ACTIVE CONTOURS MULTIOBJECTIVE OPTIMISATION BY HYBRIDS ALGORITHM - APPLICATION TO LIPS CONTOUR EXTRACTION

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Abstract
In this paper we propose an evolution of Multiobjective Genetic Snakes (MGS) [12] by adding a new genetic hybrid algorithm and local search technique in a multiobjective context. We propose to use the finite difference method [7] for the local method to keep the energy multiobjective optimisation. The application context of this work is the noised and bad segmented images segmentation.
We apply this new algorithm on the lip's contours extraction in real images. The internal and external contours of the lips are coded according to the model of double concentric snakes. Two energies are used to deform the snakes, the first one is a distance map based on gradient energy. The second one is region based and is used to control the deformation.
This local search algorithm is implement in the classical multiobjective genetic algorithm NSGA2 [14] with the representation of MGS. It has been tested on noised images of lips.

Keywords: active contours, hybrid algorithms, labial contours, multiobjective optimisation, Pareto set.

1 Introduction

Since their creation [7], active contours have been much modified to respect researchers requirements [6]. This evolution has gone on in particular since the creation of levels sets [3,10]. However the problems of active contours initialisation is left [4], as well as the energies coefficients determination [8]. The Genetic Snakes (GS) [1] represent a solution to the initialisation problem through the global analysis of the image. The Multiobjective Genetic Snakes (MGS) [12] have been proposed to improve convergence speed and to make energies determination easier. However, one of the main problems of genetics algorithms is the convergence precision. Consequently, the MGS doesn't allow a good segmentation of lips contours in noised images. A common solution used to improve this precision is hybrid technique GA and local search [13]. The implementation of this kind of algorithm within multiobjective context is a partial one because it only concerns the GA [2].Thus we propose an hybrid genetics snakes method with a complete multiobjective implementation by adding an algorithm of classical snakes, the finite difference method (FDM) [7].This paper is organized in three others sections. The second section describes the genetics snakes chromosome coding and the energies evaluation within the Pareto's principle. The third one presents the local search method, the snakes finite difference method, of our hybrid algorithm and its implementation. Section four describes the application of our method to the lips contours extraction and shows results.

2 Multiobjective Genetics Snakes

In this section we will briefly present here the representation of the Multiobjective Genetic Snakes. This technique introduce the multiobjective optimisation into a genetic snakes algorithm and the double snakes coding.
The genetic algorithm principle consists in applying genetic operators (cross over and mutation) on a population of chromosomes. Then these chromosomes are evaluated according to the energies of the problem and represent the new generation of the algorithm. Each chromosome is composed by genes which are the variables of the problem. The values of these variables compose the set of candidates. In the MGS, candidates are the gradient and skin image edges obtained by the filter of Canny-Derriche. The chromosomes of the algorithm are a set of randomly initialized mouth contours (figure 1). They are composed by the edges candidates and coded according to the double snakes model which we'll present in the next section. The chromosomes evaluation is performed by Pareto multiobjective optimisation of gradient and region based energies (section 2.3).

2.1 Double snakes coding

The aim of the double snakes coding is to represent a surface with a hole in a two dimensions approach. Indeed the region enveloped by a single contour is not homogeneous its association to a global minimum of region based energy is difficult. With the double snakes model, the region of interest can be extracted alone.
Within this principle, the mouth contours are represented by the inner and the outer contours :

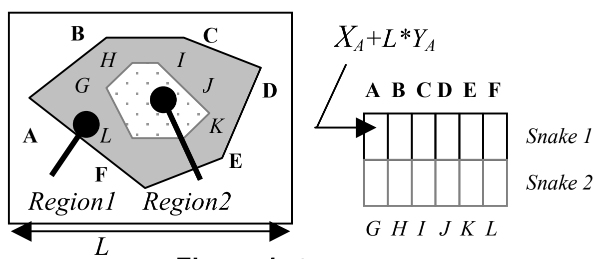

Figure 1. Contours coding

The position of the nodes of the contours are represented by their index in the image. Both contours envelop two regions, the centre of the mouth and the lips. These regions are respectively a minimum and a maximum of the red chromatic component. These region energies will be associated to a gradient based energy.

2.2 Multiobjective evaluation

Chromosomes are ranking on the basis of Pareto non-domination. If E_i are the active contours energies, a contour C is called "non dominated" if it doesn't exist an other contour such all its energies are better. With this principle a group of optimal contours (Pareto's set) can be defined at each generation and a rank can be calculated for each population contour [15]. At the end of the algorithm the Pareto's set is obtained. The final step consist in selecting the optimal bi-snakes configuration. This configuration can be obtained by minimizing the Euclidian distance between the selected contours and the origin of their set.

2.3 Energies

The region based energies are determinate from the image red chromatic component (*ImChromatic*) and from a binary region image (*ImBinary*). This binary image is calculated from *ImChromatic* during the preprocessing.
In the MGS, the region based energies are obtained by filling contours with a morphological algorithm. This method needs a large computation time, thus we use here the Green-Riemann's theorem to estimate the surface (defined by the contour {x,y}) integration of the region descriptor D [16].

The contour is obtained by the Bresenham's lines computation between each node. This contours discretization induce errors. All pixels belonging to the contours are not taken in account contrary to some pixels not belonging to the region. Moreover, information about the number of pixels belonging to the region is useful to avoid contours collapsing. Thus we use the discrete Green's theorem to fill the region [11] to extract pixels $\{p_i\}$ inside the contours. We also define the number of binary pixels N_1 (pixels at 1 in *ImBinary*) inside the contours and respectively the number of non binary pixels N_0 (pixels at 0 in *ImBinary*). We use two regions descriptors, one relative to the homogeneity (equation 2-a) and one relative to the accumulation of pixels (equation 2-b).

$$\text{a}: E^{R}_{\text{homogenity}} = \text{var}(R) = \frac{1}{N_i}\sum_{k=1}^{N_i}\{\text{Mean}(\text{ImChromatic}(p_i)) - \text{ImChromatic}(pi)\} \quad \text{- b}: E^{R}_{\text{accumulation}} = \alpha.N_1 - \beta.N_0$$

Equation 1. Region descriptors

In equation 2 α and β are weighting coefficients. Within the double snakes model, the region of lips and the region of the centre of the mouth each characterized by the two descriptors. The lips region (region 1 in figure 1) is obtained by removing the centre region (region 2 in figure 1) from that one inside the outer contour.
The gradient information of edges candidates is not always sufficient and so we define a gradient based energy to keep the contour along the lips. We use the classical gradient energy with a density coefficient to favor continuous succession of edges :

$$E_{\text{gradient}} = \exp\left(-\left(N_{\text{edges}}/N\right)\cdot\sum_{k=1}^{N}\left|\nabla\text{ImChromatic}(x(k),y(k))\right|\right)$$

Equation 2. Gradient based energy

N is the contour size {x,y} and N_{edges} the gradient edges belonging to the contour number.

3 Local search algorithm

With the MGS representation, we can obtain contours near the energies minima. To improve the convergence of theses contours we propose a new hybrid algorithm in a multiobjective context. Our aim is to make converge the chromosomes on local minima. Applying active contours during the genetic algorithm could give better configurations and so help the global convergence of the algorithm. Thus, the classical snakes algorithm will be applied on a little neighbourhood of each selected chromosome.

3.1 Model

It is usual to apply Hill Climbing Operator (HCO) as local search method in hybrid algorithms. We propose to use the classical snakes algorithm [7] to keep a multiobjective deformation. Indeed this active contours algorithm make it possible to use several image energies and integrate cohesion energy into the deformation equation. This method is based on the resolution of the Euler-Lagrange equation by partial differential equation.
Thus the total energy is :

$$E_{total}(\nu) = \int_0^1 \left(E_{int}(\nu(s)) + E_{ext}(\nu(s))\right)ds$$

E_{int} represents energies of curvature and tension. The external energy represents image energies. Then the deformation is performed by the Euler-Lagrange equation ($\nu(s)$ are the pixels contours {x(s),y(s)}) :

$$\frac{\partial}{\partial t}\left(\mu\frac{\partial\nu}{\partial t}\right) + \gamma\frac{\partial\nu}{\partial t} - \frac{\partial E_{totale}(\nu)}{\partial t} = f(\nu)$$

3.2 Energies

The determination of internal energy coefficients, α and β, is difficult. Some authors have proposed some approaches to calculate them in accordance with the first and second contour derivate. Considering the local convergence and the computation time constraints we will manually determine the coefficients internal energy.
External energies are the image forces and so are submitted to the image noise. In order to control snake deformation and to improve robustness we use two external energies. The first one deforms the active contours and the second one controls the deformation. In noisy images, edges are often fuzzy so it is hard to exploit their direction. Thus we define a distance energy (equation 4) between the current node and edges candidates. To satisfy a multiobjective energy evaluation the selected edges candidates must not deteriorate the region based energy E_{region} corresponding to the current contour. At this step of the algorithm our aim is to find the local minimum so we search candidates inside a little neighbourhood V of the current node.

$$E_{\nu=x,y} = t_{node} - t_G \text{ with } G = \underset{\nu\in V}{Max}\left(\nabla I(\nu).Cr(\nu)\right) \qquad \text{with } E_{\text{region}}(node)\begin{cases} E_{region1} \text{ if node} \in \text{outer contour} \\ E_{region2} \text{ if node} \in \text{inner contour} \end{cases}$$

$$Cr(\nu)\begin{cases} 1 \text{ if } E_{region}(\nu) \leq E_{region}(node) \\ 0 \text{ else} \end{cases}$$

Equation 4. External energy

The region energy E_{region} can be the homogeneity one or the accumulation one. We prefer using the energy of homogeneity cause it's more precise and the risk of collapsing is minimal during this step. This multi energies representation is more efficient than a simple weighted sum but its adjustment is more difficult than the Pareto representation.

3.3 Implementation

The local search method is used to improve the exploitation characteristic of GA. This improvement is performed by finding the local minimum of chromosomes at each generation of the GA.
Thus we apply the finite difference method on the chromosomes of the Pareto's frontier at certain iterations to let the genetic algorithm converge near a minimum and to minimize time computation.
In fact, the principle of the hybrid approach is that GA place contours near the global minimum then the classical snakes algorithm fall them on the local minimum.

4 Application to lips contour extraction

mouth Images and videos are difficult to segment because the region image is often noised. This noise can be due to the tongue, luminosity reflections, etc … . An other noise source is the mouth shape variation. For these reasons, lips contours extraction is difficult to automate and is useful in human and computer communication systems like AVSR (Audi Visual Speech Recognition) systems, avatars.

4.1 Coding and image preprocessing

We use the double concentric snakes with eight nodes for each contour to modelize lips contours. Image preprocessing concerns the candidates definition set and energies determination.
The active contour has to respect the model configuration thus we do not have intersections. To reduce the number of possible configurations, nodes have to be rank in the image. For these reasons we have to determinate outer contour nodes evolvement area. The determination of theses areas is based on the centre of the mouth [12]. The inner nodes evolvement area is a triangle defined by the outer node correspondent, the follow-

ing outer node and the mouth centre. During image preprocessing we construct a skin image of the mouth. This binary image is based on the HUE image.

4.2 Results

We have test our algorithm on European Data Base M2VTS images (Multi Modal Checking for Teleservices and Security applications [9]).Here are some results (figure 22) obtained on fifty iterations with the two region based energies and the gradient based one, and with a population of twenty chromosomes. The local search algorithm is applied every 10 generations. We present contours on the region image obtained during pre-processing. On the first lines we show results of MGS without local search algorithm and on the second line, the results of our hybrid algorithms apply on the external contour.

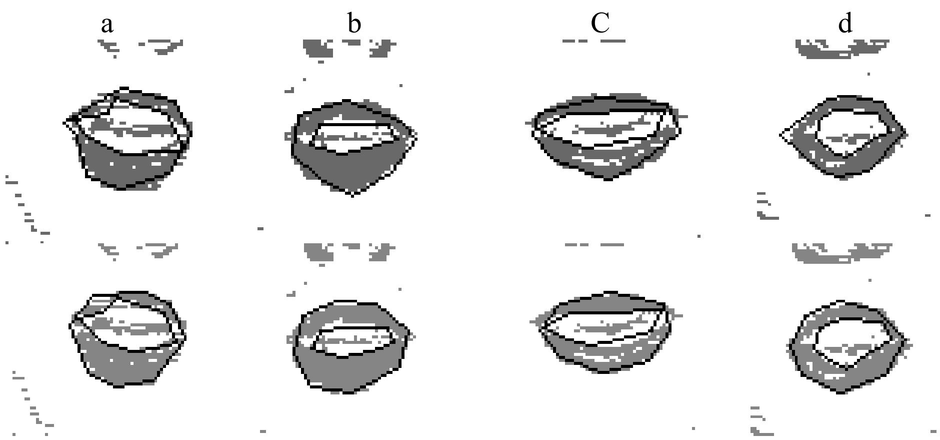

Figure 2. Examples of final results

The weighting coefficient in the region based energies make algorithm robust to noise on the region information. Thus we can see (figures a, b, c, d) that contours can envelop the mouth in spite of the tongue. On the same way figures d and e show that the algorithm is robust to luminosity reflection. On the figures f and g we see that we can extract lips contours in badly segmented images. We show (figure 3) the effect of the classical active contours during the genetic algorithm. The black doted contour is the current contour obtained by genetic algorithms and the white contour is the result oh the local search algorithm. On these examples, the local part algorithm is only apply on the external contour.

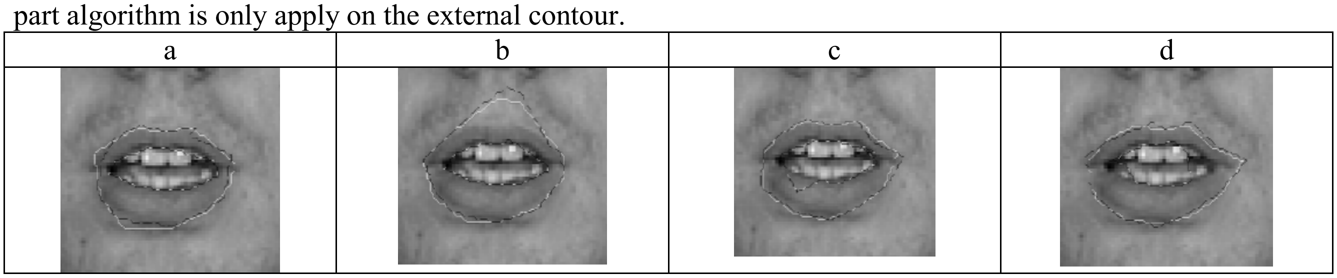

Figure 3 . implementation of classical snakes during GA

We can see that the classical snakes make chromosome converge in a little neighbourhood towards the real contours and so fit better the mouth.

5 Conclusion

In this paper we proposed a new implementation of a hybrid algorithm GA / local search in a multiobjective context. This new algorithm improves convergence of Multiobjective Genetic Snakes quality and reduces the

number of iterations. With this approach we can extract lips contours without being initialised near the lips. Moreover, our algorithm is robust to the tongue presence, luminosity reflections and badly segmentation. Nevertheless, more an image is noised and more the number of generations has to be important.
In our future works , we'll implement our algorithm on all the M2VTS Database to have quantitative comparison between the classical MGS and our hybrid method.

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