Using evolutionary graph for image segmentation

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Abstract: - This paper presents a new method of no supervised image segmentation. It rests on an original strategy which consists in making progress an evolutionary graph which composes the segmented image. The evolution injunction is established statistically after the crossing of a region. The matrix of space composition of the areas in each class is then given. A map of space delimitation of the regions is established by a new way of contours localization and refinement. At last, the segmented image is erected by the combination of the chart of contours and the matrix of the regions.

Key-Words: - Evolutionary graph, transition, node, class, contour, region.

1 Introduction

The segmentation of image is a pre-treatment, which improves the state of the information contained in the image before the desired treatment and application. The objective is to separate, in the most faithfully possible way, the objects and the bottom which make the image [1] [2].

Image segmentation has applications in many practice fields, it has outlets in the forms recognition, the objects detection, the analysis of medical image, robotics [3], or in the field of the images by satellites and well of others still.

Several developed techniques of segmentation are based on a preset number of classes in the initial stage of the algorithm, which ensure the classification of each pixel of the image in its most probable class. Segmentation by region based approaches, the segmentation by contours detection, segmentation by thresholds, and that based on the method of the k-means. Classification by the theory of the obviousness, also called Dempster-Shafer theory or theory of the belief functions, it makes it possible to process on the one hand dubious data and on the other hand to combine information coming from several sources, before the use of the decision rules for the assignement class selection [4] [5] [6]. Classification by the hidden chains of Markov [7] [8]. Bayesian Classification which is based on the determination of the conditional probabilities to estimate the membership of an individual to each class [9]. Fuzzy classification [10].

This paper presents a new method of image segmentation based on the evolution of a graph, which traces the regroupings of the occupants of an image. In a first place, the methodology, which is articulated around two principal phases, is represented in the second section. The stage of creation of the classes graph is first of all carried out; it is illustrated in the third section. The wiliness in this phase is to push back the decision-making at the end of the crossing of a region. At the end of this stage, the border of each area is vague. In the third section the stage of a contours map creation is represented. The role of this phase is well to detect the borders of each region.

The originality in this phase is the procedure of the contour point detection. At the end of the section the final phase of the segmentation is described. In this part, the image of the classes is established starting from the graph and of the map of contours. Experimental results are shown in section 4 and Section 5 draws conclusions and future works.

2 General methodology
The goal of the method consists in traversing the image and to establish in parallel a graph which evolves depending on the state of the course carried out. At the end of the course, the resulting graph represents a descriptor of the components of the image to be segmented. Each node of the graph represents a class. An edge describes the transition step between the two classes represented by the two close nodes.

3 Procedure of segmentation
The method of segmentation suggested in this article gathers the following stages:

3.1 Course of the image
In order to avoid the jump in the sweeping, which can generate a change of region without detection of transition, a way which wind the image is selected.

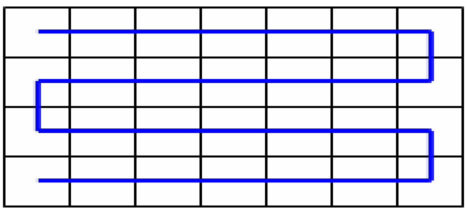

Fig.1 : Image sweeping

3.2 Initial state
The starting region is represented by the single node which forms the graph in its initial state. With each step of course, and in order to measure the state of the way, a vector of attributes characterizing the site is calculated. It is composed of the central pixel gray level, the average and the standard deviation of the3 by 3 window of vicinity.

3.3 Detection of a transition
In the presence of a relatively significant fluctuation of the attribute standard deviation, the membership of the vicinity of the current site to a contour indicating the crossing of a border of a new region becomes very probable. A threshold is predetermined to indicate the approach of a transition.

3.4 First transition
In order to minimize the error probability of decision, the first transition from a border will be memorized like a contour limits upstream. The decision-making concerning the assignment of this portion of area included between two borders will be made while being based on the information provided by the whole of the pixels visited along the portion, and that after the detection of contour limits downstream.

3.5 Second transition
After the detection of the second contour, the portion of traversed area is identified and a decision is made either to assign the portion to an already existing class, or for the creation of a new node in the graph which translates the presence of a new class.

3.6 Creation of a new node
If the criterion of creation of a new class is satisfied, a new node in the graph is created. The criterion of homogeneity to be tested is as follows:

$$e_i = \exp(-\frac{x_i}{x_{moy.}}) \quad (1)$$

$$x_i = \sqrt{(\mu_i - \mu_0)^2 + (\sigma_i - \sigma_0)^2} \quad (2)$$

$$x_{moy.} = \frac{\sum_{i=1}^{i=c} x_i}{c} \quad (3)$$

Where μ_i and σ_i being the average and the standard deviation of class i. μ_0 and σ_0 represent the average and the standard deviation of the portion of the traversed region.

The maximum max (e_i) indicates the class, which is statistically nearest to the region to be identified, and which can form part of it. The decision to generate a new class is made if max (e_i) is lower than a priori preset threshold.

3.7 Matrix of classes

The matrix of the classes is an element of R^3 which decompose the image to class's maps. Each chart represents a node of the graph. In this manner the class can be broken up into under classes or regions which constitute it. The chart Cr_i of class i is formed by the pixels assignment in plan i, of the class's matrix, after each identification of one membership of the Cl_i class.

$$Cr_i = \{p / p \in Cl_i.\} \qquad (4)$$

Regions R_i of each class are determined on a level of each plan of the matrix by the regroupings localization of the pixels which are spatially separate.

3.8 Map of contours

The chart of contours is a plan on which the separation curves of the various regions which constitute the image are plotted. Contours are the places of significant variations of information levels of gray. Moreover, the transition being strict, a contour must be a chain of pixels thickness 1. This restriction on the nature of contour is imposed with an aim of separating well the regions while preserving the forms which are probably closest to the real scene of the image.

The transition from a region to another is detected by a relatively significant variation. The probability of a contour presence increases if the gradient is locally maximal or if the derivative second presents a passage by zero.

Initially, two matrixes are determined, the matrix of the standard of the gradient, which expresses the rate of variation in the image. This amplitude is:

$$G(s) = Max_{di}\left[abs(s^+ - s^-) + abs(s - s^-)\right] \qquad (5)$$

This formula of computation allots to the site border the maximum of variation and eliminates the situation from the two lines at the edge of a transition resulting from a classic calculation of the gradient.

The second matrix memorizes the direction of the local maximum of the variation. This direction is determined by the localization of the minimum of variation in the vector of variation V which represents the direction of passage of contour. The required direction is perpendicular to the direction of contour.

$$d_i = i \pm 2 \ \ such\ as\ V_i\ is\ \min imal \qquad (6)$$

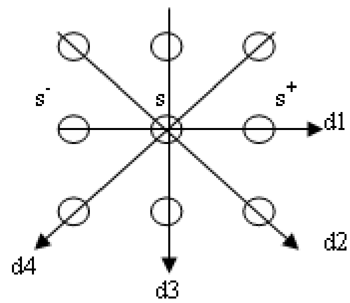

Fig.2: choice of the directions

In second place, the chart of contours is established from the map of the variations and the matrix of the directions. The observed site is taken as a point of contour if it presents a local maximum in the direction of the maximum variation.

3.9 The segmented image

The segmented image is given using the graph of the regions and the chart of contours. The equation of composition of the segmented image is given by:

$$I_s = C_l + I_c + F_v \qquad (7)$$

The site s of the segmented image I_s takes the Cl_i value of the class of the zone where it is located given by the node of the graph, or the contour value of the chart of contour I_c or the F_v value of the class in progress in the vicinity of a contour.

$$F_V(s) = 0 \quad if\ \ s \in Cl\ or\ s \in Ic \qquad (8)$$

$$F_v(s) = Cl_i(s) \quad if\ \ s \in Cl_i \\ in\, the\, vicinity\, of\ \ a\, contour \qquad (9)$$

4 Results obtained

We tested our algorithm of segmentation on an image representing coins Fig.3.

We illustrate on figures 4 and the 5 results of the segmentation. These results show a good segmentation representing the shapes of the parts. The figure 6 presents the segmented image before the contours improvement. The figure 7 shows one class in the class's matrix.

Fig. 3: Image to segment

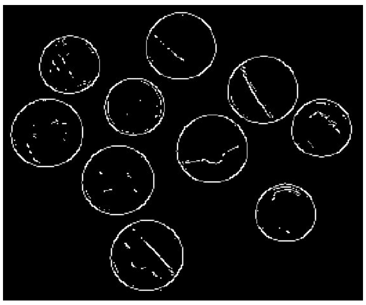

Fig. 4: Image of contours

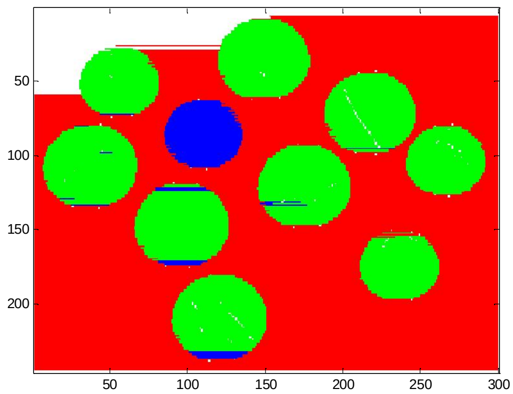

Fig. 5: Segmented image

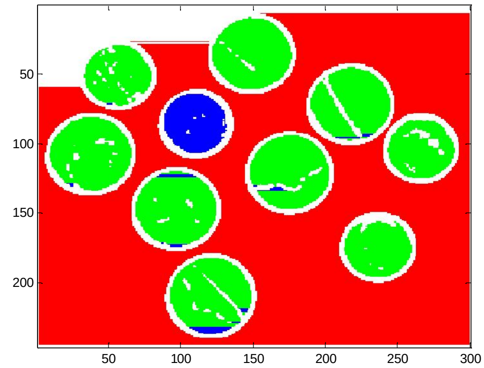

Fig. 6: Segmented image without edge improvement

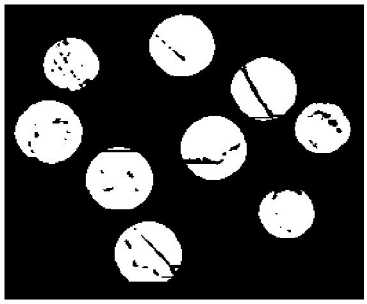

Fig. 7: Image of one class in the class matrix

5 Conclusion

In this work, we describe a new approach of no supervised segmentation method.

We use an original strategy, which consists in making progress an evolutionary graph, which composes the segmented image to detect the number of the classes and there localisation. In the final phase of the segmentation, the regions edge of the segmented image is improved.

This work is a part of an application in the field of robotics to help a robot equipped with a camera in its evolution.

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