Supervised segmentation of textures in backscatter images

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Abstract

In this paper we present an application of statistical pattern recognition for segmentation of backscatter images (BSE) in product analysis of laundry detergents. Currently, application experts segment BSE images interactively which is both time consuming and expert dependent. We present a new, automatic, procedure for supervised BSE segmentation which is trained using additional multi-spectral EDX images. Each time a new feature selection procedure is employed to find a convenient feature subset for a particular segmentation problem. The performance of the presented algorithm is evaluated using ground-truth segmentation results. It is compared with that of interactive segmentation performed by the analyst.

1 Introduction

Product analysis is today closely connected with various imaging techniques. Image segmentation plays an important role in identifying image areas that correspond to underlying physical modalities. In this paper, we present an application of statistical pattern recognition for the segmentation of backscatter images (BSE) acquired by scanning electron microscopy (SEM) [2]. Backscatter images are widely used as an effective tool for detailed analysis of material structure. Our application domain is structural analysis of laundry detergents. Powder properties of laundry detergent are determined by the internal arrangement of the main powder constituents (solids, actives, and pores). Our goal is to label these powder components in BSE images for further interpretation by the application expert.

Development of new detergent formulation involves processing of a batch of backscatter images. Currently, the product analyst segments these images interactively what is both time consuming and an inaccurate operation. Moreover, the results delivered by different experts may considerably differ. One of the reasons is that the analyst bases her decisions on the single-band BSE which lacks information about underlying chemical composition.

We propose to use a different imaging modality to obtain label information for BSE images. Supervised pattern recognition methods may be then used to find well discriminating features and to train the corresponding BSE classifier. This new image is acquired by the method of Energy-dispersive X-ray microanalysis (EDX). The EDX method produces a multi-spectral image with bands capturing the presence of various chemical elements in the sample. EDX images have a lower resolution and need a considerably longer acquisition time than the backscatters (around one hour compared to minutes for the BSE). Because the generation of the EDX image is also more expensive, they are acquired just for a fraction of the formulation samples. This is sufficient for our approach as we require just one BSE/EDX pair for training. It is important that the powder specimen is prepared (embedded) in the same way for both BSE and EDX images. This enables us to acquire and process both types of images for the same sample.

In the following section, the supervised segmentation algorithm for BSE images is explained. We briefly introduce feature types used for BSE segmentation and the feature selection mechanism. Several experiments with different powder formulations have been performed and their results are presented in the section 3. Finally, we give conclusions.

2 Supervised BSE segmentation algorithm

The supervised BSE segmentation algorithm may be split into two steps. In the first one, BSE and EDX images of the same specimen are used for training of the BSE classifier. In the second, new BSE images are labeled by the trained classifier. The segmentation process is shown in the Figure 1.

In order to train the BSE classifier, a labeled backscatter image is needed. The labels may be generated by segmenting the EDX image of the same powder specimen. The segmentation of EDX is performed by a multi-spectral segmen-

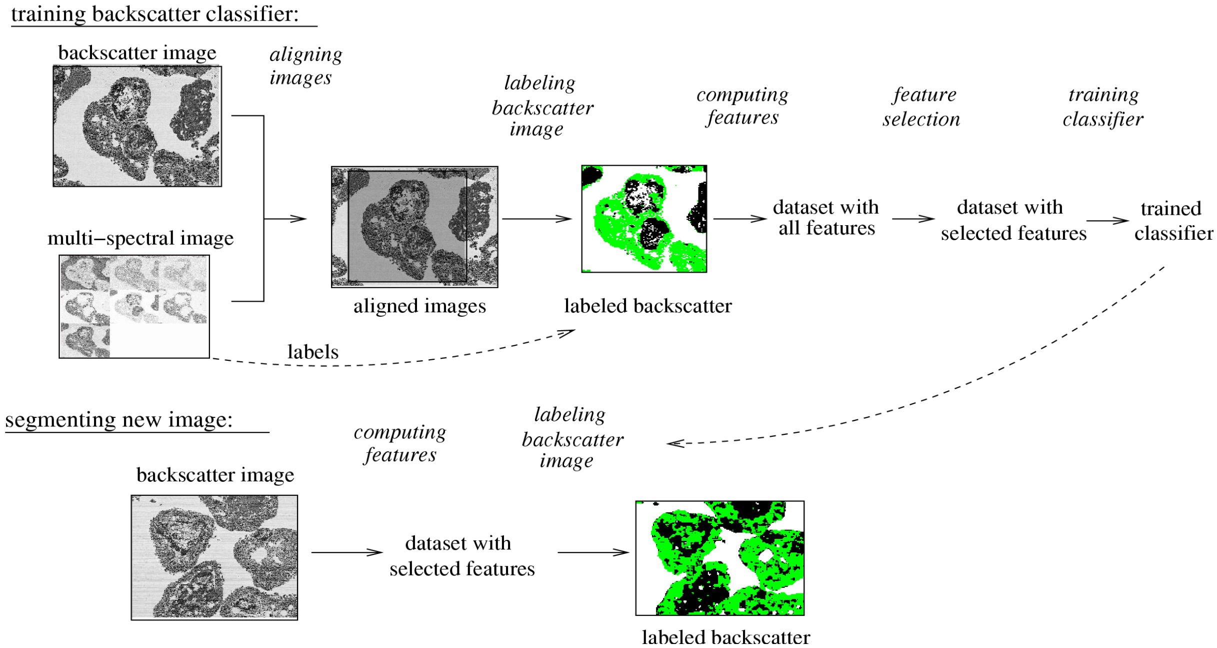

Figure 1. Supervised algorithm for segmentation of backscatter images.

tation algorithm we proposed in [7]. It uses both spectral and spatial information by combining corresponding classifiers. The algorithm has proved to be a robust tool for the segmentation of multi-band images of laundry detergents.

In the second step of the training procedure, the BSE image is labeled by the generated set of labels. EDX and BSE images of the investigated detergent sample are acquired via different sensors. In our setup, the lower-resolution EDX image covers just a part of the high-resolution BSE. Therefore, both images must be aligned. The scale difference is defined by the sensor setup and may be estimated from image data beforehand. Therefore, we align two images with the same resolution by maximizing the cross-correlation.

The labeled BSE image is used for the classifier training. Usually, three to five classes are identified in the BSE images which correspond to different structures in powder particles such as various types of particle binder or active phases. Both, image intensity and texture pattern carry the information about different detergent components in the backscatter image. In order to describe these patterns, we have chosen features that performed well in different comparisons of texture classification techniques [6, 9, 10] and are relatively easy to compute:

intensity - simple intensity statistics in the local neighborhood (4 features)

SGLD - features computed on histograms of *gray-level differences* between neighboring pixels [6] (4 features)

CM - features based on the *cooccurrence matrix* [9]. (4 features)

LBP - *Local Binary Patterns* [6, 4]. Three groups of LBP features (17,25, and 9 features, respectively).

DCT - features based on *Discrete Cosine Transform* [5, 9] (8 features).

Gabor - *Gabor filters* [9] with different smoothing and frequencies (24 features)

Feature values are computed in a window sliding over the BSE image. Selection of appropriate window size is described in more detail in the next section.

The complete set of 95 features in computed on the training image. Then, the forward feature selection [1] is used to choose the convenient feature subset. The BSE classifier is trained on the reduced feature set. This classifier is used later for the segmentation of other backscatter images from the same powder formulation.

It should be noted, that different texture classifier is needed for each new batch of BSE images due to varying detergent structures to be labeled. Computation of texture features in high-resolution BSE images is a time-consuming operation (computation of all 95 features takes about 1.5 hour per image on 1Ghz PC). Feature selection step serves, in this setup, for two different purposes: to find well discriminating feature subset and to reduce the necessary feature acquisition time. We have proposed two algorithms to include the measurement cost into the selection process in [8].

3 Experiments

In this section we describe a set of experiments performed on images of laundry detergents from several dif-

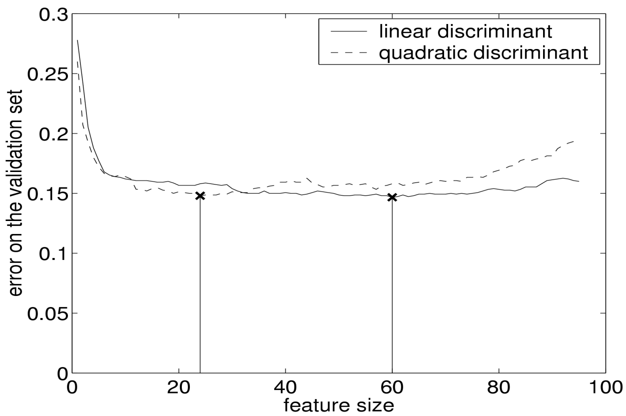

Figure 2. Feature selection: error on the validation set as a function of the feature size. Minimum error is denoted by crosses.

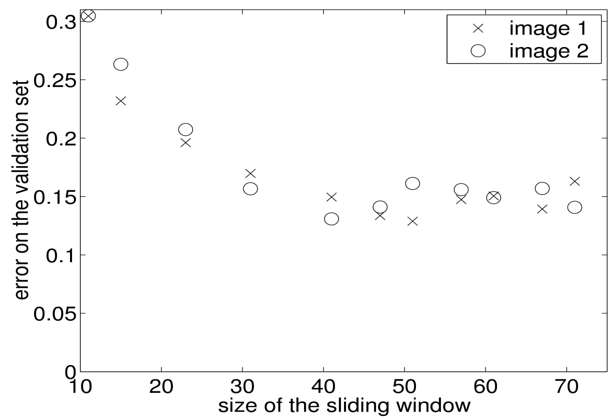

Figure 3. Selection of the window size for feature computation

ferent powder formulations. The size of backscatter images is 1024×1364 pixels. The sliding window is placed over the BSE image with steps of eight pixels what implies the dataset size of about 15000 samples. Multi-spectral images, providing the labels for the classifier training, are 128×128 pixels. Three different structure types were identified by the multi-spectral segmentation process – background (porosity), solids (powder binder) and actives. In all experiments, different BSE/EDX images were used for training and different BSE images for testing.

First, we discuss the performance of the presented algorithm. The training BSE image was labeled using the corresponding EDX image. The complete set of 95 features was computed on the backscatter image. The forward feature selection was run on the data subset (1500 data samples) with the error of a classifier on an independent test set as criterion. Typical behavior of the linear and quadratic discriminant assuming normal densities during the feature selection is given in the Figure 2. It appears, that the discrimination boundary between classes is usually nonlinear. Quadratic classifier can, therefore, provide comparable performance to the linear discriminant with a smaller feature subset. It follows from our experiments with more images, that the usual number of features, selected using the quadratic discriminant, is quite high (around 25) considering the three class problem with easily separable background class. Nevertheless, such solution is satisfactory to reach our main goal: to choose features for the segmentation of BSE textures automatically, without user interaction.

The quadratic classifier is trained on the chosen feature subset. Then, a different BSE image from the same formulation is segmented by this trained classifier. The results of three such experiments are presented in the Figure 4. The test backscatter images are shown in the top row (**A**). The desired segmentation outputs (ground truth) are given as **B**. They were established by segmenting the corresponding multi-spectral data and validated by the application expert. Results of the interactive segmentation procedure performed by the expert are labeled **C**. Unsupervised segmentations by ISODATA thresholding [3] of image histogram are given for comparison as **D**. Finally, the output of supervised segmentation algorithm is presented as **E**.

The classes inside the particles are completely mixed in the results of interactive segmentation and ISODATA thresholding. Obviously, intensity information is not sufficient for the segmentation of these BSE images. The results of the presented supervised segmentation algorithm are close to the ground truth images (the label mismatch is between 0.15 and 0.24). It is important that the segmentation results capture the arrangement of actives and pores inside the powder particles. Results achieved by the supervised segmentation are judged as satisfactory by the application experts.

It follows from our experiments, that LBP, CM, SGLD and intensity features outperform the Gabor and DCT filters both in the discriminative power and in the computational time.

3.1 Selecting the size of the sliding window

Texture and intensity features are computed within the window sliding over the BSE image. The appropriate size of the window depends on the investigated powder formulation and used magnification. In this section, we try to find the best window size for a given segmentation task.

A smaller classification task is performed for each window size separately. The classification error on the test set is then used as a criterion for choosing the appropriate window size. Figure 3 shows the classification error as a function of window size for two BSE images of the same formulation. For each window size a dataset was computed with all 95 features and 2000 samples. The appropriate feature subset is chosen by the forward feature selection. The classifier (in

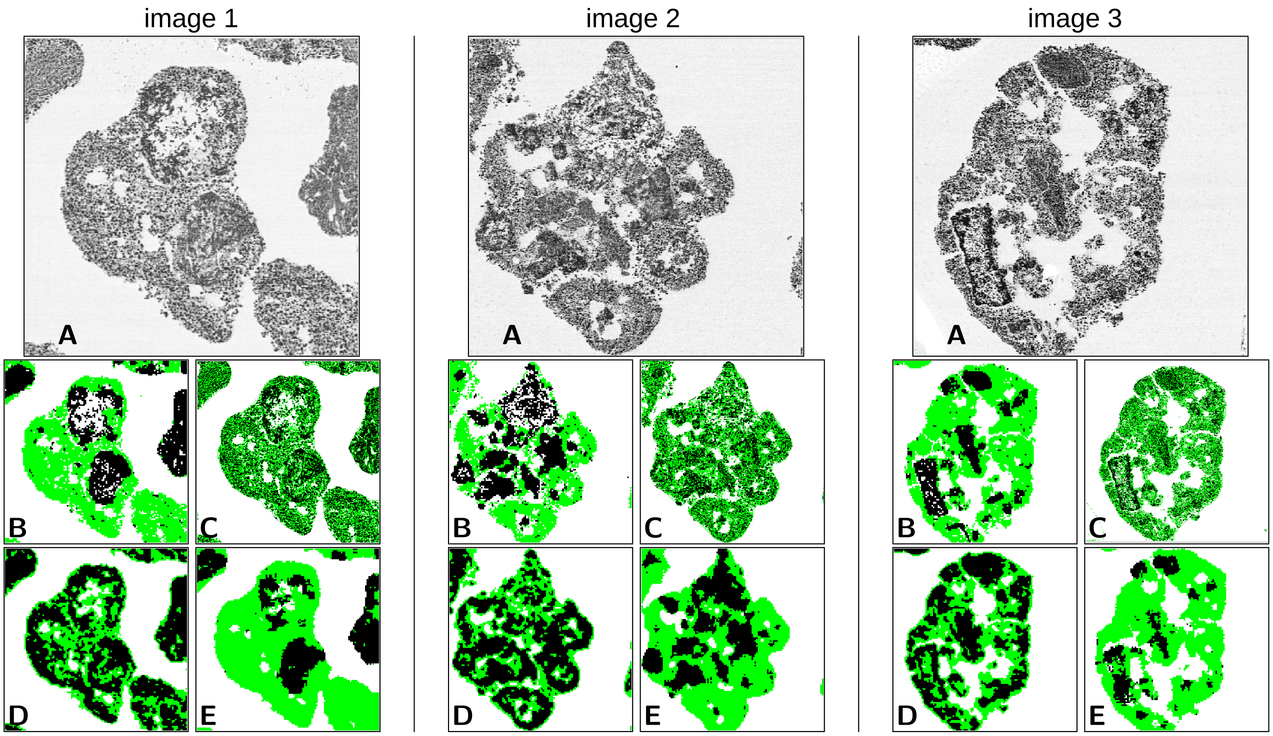

Figure 4. Segmentation results for three BSE images. Letters 'A' denote backscatter images, 'B' the ground truth segmentations, 'C' interactive segmentations by application experts, 'D' results of ISODATA thresholding, and 'E' results of the supervised segmentation algorithm.

this experiment linear discriminant) is trained on a part of the training data (250 samples per class). The classification error on the rest of the data is shown in the graph. It can be seen, that the optimal value of the window size for the investigated formulation is around 45 pixels.

4 Conclusions

We present an application of statistical pattern recognition for the segmentation of BSE images of laundry detergents. The BSE classifier is trained using the label information from a multi-spectral image. The feature selection is performed for each new formulation of powder in order to choose well performing feature subset and to reduce the computational time. The selection of appropriate window size for feature computation is proposed. The segmentation algorithm outperforms currently used interactive segmentation and unsupervised ISODATA thresholding.

References

[1] P. A. Devijver and J. Kittler. *Pattern Recognition: A Statistical Approach*. Prenticel Hall, 1982.

[2] J. Goldstein, D. Newbury, P. Echlin, D. Joy, A. Romig, C. Lyman, C. Fiori, and E. Lifshin. *Scanning Electron Microscopy and X-Ray Microanalysis*. Plenum Press, New York, 1992.

[3] C. Luengo Hendriks, L. van Vliet, B. Rieger, and M. van Ginkel. *DIPimage user manual: a scientific image processing toolbox*. Pattern Recognition Group, TU Delft, 2001.

[4] T. Mäenpää, T. Ojala, M. Pietikäinen, and M. Soriano. Robust texture classification by subsets of local binary patterns. In *Proc. 15th International Conference on Pattern Recognition*, volume 3, pages 947–950, Barcelona, Spain, 2000.

[5] I. Ng, T. Tan, and J. Kittler. On local linear transform and gabor filter representation of texture. In *Proc. 11th International Conference on Pattern Recognition*, volume 3, pages 627–632, The Hague, The Netherlands, 1992.

[6] T. Ojala, M. Pietiäinen, and D. Harwood. A comparative study of texture measures with classification based on feature distributions. *Pattern Recognition*, 29(1):51–59, 1996.

[7] P. Paclík, R. P. Duin, and G. M. van Kempen. Multi-spectral Image Segmentation Algorithm Combining Spatial and Spectral Information. In *Proceedings of SCIA 2001 conference*, pages 230–235, 2001.

[8] P. Paclík, R. P. Duin, G. M. van Kempen, and R. Kohlus. On feature selection with measurement cost and grouped features. accepted for Statistical Pattern Recognition Workshop, SPR2002, Windsor, Canada, August 6-9, 2002.

[9] T. Randen and J. H. Husøoy. Filtering for texture classification: A comparative study. *IEEE Trans. Pattern Analysis and Machine Inteligence*, 21(4):291–310, 1999.

[10] T. R. Reed and J. M. H. du Buf. A review of recent texture segmentation segmentation and feature extraction techniques. *CVGIP: Image Understanding*, 57(3):359–372, 1993.