruct the binary image.

\[
\mathbf{F}^{-1}(\theta) = \mathbf{I}_c \text{ where } \begin{cases} 
\mathbf{c}^* = \arg\min_{\mathbf{c} \in \mathcal{G}} \| \mathbf{F} \mathbf{c} - \theta \|_2^2 \\
\text{s.t.} \| \mathbf{c} \|_1 \leq \lambda 
\end{cases} \tag{3}
\]

\( \lambda \) is the sparsity regularisation parameter. As shown in Fig. 2 and (2), seeking proper \( \mathbf{I} \) and \( \mathbf{F} \) is necessary for the coupled dictionary. Similar to super-resolution sparse coding

\[
\mathbf{F}^{-1}(\theta) = \mathbf{I}_c^* \text{ where } \begin{cases} 
\mathbf{c}^* = \arg\min_{\mathbf{c} \in \mathcal{G}} \| \mathbf{F} \mathbf{c} - \theta \|_2^2 \\
\text{s.t.} \| \mathbf{c} \|_1 \leq \lambda 
\end{cases} \tag{4}
\]