ADAPTIVE AND COOPERATIVE SEGMENTATION SYSTEM FOR MONO- AND MULTI-COMPONENT IMAGES

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Keywords: Image segmentation, Classification, Detection, Texture features, Adaptive segmentation, Multi-component imagery.

Abstract: We present a cooperative and adaptive system for multi-component image segmentation, in which segmentation methods used are based upon the classification of pixels represented by statistical features chosen with respect to the nature of the regions to segment. One originality of this system is its adaptive characteristic: it allows taking into account the local context in the image to automatically adapt the segmentation process to the nature of specific regions which can be uniform or textured. The method used for the detection of the regions' nature is based on a classification of pixels with respect to the uniformity index of Haralick. Then a cooperative approach is set up for the textured areas which can combine results incoming from different classification methods and choose the best result at the pixel level using an assessment index. In order to validate the system and show the relevance of the adaptive procedure used, experimental results are presented for the segmentation of synthetic and real multi-component CASI images.

1 INTRODUCTION

Segmentation is a central step in image processing because it largely conditions the quality of a further interpretation. Referring to the literature, one realizes that image segmentation is a difficult problem which is far from being solved and that numerous works are still dedicated to it (Leung et al., 2004), (Clausi and Deng, 2005), (Chung et al., 2005). Many existing methods provide satisfactory results when applied to a particular image type, or require some prior knowledge – which is not always available – to perform well. Existing segmentation methods are based either on the merging of pixels with similar characteristics (Jain et al., 1999), some use a spatial-based strategy, and some others use theoretical approaches such as fuzzy sets. Moreover, the increasing use of multi-modal and multispectral imaging systems also makes this task more and more difficult.

It is generally recognized that using only one segmentation technique cannot handle the sets of all region primitives in an image, and that a cooperation of several techniques often provides better results.

In this communication, we present a parallel adaptive and cooperative approach for the segmentation by classification of multi-component images. This approach is original in the sense of its adaptive abilities. Indeed, it allows to account for the local context in the image to reduce the complexity of the segmentation task. This is done by first separating the uniform regions (non textured) from the textured regions before each type of region is processed independently. This approach, previously developed in (Rosenberger and Chehdi, 2003) in the case of mono-component images, is herein optimized and extended to the case of multi-component images through a scalar scheme.

The organization of this paper will be the following. In the next section, we shall first describe our methodology and the proposed adaptive and cooperative approach in details. Then we shall present some experiments and results which were obtained by applying our approach on synthetic and multispectral CASI images. A conclusion will follow in the last section.

Moghrani M., Cariou C. and Chehdi K. (2007).
ADAPTIVE AND COOPERATIVE SEGMENTATION SYSTEM FOR MONO- AND MULTI-COMPONENT IMAGES.
In *Proceedings of the Second International Conference on Signal Processing and Multimedia Applications*, pages 200-203
DOI: 10.5220/0002141002000203

2 THE DEVELOPED SYSTEM

The literature abounds of segmentation techniques which can be used for mono- and multi-component images. However, one can categorize them into different classes which are structural methods, statistical methods and hybrid methods. In the present study, we have chosen to deal with the statistical approach of segmentation by unsupervised classification. The idea is to bring as few prior information as possible to the classification process, in order for this approach to preserve its generality and to be able to handle either the cases of regions with low and high complexity content.

However, the amount of possible statistical features which are available to operate a classification rapidly becomes a problem because it provides a large quantity of information which is not always necessary to reach the segmentation goal. This problem is eventually more crucial when dealing with multi-component images, for which the multiplicity of potential features is very large with respect to the true quantity of information of the image.

The segmentation approach proposed herein can avoid this problem, by splitting the sets of low and high complexity regions (typically uniform and textured regions), in a way to extract adapted statistical features which will be then used in a classification step. This corresponds to the adaptive skills of our approach. Moreover, a cooperative procedure is also considered next. Indeed, for the textured regions which are detected, we set up a competitive scheme involving several classification methods and an intermediary fusion process. In this way, the processing of multi-component images is simplified by a fusion of the segmentation results which are obtained for each image component. An overview of the proposed system for mono-component image is shown in Figure 1. This system is made of three modules: the first one performs the detection of the regions' nature, the second one performs the classification of pixels based on statistical features selected conditionally to the regions nature, and the last one performs the fusion of the conditional classifications.

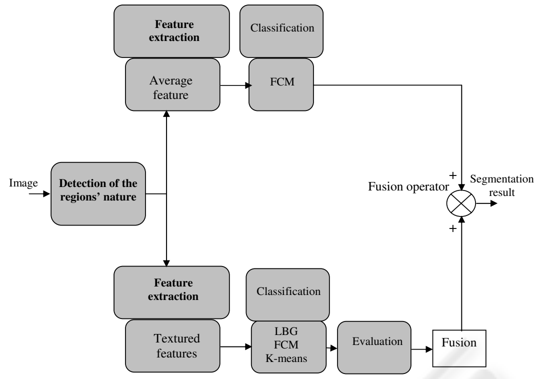

Figure 1: Overview of the proposed parallel segmentation system.

2.1 Detection of the Regions' Nature

Before we operate the segmentation by pixel classification in itself, we propose to first identify the low complexity, uniform regions which are present in a mono-component image. For this, we make use of the uniformity index of Haralick (Haralick, 1973), which is issued from the co-occurrence matrices. The uniformity index characterizes the frequency of occurrences of identical intensity levels between neighboring pixels. In our case, it is calculated by averaging the traces of the co-occurrence matrices computed at directions 0, 45, 90 and 135 degrees and unit distance after re-quantization of pixel intensities to 32 levels.

In order to detect the regions' nature, we propose to perform a classification of pixels by means of the fuzzy *c*-means (FCM) algorithm and to use uniformity measurements into a feature vector for each individual. This vector corresponds to uniformity indices computed in a multi-resolution scheme within five analysis windows with different sizes (3x3, 5x5, 9x9, 13x13 and 17x17) surrounding the pixel to which it is affected.

To validate our approach, we have performed tests using 100 synthetic images made of three uniform regions (constant plus Gaussian noise with standard deviation $\sigma = 5$) and two textured regions using Brodatz textures (Brodatz, 1966). The average correct detection rate was found to be greater than 94%. Figure 2 shows a result of the detection of the regions' nature on two sample synthetic images. The detection results are visually coherent, the uniform and textured regions being correctly identified for the three considered bands.

2.2 Adaptive Partitioning of Uniform and Textured Regions

2.2.1 Features Extraction

This module consists in extracting the features which are adapted to the nature of the region under consideration. For uniform regions, we have used a single feature which is the local average intensity computed within a 3x3 window, which we assume to be a sufficient statistic to describe low complexity regions. For textured regions, we have used 23 classical tex-

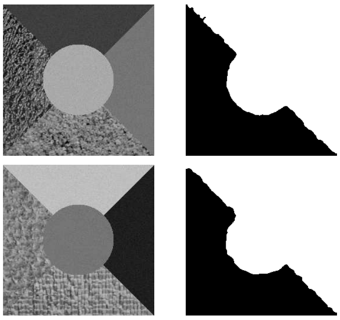

Figure 2: Detection of the regions' nature. Column 1 : original images; column 2: detection result (textured regions are in black).

ture features, namely: the first four FOS (first order statistics) (mean, variance, skewness, kurtosis), and a set of 19 texture features obtained after reduction of 30 features by the method described in (Rosenberger and Cariou, 2001).

2.2.2 Adaptive Classification

In a way to obtain an automatic and segmentation system, we have chosen to perform the segmentation via an unsupervised classification approach. For this, we have selected three classifiers, namely the classical *k*-means (MacQueen, 1967), the fuzzy *c*-means (FCM, (Bezdek, 1981)), and a modified version of the Linde-Buzo-Gray classifier (LBG, (Linde et al., 1980)) described in (Rosenberger and Chehdi, 2003).

The choice of these techniques is motivated by their good behavior for the unsupervised classification of large datasets, which is interesting for instance in multispectral image segmentation. To simplify our system, we have used only the FCM algorithm to classify pixels which belong to the uniformed regions previously detected.

For the textured regions, we have chosen to set up a competition between the three retained classifiers. This means that the pixels which belong to the textured regions are classified in parallel with the three algorithms, providing three different classification results and corresponding segmentations. The resulting partitions are then analyzed to keep the most coherent ones, through an assessment procedure.

2.2.3 Assessment of Classification Results

The assessment of a classification result requires to set up a measure of the coherence of the result. In our system, we have adopted the measure of the intra-class disparity presented in (Rosenberger and Chehdi, 2003) as a coherence measure. We have experimented this step by using a set of 10 synthetic images (with ground truth) similar to those presented in Figure 2. More precisely, we have computed the correct classification rate and the corresponding assessment index obtained after processing the textured regions. The magnitudes of the correlation ratios between the two variables (FCM: 0.52 ; *k*-means: 0.78 ; LBG: 0.85) are enough high to motivate the use of the intra-class disparity as a measure of the validity of the clusters provided by the classification method.

2.2.4 Fusion of Parallel Segmentation Results

Fusion is an important task in our system in that it must take into account the most reliable among intermediary results. Many fusion methods can be considered (Bloch, 2003), but they generally require some prior knowledge or information which may not be available in practice to the user.

In this work, we introduce a fusion method for textured regions for which competitive classifications are set up. The fusion is based upon the assessment of the clusters derived from the previous step, and which is very simple to implement. Indeed, for every pixel within textured regions, the output classification is taken as the result of the classification method which provided the best assessment index (i.e. the lowest intra-class disparity) among the three classification results (given by *k*-means, FCM, and LBG). Next, the fusion between the uniform and textured regions is performed by simply mapping the corresponding segmentations into a final result.

In the case of multispectral images, the fusion of the classification results obtained for each spectral band is reported in a final segmentation in a similar way, by accounting for the assessment index available for every region in each band.

3 EXPERIMENTAL RESULTS

To validate our approach, we have used three synthetic images from the image database described above, and remote sensing images acquired by a CASI multispectral sensor. In the case of synthetic images, Table 1 gives the mean rate of correct regions' nature detection (RND) as well as the final classification mean rate obtained with such a prior detection. These results show the relevance and the efficiency of our approach of prior identification of the regions' nature when compared to the blind approach, i.e. the use of the same classifier (here the FCM) to segment the whole image. Figure 3 depicts the segmentation results obtained for a 3-bands CASI image. In this case, the RND and the different adapted classifications methods are applied band by band, then a fusion procedure takes place at the end. The different structures are correctly emphasized (roads, fields, trees). However, the final fusion result shows an over-segmentation of the areas which reveals the richness of the spectral information and the complementarity of this information in different spectral bands. Despite the fact that no ground truth was available to assess this result, one can notice the improvement in the classification induced by our methodology in comparison with the blind classification.

Table 1: Classification rates for synthetic images.

	Average classification rate (%)
RND	99.05
uniform regions	98.83
textured regions	96.91
final	**96.69**
without RND	**73.48**

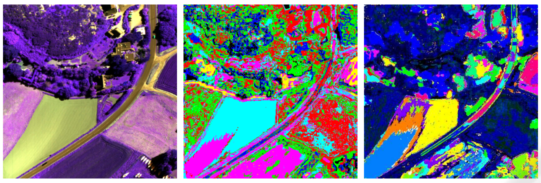

Figure 3: Classification of a multi-band CASI image. Left: original 3 band image; Middle: fusion result without the RND; Right: fusion result with prior RND.

4 CONCLUSION

In this communication, we have presented a cooperative and adaptive system dedicated to the segmentation of mono- and multi-component images. Firstly we have shown that a prior partitioning of a mono-component image into two distinct classes is important to correctly adapt segmentation methods to the more or less complex nature of the local information. Moreover, the gain in computation load is significant because the feature extraction is drastically reduced on uniform regions. Secondly, we have introduced a cooperative process between classification methods which enables to select the best results from each, based on the use of an assessment index of cluster coherence. Our preliminary results on synthetic images are quite encouraging and at least far better than a direct classification approach without prior identification of the regions' nature. Finally, we have extended this methodology to multi-component images and tested it on a real CASI image. Once more, the results are coherent and better than those obtained by a direct approach, despite our method deserves to be validated on a significant set of real images with available ground truth.

ACKNOWLEDGEMENTS

This work is supported by the European Union and co-financed by the ERDF and the Regional Council of Brittany through the Interreg3B project number 190 PIMHAI.

REFERENCES

Bezdek, J. (1981). *Pattern recognition with fuzzy objective function algorithms*. Plenum Press, New York.

Bloch, I. (2003). *Fusion d'informations en traitement du signal et des images*. Lavoisier, Paris (in French).

Brodatz, P. (1966). *Textures: A Photographic Album for Artists and Designers*. Dover Publications, New York.

Chung, R. H. Y., Yung, N. H. C., and Cheung, P. Y. S. (2005). An efficient parameterless quadrilateral-based image segmentation method. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(9):1446–1458.

Clausi, D. and Deng, H. (2005). Design-based texture feature fusion using Gabor filter an co-occurrence probabilities. *IEEE Transactions on Image Processing*, 14:925–936.

Haralick, R. (1973). Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, 3(6):610–621.

Jain, A. K., Murty, M., and Flynn, P. (1999). Data clustering: a review. *ACM computing Surveys*, 31(3):265–322.

Leung, S. H., Wang, S. L., and Lau, W. H. (2004). Lip image segmentation using fuzzy clustering incorporating an elliptic shape function. *IEEE Transactions on Image Processing*, 13:63–71.

Linde, Y., Buzo, A., and Gray, R. (1980). An algorithm for vector quantizer design. *IEEE Transaction on Communications*, 28(1):84–94.

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, 1:281–297.

Rosenberger, C. and Cariou, C. (2001). Contribution to texture analysis. In *Proc. Intern. Conf. on Quality Control and Artificial Vision (QCAV 2001)*, Le Creusot, France.

Rosenberger, C. and Chehdi, K. (2003). Unsupervised segmentation of multi-spectral images. In *Proc. Intern. Conf. on Advanced Concepts for Intelligent Vision Systems (ACIVS 2003)*, Ghent, Belgium.