A MULTI-AGENT MODEL FOR ADAPTIVE IMAGE SEGMENTATION WITH CONNECTED HOMOGENEOUS REGIONS

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ABSTRACT

In this paper we introduce a new multi-agent based approach with which a 2D image could be segmented into it's connected homogeneous regions. it consists in an adaptive approach in the sense that it does not need neither thresholds nor calibration. Moreover, the approach is robust and is stable against the presence of noise in the image. It can be included as it is in classical image processing systems, while being a new approach to enhance as a perspective toward a self-adaptive artificial vision system. Experiment results on synthetic and real images have shown that the approach is well appropriate to image segmentation without any kind of parameter learning.

KEY WORDS: Image processing, multi-agent systems, adaptive systems, image segmentation, homogeneous regions.

1 Introduction

Multi-agent paradigm was used to overcome segmentation specific problems. It was used according to two ways [6]: Multi-agent systems (MAS) at macro level [1, 4, 10, 12, 13]. In such systems, agents are developed to use classical tools of image processing, providing results of high level, and enabling agents to negotiate between them. At micro level [8, 2, 11, 5, 6, 9] agents are organized as artificial social systems, producing results as emergent structures within the established organization.

With macro approaches, heuristics should be used in order to coordinate the used algorithms.

These approaches use multi-agent systems for their software engineering properties. However, they remain difficult to generalize. Furthermore, cooperation protocols are bad defined in this case, because classical algorithms have not expected communication while resolving image processing problems.

Micro based approaches are more interesting, and thanks to their riginality, they are well adapted with multi-agent systems. Because of the emergence property produced in such MAS, the presence of a high number of agents swarming in the system enables this last to be robust and convergent.

This is not the case with macro based approaches, because agents produce results of high granularity.

Their errors cannot be corrected by other agents. In fact, macro based approaches do not enable the generation of emergent phenomenons.

Generally, the proposed MAS approaches are not easy to generalize and they have strongly different foundations. Moreover, each MAS based method depends finally on the representation of the treated problem. For this reason, MAS can not adapt themselves with new situations, because they are beforehand fixed and can not consider solutions outside what the designer had expected.

Conceiving self-adaptive MAS can be a solution of the problem. Indeed, if the system is able to manage its own representations, it should adapt itself when encountering new information not treated during conception. From these representations, it should be able to produce new solutions i.e. new algorithms of segmentation and object recognition. This ability of self-adaptation is much more a problem of artificial vision, than a problem of image processing.

Regarding the problem of parameter learning, a self-adaptive MAS can be considered to resolve this problem. In such a system, agents can explore the space of possible solutions, while they communicate and negotiate in order to self-adapt their parameters aiming to best segment the image. Systems so designed are able to self-adapt with non unexpected images, in the sens that new parameters (thresholds) are automatically obtained, thanks to interaction between agents. Several models or interaction can be considered. In instance, negotiation between agents is performed to resolve conflict situations. Cooperation is performed when some agents need specific capabilities that they do not have, but other agents are.

In this paper we introduce a new MAS based approach for image segmentation. It claims to be self-adaptive in the sense that it produces its self representation. So, an image segmentation is produced without considering any priors about information distribution within the image, neither any thresholds. In other terms, no learning is needed for the proposed system. In addition, the general model is able to be adapted in order to work with signals of any dimensions, and with colored or gray level images.

The remain of the paper is organized as follows : In section 2, we introduce our system for image segmentation and provide sufficient details necessary to understand the underlying approach.

Section 3 is devoted to experimental results and evaluation. We conclude our paper with a conclusion in which we summarize our work and underline some of its perspectives.

2 The Proposed MAS for Image Segmentation

2.1 Overview

Our proposed system is made of two components : a segmentation component; and an evaluation component. The segmentation component is implemented as a multi-agent system that produces an optimal segmentation of an image into it's homogeneous regions, considering a specific evaluation.

The MAS consists in high number of situated agents, called region agents, which are embedded in the image. In addition, an evaluator agent is used to compute the evaluation of a given segmentation produced by the set of the region agents. The system does not need any threshold fixed by the user to work. So, it adapts itself regarding the content of the analyzed image. Moreover, no learning step is needed anymore for the proposed approach. In addition, the general model is able to be adapted in order to work with signals of any dimensions, and with colored or gray level images.

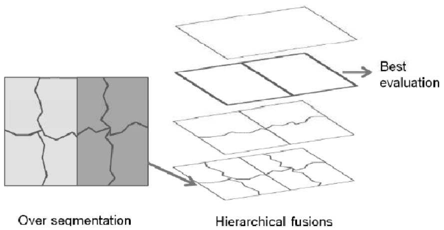

Figure 1: The Strategy used by the system to segment an image.

The evaluation sub-system works according to a function (see section 2.2) that computes a global evaluation according to some statistics, returned by local agents. To reach the best evaluation, a strategy has been elaborated (see figure 1). The first step of this strategy consists in producing the possible worst over segmentation. As we will see in the next subsection, it is easier to reach a given segmentation corresponding to a given evaluation, instead of seeking directly the best evaluation, because its value is simply unknown. From the worst over segmentation, and through intermediate segmentations, the system will progressively steps to the worst under segmentation. The best returned segmentation by the system should be one of the obtained intermediate segmentations. To produce these segmentations, the system makes hierarchical fusions of pair of regions, starting from the worst over segmentation, until it remains only one region. After each fusion, an evaluation of the obtained segmentation is computed. If the latter segmentation is the best one, obtained until at present, it is memorized in order to be compared with next segmentations that will be computed in next steps. At the end, the system returns the best segmentation.

During the first step, which consists in producing the worst over segmentation covering all the pixels of the image, region agents proceed to grow their respective regions, pixel by pixel. They aim also to merge with their neighbors, if their respective regions are homogeneous. A set of regions is homogeneous, if its standard-deviation is below a given threshold. This threshold evolves according to the global partial obtained segmentation, and its evaluation. Indeed, before the image is not completely explored, the evaluator agent computes the standard-deviation threshold. To do that, it perceives the global current segmentation and decides which region agent can have its constrains relaxed, by according to it a higher standard-deviation threshold. At the end of the fist step, each pixel of the image must be visited and labeled by one region agent.

When the first step is achieved, the evaluator agent asks each region agent to return the best fusion among all possible fusions by considering all its neighbors. These desired fusions are evaluated, and only one fusion is carried out. Then, the new obtained segmentation is compared with the currently memorized one. The best one is kept and the evaluator starts the next fusion cycle. When no fusion is possible, i.e. when it remains only one region agent, the system returns the memorized segmentation as the final best result.

2.2 Evaluation

The objective of our system is to reach the best segmentation by minimizing the next function:

$$\alpha = \left(\frac{N_R - 1}{N_P}\right)^{\frac{1}{Dim}} + \frac{2 \times \sum_{i=0}^{N_R-1} (\sigma_{R_i} \times N_{R_i})}{N_P} \quad (1)$$

where:
_ NR is the number of regions currently present on the system,
_ NP is the number of pixels present on the image,
_ Dim is the dimension of the image (2 for 2D images),
_ _Ri is the standard deviation of the region i,
_ NRi is the number of pixels of the region i.

The given equation tends to minimize the number of regions that are present on the image (the memory used), and at the same time to minimize the error on prediction of the luminance of each pixel (prediction of the information), expressed by the minimization of the standard deviation of each region.

The minimization of this expression consists first in the minimization of the number of regions produced by the segmentation, and the minimization of the weighted standard deviation of each region. If the segmentation is arbitrary, the standard deviation of each region tends to be abnormally high. Otherwise, if the standard deviation of each region is small, it results in an over segmentation which produces a high number of regions, especially if noise is present on the image. Our model aims at finding an equilibrium between these two states.

After evaluation, each region agent has to decide if it must grow its region, merge with neighboring agents, or stop its activity considering that it is satisfied and its current region is the correct one.

There is no way according to agents to compute a global evaluation of a given segmentation, with what a best segmentation can be directly obtained. To deal with this problem, we proposed the strategy seen in section 2.1. It consists in producing first the worst over segmentation, and then searching for the best segmentation throw hierarchical fusions. So, from equation 1, we obtain the evaluation of the worst under segmentation as fellow:

$$\alpha_{Worst} = \sigma_I \qquad (2)$$

where : _I is the standard deviation of luminance in the whole image. Note that every _ is normalized; (_ 2 [0::1]).

_Worst corresponds to the segmentation of the image in only a single region. Obviously, the worst over segmentation can not have an evaluation worst than under segmentation one.

3 Experimental Results and Evaluation

3.1 Experiments on Medical Images

We have experimented our model on medical images (see figure 2). With an 256x256 noise free image, the segmentation process spends 20 seconds. But with noised images, the segmentation time can reaches 300 seconds. The system is able to detect both large and small regions. It is sufficiently sensitive to discriminate regions in images with low contrast. It is also robust in front of noise. Since they are naturally heterogenous, bone regions are over segmented.

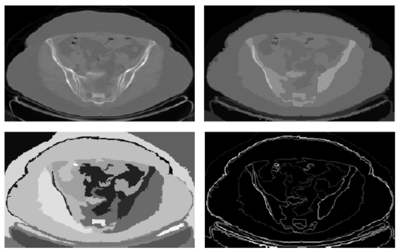

Figure 2: Segmentation of a medical image. The original image is on the top-left. The segmented image is on the top-right. The bottom-left image corresponds to the segmentation with contrasted regions. The bottom-right image corresponds to the contours of the segmentation.

We wanted also to compare our method with the multi-agent system presented in [3]. This multiagent works through cooperation between region agents and contour agents. The goal of agents is to determine if they must fusion or preserve regions. The system constructs an irregular pyramid, and converges to a segmentation thanks to 6 thresholds, fixed by the user. This method is a little bit similar to our model, because there are region agents which have to negotiate their fusion according to some constraints. However, our model does not need any threshold, fixed by the user to work. So, it is not necessary to preselect thresholds by using learning images. Our objective was to compare the result provided by [3] on mammography segmentation, with the result provided by our model. The figure 3 lets us see the ideal partition of the breast we must look for. As we can see on the figure 4, our model is able to distinct glandular tissue from muscle, whereas luminance between these two regions is very similar. Moreover, it does not over segment bones and skin as it is the case with the compared model (see the right image on figure 3). However, it differentiates several kind of glandular tissues, whereas the ideal partition (see figure 3) describes only one glandular tissue. So, these regions must be merged. For us, this kind of decision must be done according to the other knowledge provided by other subsystems, embedded in a global artificial vision system. Now, our system provides exactly what we expect from. It is able to distinct every homogeneous regions present on the image, without threshold, and without any additional information.

Figure 3: Left: a computed tomography breast image. Middle: the ideal partition (hand made) and regions labels of the computed tomography breast image. Right: the result provided by [3].

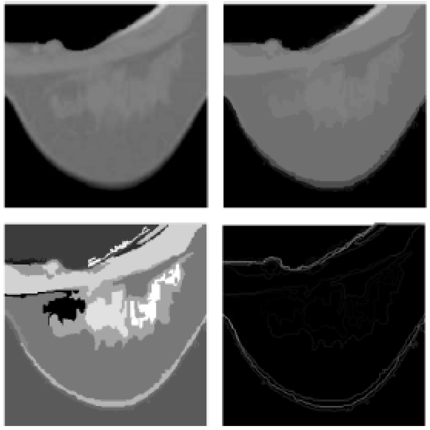

Figure 4: Segmentation of a computed tomography breast image. The original image is on the top-left. The segmented image is on the top-right. The bottom-left image corresponds to the segmentation with contrasted regions. The bottom-right image corresponds to the contours of the segmentation.

3.2 Benchmark on Natural Images

We have also experimented our model through the Berkeley benchmark presented in [7]. For each natural image of the database, the benchmark computes a score of the resulted segmentation. Then, it computes a global score for all the images.

Although our MAS is not really adapted to images given by the benchmark, which have lot of heterogeneous regions, we have obtained 0:54 as global score on gray level images, and 0:55 on colored ones. For comparing, human segmentation (hand made) given by the benchmark has a global score of 0:79 on both gray level images and colored ones. The figure 5 shows results given by several algorithms on gray level images. The best algorithm has a score of 0:68 on gray level images. The random test has a score of 0:41 on gray level images.

Rank	Score	Algorithm
0	0.79	Humans
1	0.68	Global Probability of Boundary
2	0.66	xren
3	0.64	Boosted Edge Learning
4	0.63	Brightness / Texture Gradients
5	0.60	Brightness Gradient
6	0.58	Texture Gradient
7	0.58	Multiscale Gradient Magnitude
8	0.57	Second Moment Matrix
9	0.56	Gradient Magnitude
9	**0.54**	**Adaptive Segmentation for Homogeneous Regions**
11	0.48	Segmentation Induced by Scale Invariance
12	0.41	Random

Figure 5: Results obtained with the Berkeley benchmark [7] on gray level images.

4 Conclusion

We have presented a MAS model as a new approach for image segmentation. The developed system allows to segment images into homogeneous regions. It is able to adapt itself with new kinds of images without any threshold fixed by the user. It can be also used with any type of sensorial signals with any dimension. The system is able to handle images with both small or large regions. It allows also to discriminate low regions in low-contrasted images. This task is very hard especially without learning of system thresholds.

However the system uses too much memory. We have estimated that 100MB is necessary for a 512 _ 512 image. This is not really important with recent computers. However, 40Gb is necessary for a 3D image with size of 512x512x512 voxels. It can be explained that the system needs at least a number of agents equal to the half of the number of voxels. To avoid the memory problem, we advocate the use of a multi-scale approach, where top-down and bottom up processes are applied.

In this case, the system should not instantiate too much agents.

We aim also to adapt our model with images having dominated heterogeneous regions. To do that, we will focus on the use of autocorrelation evaluation instead of standard deviation.

In perspective, we hope to develop a model where each agent can take its decision according the interference produced by the potential choices of each agent, as it is the case in the quantum mechanics. So, we will be able to remove the evaluator agent.

References

[1] Yazid Abchiche, Patrice Dalle, and Yohann Magnien. Construction adaptative de concepts par structuration d’entités de traitement d’images. In RFIA 2002, pages 1043–1051, Angers, January 2002. AFRIF-AFIA.

[2] Amine M. Boumaza and Jean Louchet. Dynamic flies: Using real-time parisian evolution in robotics. In Proceedings of the EvoWorkshops on Applications of Evolutionary Computing, pages 288–297, London, UK, 2001. Springer-Verlag.

[3] Edouard Duchesnay, Jean-Jacques Montois, and Yann Jacquelet. Cooperative agents society organized as an irregular pyramid: A mammography segmentation application. Pattern Recognition Letters, 24(14):2435–2445, 2003.

[4] Radia Haroun, Fatima Boumghar, Salima Hassas, and Latifa Hamami. A Massive Multi-agent System for Brain MRI Segmentation. In MMAS, pages 174–186, 2004.

[5] Jiming Liu and Yuan Y. Tang. Adaptive image segmentation with distributed behavior-based agents. IEEE Transactions on Pattern Analysis and Machine Intelligence, 21(6):544–551, 1999.

[6] Jason Mahdjoub, Zahia Guessoum, Fabien Michel, and Michel Herbin. A multi-agent approach for the edge detection in image processings. In EUMAS ’06: Proceedings of the Fourth

European Workshop on Multi-Agent Systems, 2006.

[7] D. Martin, C. Fowlkes, D. Tal, and J. Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In Proc. 8th Int'l Conf. Computer Vision, volume 2, pages 416–423, July 2001.

[8] SmaÃCÂrne. Mazouzi, Mohamed C. Batouche, and Zahia Guessoum. A self-adaptative multiagent system for segmentation and reconstruction of 3d scenes. In AISTA 2004 in cooperation with the IEEE Computer Society Proceedings, Luxembourg, November 2004.

[9] Carla Pereira, Jason Mahdjoub, Zahia Guessoum, Luís Gonçalves, and Manuel Ferreira. Using mas to detect retinal blood vessel. In 10th International Conference on Practical Applications of Agents and Multi-Agent Systems, University of Salamanca (Spain), March 2012. Springer.

[10] Nathalie Richard, Michel Dojat, and Catherine Garbay. Dynamic Adaptation of Cooperative Agents for MRI Brain Scans Segmentation. In AIME '01: Proceedings of the 8th Conference on AI in Medicine in Europe, pages 349–358, London, UK, 2001. Springer-Verlag.

[11] Vincent Rodin, Abdessalam Benzinou, Anne Guillaud, P. Ballet, F. Harrouet, J. Tisseau, and Jean Le Bihan. An immune oriented multi-agent system for biological image processing. Pattern Recognition 37 (2004), pages 631–645, October 2004.

[12] Hakim Settache, Christine Porquet, and Su Ruan. Une plate-forme multi agents pour la segmentation d'images : application dans le domaine des IRM cérébrales 2D. Technical report, Université de Caen, 2002.

[13] Keiji Yanai. An image understanding system for various images based on multi-agent architecture. In Proc. of 3rd International Conference on Computational Intelligence and Multimedia Applications, pages 186–190, New Dehli India, December 1999.