International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:1, No:6, 2007

A Selective Markovianity Approach for Image Segmentation

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***Abstract*—**A new Markovianity approach is introduced in this paper. This approach reduces the response time of classic Markov Random Fields approach. First, one region is determined by a clustering technique. Then, this region is excluded from the study. The remaining pixel form the study zone and they are selected for a Markovianity segmentation task. With Selective Markovianity approach, segmentation process is faster than classic one.

***Keywords*—**Markovianity, response time, segmentation, study zone.

I. INTRODUCTION

IMAGE segmentation is an essential step of low level processing which consists in defining an image partition in regions visually distinct and uniform according to texture, color or gray level criteria. The goal of segmentation operations is to simplify the image without discarding important image features [1]. Many segmentation techniques, methods and algorithms can be found in the literature [2], [3], [7], [8], each strategy has its advantages, its disadvantages and its limits.

Among segmentation techniques the Markovianity segmentation has been the subject of various researches [4], [5], [9], [10]. This technique dues its importance to its interesting results but, as all the other segmentation approaches, it presents disadvantages whose response time constitutes the most unpleasant.

The work suggested in this paper illustrates a Markovianity segmentation method that improves the response time by adopting a selective classification strategy.

II. MARKOVIANITY SEGMENTATION

Markovianity segmentation is a labeling problem [6].

For 2D image with nxn size labeling problem take this form:

f: S → £

With S is a set of sites S= {(i,j) | 1≤ i,j ≤n}

and £ is a set of labels £ ={ℓ_1,…, ℓ_m}

Segmentation with MRF (Markov Random Field) consists of determining a label for each image pixel. The pixels with the same labels make up a region. The difficulties here are to affect the correct label to a pixel. MRF segmentation adopts a recursive process which starts with a random configuration ω_0 and converges to the wanted configuration ω_m. The equivalence with MRF and GRF (Gibbs Random Field) gives us a good way to determine one configuration ω_i [6]:

$$p(\omega_i) = Z^{-1} e^{(-U(w_i))} \quad \text{with} \quad Z = \sum_{w_i} e^{(-U(w_i))}$$

But it is very difficult to calculate this function so, some models are proposed to approximate it, like the model of Weslkowski S. and al [9], [10]:

$$H = \sum_{i,j} \Phi(\vec{X}_{i,j}, \vec{X}_{i,j+1})\delta_{l(i,j),l(i,j+1)} + \Phi(\vec{X}_{i,j}, \vec{X}_{i+1,j})\delta_{l(i,j),l(i+1,j)} + \beta\left[(1-\delta_{l(i,j),l(i,j+1)}) + (1-\delta_{l(i,j),l(i+1,j)})\right]$$

with

$$\Phi(\vec{X}_{a_1}, \vec{X}_{a_2}) = (\vec{X}_{a_1} - \vec{c}_1)^T R_{c_1}^{-1}(\vec{X}_{a_1} - \vec{c}_1) + (\vec{X}_{a_2} - \vec{c}_1)^T R_{c_1}^{-1}(\vec{X}_{a_2} - \vec{c}_1)$$

Markovianity approach gives acceptable results and even sometimes good, however, the convergence time of this approach is the major disadvantage. Segmentation with MRF models has a very poor response time which increases with the growth of image size, from where we notice its frequent use with limited size image.

Two major reasons explain the slowness of the MRF approach:

The first reason is the principle of iteration which consists of generating a configuration ω_{i+1} from a configuration ω_i. This step is the realization of one principle of MRF approach that we can not modify.

The second reason is the sweeping of all image pixels for the determination of one configuration ω_i. That means to calculate in each iteration the energy function of every pixel with his neighbors. For example, with an image of nxn size and, if we take into consideration i neighbors of one pixel and, if we have to do m iterations to have the wanted configuration then, we must calculate $i \times (n \times n) \times m$ energy function. This important number explains the great value of the response time. To reduce this value we have to avoid the sweeping of all image pixels. In other terms, to accelerate the

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segmentation process we have to reduce the number of pixels taken into account in each iteration. The Markovianity approach will adopt in this case a selective pixels approach.

III. Selective Markovianity Approach

The goal of Selective Markovianity approach is to reduce the response time of the Markovianity approach. To do so, we must modify one of the reasons given previously.

Actually, we can not modify the first reason because it is one of the principle MRF strategy, so we have to work on the second one.

The set of site S can be written as

$$S= R_1+S'$$

with R_1 is one region of the image and S' a set of image pixels not in R_1.

Then, labeling problem takes this form:

$$f: S' \rightarrow L' \qquad \text{with } L'=L-\ell_{R1}$$

ℓ_{R1} label of R1

The problem of segmentation is reduced from S to S' (S'<S) S' is the selected study zone.

With reducing S we reduce the number of pixels to be sweeped in segmentation process, so we decrease the response time.

MRF model can be used for the selective study zone S', the problem now is the determination of the region R_1.

R_1 is one region of the image which can be determined with simple clustering approach like thresholding processing.

$$b(i,j)=\begin{cases}\ell_{R1} & \textit{if } b(i,j)\le T\\ \textit{not} \text{ mod}\textit{ified} & \textit{Otherwise}\end{cases}$$

with T a threshold value

We can explain this operation by the fact that some images present dominant regions such as the bottom of an image. These regions can be easily released by thresholding process. We form then the region R_1 and we degage the set S'. S' is the new set to be considered in MRF segmentation. S' is the selective study zone.

In our approach, we have used the same model of Weslkowski S. and al [10] with the constraint that we work in selective study zone S'.

Principal steps of the algorithm:

- Image binary thresholding ,
- Selected pixels in the study zone,
- All pixel labels of the study zone are randomly initialized
- The vector mean and noise covariance's are estimated for each cluster of the study zone S'.
- Repeat
    - At each selected pixel:
        - Minimize the energy H and carry out the tests of assumptions
        - Update the labels of the selected pixels based on the Gibbs sampler result
    - Use continuously Gibbs sampling to adjust the region prototypes and to calculate the covariance matrix according to the study zone
    - Lower the temperature T

If the temperature reduction occurs rather slowly, the process converges in the probability with the global minimum [4].

IV. Results and Discussions

Table I presents the segmentation results of the two approaches. The first cell (a) presents the original image, the second (b) presents the images segmented according to the principle of the Markovianity approach and the third (c) and fourth (d) cells illustrate images segmented according to the suggested approach principle which equalizes threshold respectively to 0.3 and 0.5. Several remarks can be released:

- Selective Markovianity approach gives better results than Markovianity approach if the image presents dominant zone and if the threshold is carefully selected.
- According to the threshold, Selective Markovianity and Markovianity approaches can give the same results
- Threshold influences the quality of segmentation
- A bad value of threshold doesn't lead the segmentation process to good results.

Table II formulates the response time of Markovianity approach and selective Markovianity approach with various thresholds values. We can note that:

- Selective Markovianity approach converges more quickly than Markovianity approach particularly, if the dominant area is rather important.
- The value of threshold influences the convergence time.

International Journal of Information, Control and Computer Sciences
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TABLE I
GREY LEVEL IMAGES SEGMENTATION RESULTS BY MARKOVIANITY AND SELECTIVE MARKOVIANITY APPROACHES

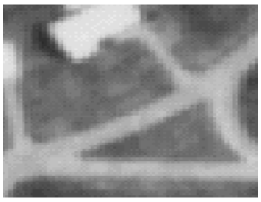
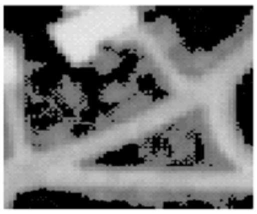
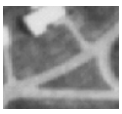
 (a) Original Image	 (b) Image segmented by Markovianity Approach
 (c) Image segmented by Selective Markovianity Approach T=0.3	 (d) Image segmented by Selective Markovianity Approach T=0.5
 (a) Original Image	 (b) Image segmented by Markovianity Approach
 (c) Image segmented by Selective Markovianity Approach T=0.3	 (d) Image segmented by Selective Markovianity Approach T=0.5

TABLE II
MARKOVIANITY AND SELECTIVE MARKOVIANITY APPROACHES RESPONSES TIMES

Original Image	**M.A. response time**	**Selective Markovianity approach response time**		
		T=0.3	**T=0.5**	**T=0.7**
	511.646	484.417	127.023	44.284
	249.729	143.226	66.556	38.325

V. CONCLUSION

The approach suggested in this work improves the response time of the Markovianity approach. Selective Markovianity approach selects the pixels on which it will apply the study and ignores the rest which reduces the study zone and accelerates the segmentation process. The ignored pixels belong to a dominant area whose determination is possible by thresholding . The results of selective Markovianity approach are satisfactory if the image includes a dominant region. However, in the case of uniform image the improvement of convergence time is weak. By the way, the used threshold value influences considerably the result and the convergence time. Nevertheless, the obtained results encourage us to improve the approach by introducing a level thresholding rather than by a binary thresholding for selecting the study zone.

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