# MULTI-SPECTRAL IMAGE SEGMENTATION ALGORITHM COMBINING SPATIAL AND SPECTRAL INFORMATION

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## ABSTRACT

To segment multi-spectral images new methods are required which operate both in spectral and spatial domains and work with a high-dimensional data. We are presenting a new segmentation method that is built from standard statistical pattern recognition algorithms. It integrates spectral and spatial domain information by a combined classifier approach. We have studied the algorithm performance on real multi-spectral images of detergent powders acquired by the method of scanning electron microscopy. The use of apriori information for the segmentation of images with the similar spectral properties is investigated. The algorithm stability and the measure of segmentation quality are discussed as well. The proposed method appears to be a robust solution for the multi-spectral image segmentation.

**keywords:** multi-spectral images, image segmentation, classifier combination, EM clustering

## 1. INTRODUCTION

Multi-spectral imaging is a valuable data analysis tool in areas like remote sensing and product inspection. A problem that often must be solved while processing multi-spectral data is image segmentation [10, 8]. In this paper we propose a new method for the segmentation of multi-spectral images. It is based on a combined classifier integrating spatial and spectral information.

Image segmentation aims at dividing the image into a set of non-overlapping regions which correspond to some interesting modalities in the data [9, 3, 7]. Four different groups of segmentation methods exist : edge-based, neighborhood-based, histogram-based and cluster-based methods [5]. The first two approaches work in the spatial domain, the last two find their base in the spectral feature space. To define the interesting regions, the edge-based approach exploits discontinuities in the image. Neigborhood-based methods are, on the contrary, based on similarities between various image parts. Both approaches use *ad-hoc* procedures like edge-following or region-growing which work reliably on gray-level or color images [5, 11], but their extension to multi-dimensional data is not straightforward.

The histogram-based methods assume that homogeneous regions in the image correspond to modes of image histogram. Therefore, these algorithms perform some version of mode seeking or multi-thresholding. Although few extensions to 3D colorspace have been presented the increase of dimensionality means the loss of segmentation speed and accuracy [5, 6]. Finally, cluster-based segmentation methods assume that interesting structures in the image form clusters in the color domain. The most appealing idea behind both histogram and cluster-based segmentation methods is that image pixels are processed as general data samples in the feature space. The clustering approach to image segmentation may be, therefore, naturally extended from 3D color to the high-dimensional spectral feature spaces. In this paper we will present and evaluate a method that integrates information from the spatial and spectral feature domain using a combined classifier approach.

The presented segmentation algorithm has been developed as a data analysis tool for product inspection, more specifically for the structure analysis of detergent powders. It is a challenge today to include more and novel active components in the formulation of modern detergent powders. To distinguish between the growing number of modalities the high-quality *spectral information* is necessary. This can be achieved, for example, by energy-dispersive X-ray microanalysis (EDX). The powder properties of laundry detergent powders are determined by their *spatial structure* – especially, by the internal structural arrangement of three major types of detergent powder components – solids, actives, and pores. The spatial structure is acquired by a scanning electron microscopy (SEM) technique. The SEM/EDX method [2] obtains chemical element information (e.g. C, Si, Na) for each pixel in the image and generates a multi-spectral image. An example of multi-spectral image is given in figure 1.

It is apparent that a reliable multi-spectral segmentation method for product structure analysis should operate on both available domains (spectral and spatial). The method must also deal with a large amount of high-dimensional and noisy data. The presented new segmentation algorithm combines standard statistical pattern recognition algorithms. It works both in spectral and spatial domains and combines attained results together. Our approach is an alternative for probabilistic relaxation [12]. It differs from it that it combines the spectral (feature) domain and the spatial domain using a combined classifier approach instead of the use of neighborhood relations in a Bayesian scheme [1]. The combined classifier approach is much more flexible as it allows for a separate treatment of both domains.

The paper is organized as follows. In the next section we present the segmentation algorithm formally. Then, we discuss the properties of the algorithm such as the segmentation stability and a criterion for the automatical stopping of an iteration process. The experimental results on real multi-spectral images are then presented. The segmentation quality is studied segmenting multi-spectral images using the apriori information obtained on different data. We also study the stability of the segmentation algorithm concerning random initialization of the initial labeling step. In the last section we summarize the main points of the paper and give a short overview of planned future development.

## 2. THE SEGMENTATION ALGORITHM

The input of the segmentation process is a multi-spectral image with $D$ spectral bands. The algorithm output is the image labeling scheme $\Lambda = \{\lambda_i\}$, $i = 1, ..., N$, $\lambda_i \in \Omega$, where $N$ denotes the number of image pixels and $\lambda_i$ are pixel labels. Labels take values from a set of mutually exclusive classes $\Omega = \{\omega_1, ..., \omega_C\}$. The algorithm separates spectral and spatial information and works with a different dataset in each data domain. In the spectral domain, a dataset $\mathcal{D}_{\mathrm{spec}}$ is built which contains a feature vector $\mathbf{x}_i \in \mathbb{R}^D$ for each image pixel. Individual features then correspond to spectral bands. The dataset therefore contains only the spectral information and all the spatial relationships are lost. In the spatial domain, a dataset $\mathcal{D}_{\mathrm{spat}}$ is created containing a feature vector $\mathbf{x}'_i \in \mathbb{R}^2$ for each image pixel. In this case, features correspond to spatial pixel coordinates and the spectral information is omitted.

The first step of the segmentation algorithm is the construction of the initial labeling $\Lambda_0$ by allocation of each feature vector $\mathbf{x}_i$ into a class $\omega \in \Omega$. The initial labeling is performed by an unsupervised clustering algorithm on the spectral dataset $\mathcal{D}_{\mathrm{spec}}$.

The second step of the segmentation algorithm is the iteration process which uses labeled spectral and spatial datasets to generate new labeling schemes. A classifier $\Psi_{\mathrm{spec}} : \mathbb{R}^D \to \Omega$ is trained on the spectral dataset $\mathcal{D}_{\mathrm{spec}}$. Class conditional aposteriori probabilities $\hat{P}_{\mathrm{spec}}(\omega_c|\mathbf{x}_i)$, $c = 1, ..., C$, are then estimated for all data samples using the trained spectral classifier. In the similar way, a spatial classifier

**Algorithm 1** segmentation of multi-spectral image

**input:** multi-spectral image $I$, number of classes $C$
**initial labeling:** find initial labeling $\Lambda_0$ by clustering algorithm
iter=0
**repeat**
 · iter=iter+1
 · create $\mathcal{D}_{\mathrm{spec}}$ (spectral data and labels $\Lambda_{\mathrm{iter}-1}$)
 · train spectral classifier $\Psi_{\mathrm{spec}}$ on dataset $\mathcal{D}_{\mathrm{spec}}$
 · estimate $\hat{P}_{\mathrm{spec}}$ running $\Psi_{\mathrm{spec}}$ on $\mathcal{D}_{\mathrm{spec}}$
 · create $\mathcal{D}_{\mathrm{spat}}$ (pixel positions and labels $\Lambda_{\mathrm{iter}-1}$)
 · train spatial classifier $\Psi_{\mathrm{spat}}$ on dataset $\mathcal{D}_{\mathrm{spat}}$
 · estimate $\hat{P}_{\mathrm{spat}}$ using $\Psi_{\mathrm{spat}}$ on $\mathcal{D}_{\mathrm{spat}}$
 · get $\hat{P}_{\mathrm{comb}}$ by combining $\hat{P}_{\mathrm{spec}}$ and $\hat{P}_{\mathrm{spat}}$ together
 · generate new labels $\Lambda_{\mathrm{iter}}$ from $\hat{P}_{\mathrm{comb}}$
**until** $\mathrm{diff}(\Lambda_{\mathrm{iter}-1}, \Lambda_{\mathrm{iter}}) = 0$
**output:** segmented image $\Lambda_{\mathrm{iter}}$

$\Psi_{\mathrm{spat}} : \mathbb{R}^2 \to \Omega$ is trained on the dataset $\mathcal{D}_{\mathrm{spat}}$. For each data sample, class conditional aposteriori probabilities $\hat{P}_{\mathrm{spat}}(\omega_c|\mathbf{x}'_i)$, $c = 1, ..., C$ are estimated.

So far, two separated datasets have been used in the segmentation process : $\mathcal{D}_{\mathrm{spec}}$ in the spectral and $\mathcal{D}_{\mathrm{spat}}$ in the spatial domain. For each individual pixel two sets of aposteriori probabilities of the class membership were computed in these domains. To generate a new image labeling, both estimates are combined together using the product combination rule :

$$\forall i, i = 1, ..., N,$$
$$\hat{P}_{\mathrm{comb}}(\omega_c|\mathbf{x}_i) = \frac{\hat{P}_{\mathrm{spec}}(\omega_c|\mathbf{x}_i)\hat{P}_{\mathrm{spat}}(\omega_c|\mathbf{x}'_i)}{\sum_{c=1}^{C} \hat{P}_{\mathrm{spec}}(\omega_c|\mathbf{x}_i)\hat{P}_{\mathrm{spat}}(\omega_c|\mathbf{x}'_i)}. \quad (1)$$

We have chosen the product rule because we assume statistical independence of both combined representations (spectral and spatial) [4]. The estimated aposteriori probability $\hat{P}_{\mathrm{comb}}(\omega_c|\mathbf{x}_i)$ generates a new labeling $\Lambda_1$ :

$$\forall i, i = 1, ..., N,$$
$$\lambda_i = \arg\max_c \{\hat{P}_{\mathrm{comb}}(\omega_c|\mathbf{x}_i)\}, \quad \Lambda_1 = \{\lambda_i\}. \quad (2)$$

The process of segmentation continues by training the spectral and spatial classifiers $\Psi_{\mathrm{spec}}$ and $\Psi_{\mathrm{spat}}$ using the new labeling scheme $\Lambda_1$ again. The segmentation algorithm is therefore an iterative procedure starting from the initial labeling estimate $\Lambda_0$. In the loop, results of spectral and spatial classifiers are combined together and new labeling schemes are developed until a stable segmentation is reached. Let us define the number of label changes between two sets of labels $\Lambda_a$ and $\Lambda_b$ $\mathrm{diff}(\Lambda_a, \Lambda_b)$ as

$$\mathrm{diff}(\Lambda_a, \Lambda_b) = \sum_{i=1}^{N} \mathcal{I}(\Lambda_a(i), \Lambda_b(i)), \quad (3)$$

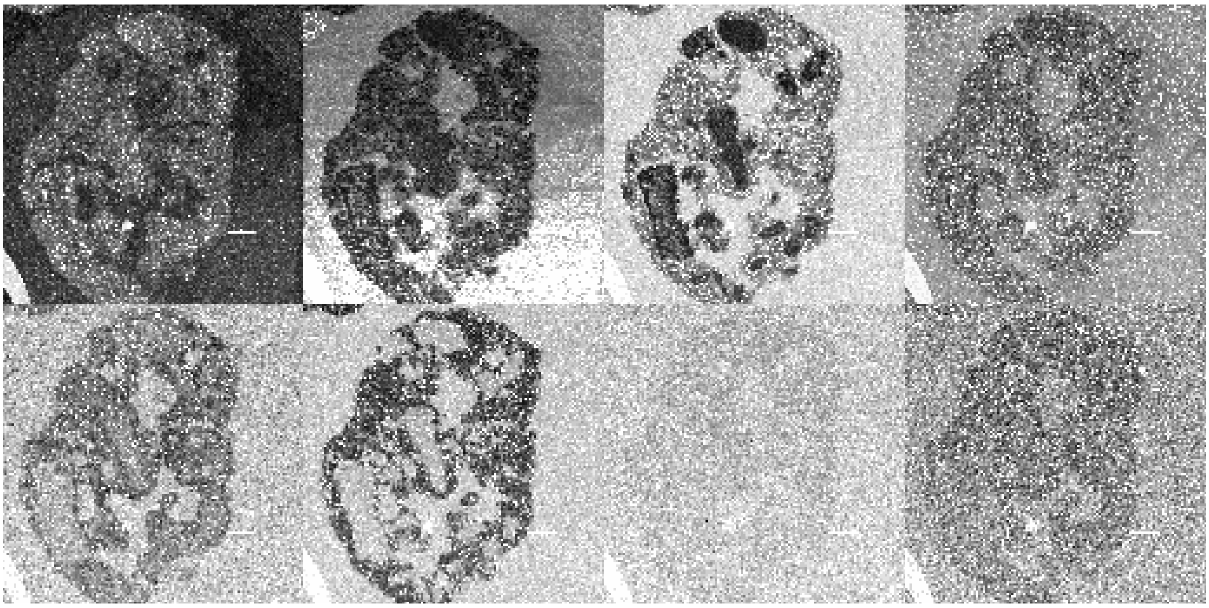

**Fig. 1**. Example of a multi-spectral image with eight spectral bands

where $\mathcal{I}$ is the indicator function :

$$\mathcal{I}(\lambda_m, \lambda_n) = \begin{cases} 1 & \text{if } \lambda_\mathrm{m} \neq \lambda_\mathrm{n} \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

Then, the labeling scheme $\Lambda_j, j \geq 1$ is stable if

$$\mathrm{diff}(\Lambda_{j-1}, \Lambda_j) \equiv 0.$$

During the segmentation, different algorithms may be used for initial labeling and for building the classifiers in the spectral and spatial domains. The final segmentation result depends on the actual dataset and is also influenced by the performance of spectral and spatial classifiers. It is hard to make any general statements about the segmentation stability.

### 2.1. Apriori information

After finishing the segmentation process, a trained classifier $\Psi_{\mathrm{spec}}$ may be stored and used subsequently to segment-out new images with a similar spectral structure. In such a case, the stored spectral classifier will generate the initial labeling $\Lambda_0$ instead of the unsupervised clustering method. In the following text we will use the term *complete segmentation* when randomly initialized clustering is used to obtain the initial labeling and *apriori information-based* segmentation when it is generated by the trained spectral classifier.

There are two advantages of such approach. The trained spectral classifier (e.g the nearest mean classifier) describes the statistical properties of the classes. The labeling corresponds to the structures of the underlying physical compound. Therefore, the trained spectral classifier may be used for the description or identification of various materials. Moreover, replacing the unsupervised initial labeling by an apriori trained spectral classifier may considerably speed-up the segmentation process. This will be experimentally studied in the next section.

## 3. EXPERIMENTS

In this section we present experiments on a set of five multi-spectral images of detergent powder microstructures acquired by SEM/EDX method. All images render materials with similar spectral structure. Images consist of eight spectral bands like carbon *C*, silicon *Si*, oxygen *O*, backscatter band and other, application-related components. Image size is in all cases $128 \times 128$ pixels. An example image is presented in figure 1.

In all performed experiments, the Expectation-Maximization (EM) clustering algorithm with a nearest mean classifier has been used to generate the initial labeling $\Lambda_0$. This is effectively the same as k-means clustering. The EM clustering was performed on a subset of 500 randomly chosen pixels/samples in the image, each time. Then, the nearest mean classifier was used to update the labels until the stable state was reached. Typically, it took from 15 to 40 iterations. After the initial labeling step, the iteration algorithm has been started with the nearest mean classifier in the spectral domain ($\Psi_{\mathrm{spec}}$). In the spatial domain, a Parzen classifier with Gaussian kernel and single smoothing parameter $\sigma = 1.0$ was used as $\Psi_{\mathrm{spat}}$. The presented segmentation method assumes that the number of clusters is known in advance. In all our experiments, we searched for three clusters/classes as devised by the application area experts.

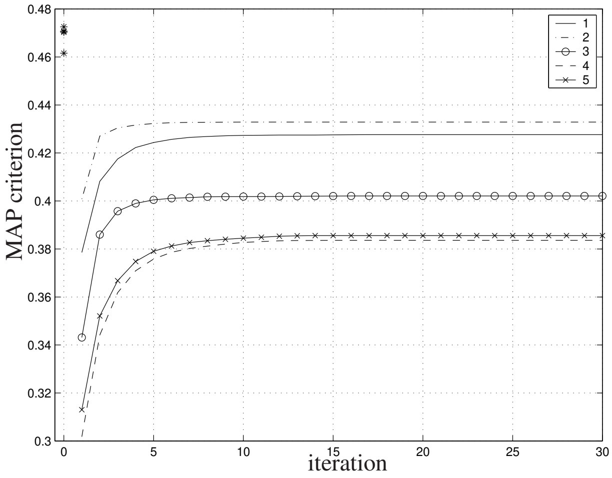


**Fig. 2**. The evolution of MAP criterion (eq.5) during the iteration process on five different multi-spectral images. Separated points (iteration zero) correspond to criteria values computed on the initial labeling.

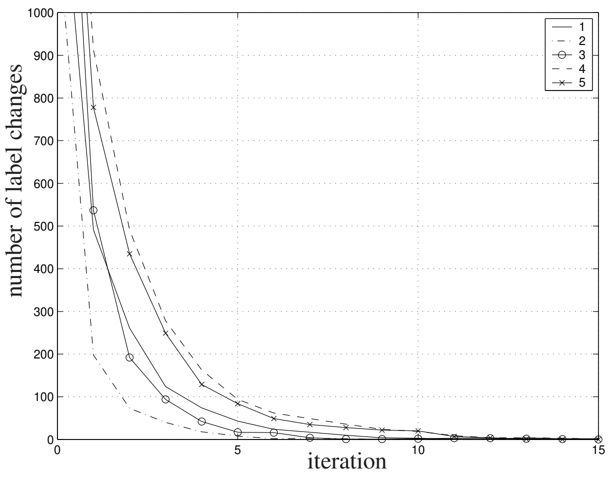


**Fig. 3**. Number of label changes between subsequent segmentation results during the iteration process (five different multi-spectral images $128 \times 128$ pixels)

In the first experiment we segmented-out all five multi-spectral images. The quality of the segmentation result may be measured, for example, by the quality of class separation by the classifier $\Psi_{\mathrm{spec}}$. Class separation is reflected by estimated aposteriori probabilities $\hat{P}_{\mathrm{comb}}(\omega|\mathbf{x})$. The maximum aposteriori probability (MAP) criterion is defined as :

$$crit = \sum_{i=1}^{N} \frac{\max_c\{\hat{P}_{\mathrm{comb}}(\omega_c|x_i)\}}{N} \tag{5}$$

The evolution of the MAP criterion is displayed in figure 2. The criterion value with index zero has been computed on the initial clustering result $\Lambda_0$. Its value is in all cases higher then the criterion value in the final stable state. This is caused by the fact that the initial clustering operates just in the spectral domain. As a result, the first labeled image doesn't reflect the spatial structures and is very noisy. Further criteria values are computed on estimates of combined aposteriori probability. Therefore, they attain lower values being affected by spatial relationships in the data.
The evolution of the number of label changes in the process of segmentation is shown in the figure 3. The number of changes decreases quickly to zero. At zero, the segmentation becomes stable and no further labeling change is possible.

The second experiment is designed to examine the effect of using apriori information in the segmentation process. Two multi-spectral images A and B are used in the experiment. In the beginning, the segmentation algorithm is run on both images generating label images $\Lambda^{\mathtt{A}}$ and $\Lambda^{\mathtt{B}}$. Now, the segmentation process is executed on the image B but with initial labels provided by the trained classifier $\Psi^{\mathtt{A}}_{\mathrm{spec}}$. The result is the labeling $\Lambda^{\mathtt{B}|\mathtt{A}}$. In the same way, the image A is segmented-out using the classifier $\Psi^{\mathtt{B}}_{\mathrm{spec}}$ and generating the labels $\Lambda^{\mathtt{A}|\mathtt{B}}$. For schematic overview of the experiment see figure 5.
We can now compare the labeling results obtained by the complete segmentation algorithm (e.g. $\Lambda^{\mathtt{A}}$) with labelings based on the apriori spectral information ($\Lambda^{\mathtt{A}|\mathtt{B}}$). The MAP criteria for all four segmentation processes are shown on figure 6. It appears that the segmentation quality is not dramatically different for complete and apriori information-based segmentations. Nevertheless, the segmentation using the apriori information is significantly faster than the complete segmentation (see results in table 1). While the spectral data clustering takes 39 seconds on average, the initial labeling by the trained spectral classifier takes just 0.9 seconds. Times were measured on a Pentium III 550 Mhz processor. The execution time of the initialization by the trained spectral classifier does not differ for different images as the same operation with the same amount of the data is performed each time. On the other hand, the speed of the clustering algorithm depends on the processed dataset and is influenced by its random initialization.

| initialization by clustering | using apriori information |
|---|---|
| 39.1 sec ($\sigma = 2.3$ sec) | 0.9 sec |

average number of iterations 16.5 ($\sigma = 0.9$)

**Table 1**. Average time and its standard deviations for the initial labeling phase, 41 measurements done on different images (Pentium III 550 Mhz processor).

The number of segmentation algorithm iterations depends on the processed dataset as well. It follows from our experiments that the number of iterations is not random when using random clustering initializations but it attains just few characteristic values.

In the last experiment, we have investigated the segmentation stability. As the segmentation process starts from the randomly initialized clustering, it may, generally, end-up each time with different labels. The experiment was designed as follows.

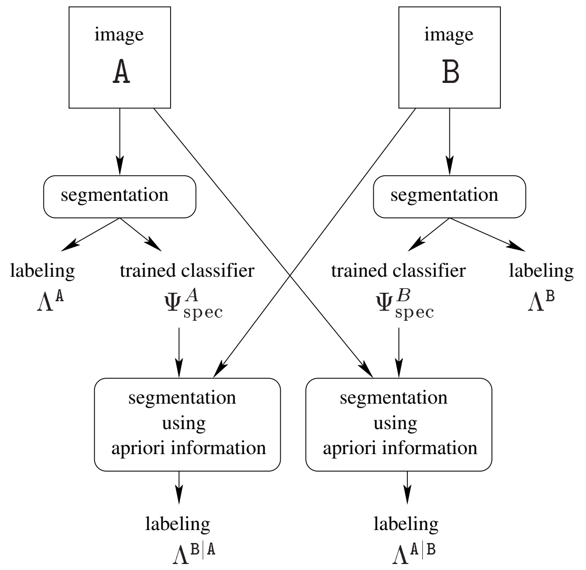


**Fig. 5**. Cross-segmentation of two images with apriori information.

Two multi-spectral images were taken and the complete cross-segmentation (see figure 5) was performed 30 times with random clustering initializations. We obtained four sets of segmentation results (two segmentation procedures for each image – complete or using the apriori information). We stacked each set of 30 images into one 3D matrix and estimated the probability that a particular pixel will be labeled differently than the 'most common' way. The number of occurrences of the most frequent label and a number of 'other' labelings were found for each pixel. From these two numbers we obtain the desired probability estimate. The results are presented in the table 2 as the average number of image pixels changing their labels. It follows from the table that the segmentations based on the apriori spectral information provide smaller average number of pixels changing their labels than complete segmentation concerning different random initializations. We have also found out that each set of segmentation results contains several completely identical solutions (label images). The number of segmentation solutions changed from one to three in all our experiments with different images. The worst case found in our dataset is shown in figure 7. For this particular image, there exist three different segmentations. The total number of pixels changing their labels is 92 (from 16384 image pixels). These pixels are shown in the right part of the figure.

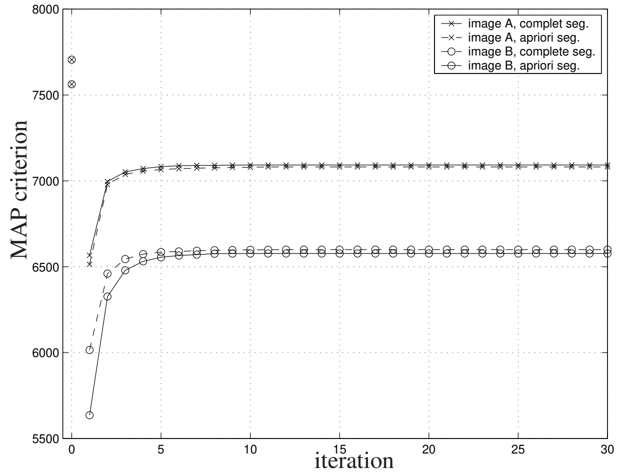


**Fig. 6**. The MAP criteria (eq.5) for two images in the cross-segmentation experiment (figure 5). The MAP criteria evolution for complete segmentations (solid lines) and for segmentation with apriori information (dashed lines) are shown. Separated points (iteration zero) correspond to criteria values computed on the initial labeling.

| segmentation | $\hat{\mu}$ |
|---|---|
| image A, complete segmentation | 1.36 |
| image A, using apriori inf. from B | 0.0 |
| image B, complete segmentation | 42.5 |
| image B, using apriori inf. from A | 1.15 |

**Table 2**. Average number of image pixels ($\hat{\mu}$) changing their labels in a set of segmentation results. Each table row represents a set of 30 randomly initialized segmentations (experiment schema in figure 5). Total number of image pixels is 16384.

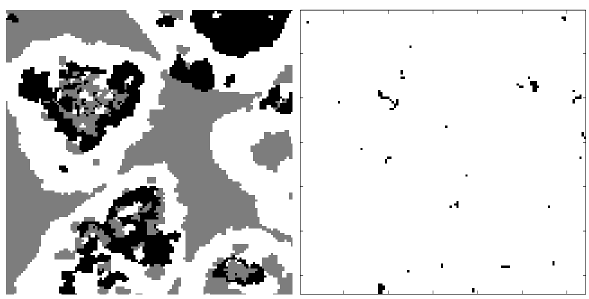

**Fig. 7**. Segmentation stability. The left image is a segmentation result. The image on the right shows pixels with a non-zero probability of label change. The image has been generated from a set of segmentations started by different random initilizations of the initial labeling algorithm.

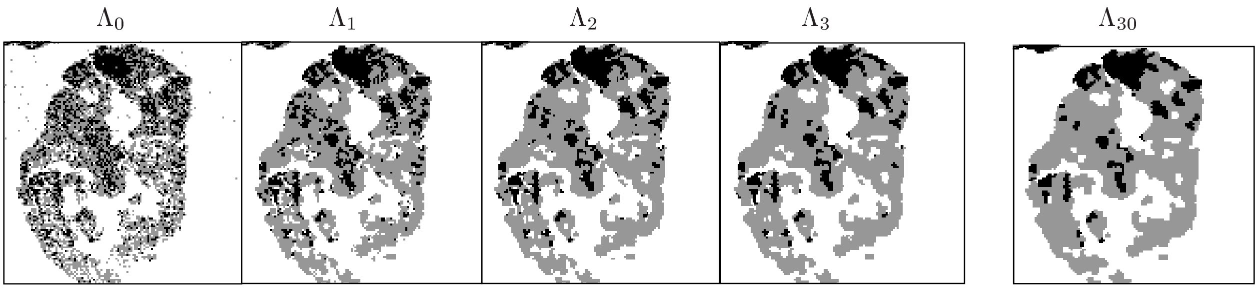


**Fig. 4**. Segmentation results. Initial labeling $\Lambda_0$, results of first three iterations $\Lambda_1, \Lambda_2, \Lambda_3$, and a stable segmentation result $\Lambda_{30}$ are given.

## 4. CONCLUSION

A new algorithm for segmentation of multi-spectral images has been presented. It has been designed using statistical pattern recognition methods only. Therefore, it can be used for noisy multi-spectral images with a large number of spectral bands. The algorithm starts by generating the initial image labeling using the unsupervised clustering method in the spectral domain. The segmentation is then performed in the loop in both – spectral and spatial domains. In the end of each iteration, results (estimates of aposteriori probabilities) are combined and a new labeling scheme is generated. The segmentation result gradually improves over the iterations until a stable state is reached. The number of label changes in subsequent segmented images has been used as a simple measure of segmentation stability. The MAP criterion been devised to measure the segmentation quality by means of the actual class separation in the feature space.

The algorithm has been successfully applied on real multi-spectral images of detergent powder microstructures acquired by SEM/EDX method. Apriori information about the spectral domain may be stored and used for segmentation of similar images. This approach considerably speeds up the segmentation process. Moreover, it allows the extraction of statistical properties for the description of segmented modalities.

There are a few parameters in the method to be set, such as the smoothing parameter of the Parzen classifier operating in the spatial domain. It appears that the algorithm performed satisfactory in all experiments with one basic parameter setting.

The automatical estimation of a cluster count in the initial labeling step could considerably increase the algorithm applicability. It is the subject for further research.

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