Medical Image Analysis Using Potential Active Contours

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Summary. Potential contours are methods for automatic image analysis. They can be interpreted as contextual classifiers that use expert knowledge and operate in supervised or unsupervised mode. In the present paper, potential contours adapted in the supervised way are examined on medical images.

1 Introduction

Medical imaging [1] is an important application area of image processing [2]. Within medical image processing, segmentation is one of the most difficult tasks. Originally, active contour methods were developed as tools for a low-level image segmentation with ability for use of high-level information [3, 4]. The main idea is to find an optimal contour in the space of considered contours representing certain region on the image. The search is performed in an evolution process (optimization) in which the given objective function, called energy, evaluates the quality of contour. As shown in [5, 6], contours are contextual classifiers of pixels (one part of pixels belongs to the interior and another one - to the exterior of given contour, and active contours are methods of optimal construction of classifiers. Potential active contour possesses ability to evolve with change of the location or number of control points, and with modification of parameters of potential functions. The search of optimal contour is performed by optimization of some performance index E called *energy* in the theory of active contours. In E almost any type of information can be used assuming that we are able to implement this information in the computer oriented form.

The search of the optimal contour may be driven in many ways - e.g. by use of simulated annealing or genetic algorithm which perform global search and do not use gradient. In our work we apply the first mentioned method.

Adaptation is another interesting and powerful mechanism [7]. Discrimination ability of a given contour is limited and it depends on the number of control points (assuming that other parameters are fixed). Flexibility of the potential active contours can be improved if we incorporate the change of the number

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of control points into the optimization procedure. For example, we can start with small number of that points and add new ones, if necessary. The rate of misclassification in some area can be the reason for introducing a few new control points.

2 Preprocessing

External energy function in the [resented application operates on greyscale images. The value of contour energy depends on the intensity of each pixel. A contour with the lowest energy value is one that covers only black pixels of the image. A contour that covers only white pixels has the highest energy value. Therefore, the annealing mechanism, which uses external energy, adjusts the contour to dark pixels. For example, in Fig.1a the contour is adjusted to black pixels of the circle.

Preprocessing of the input picture, which consists in the blurring of black contours, improves segmentation. Every image undergoes a preparation process, during which the color of pixels is scaled so that their shades can change fluidly from white (the color of background) to black (the color of object). The algorithm

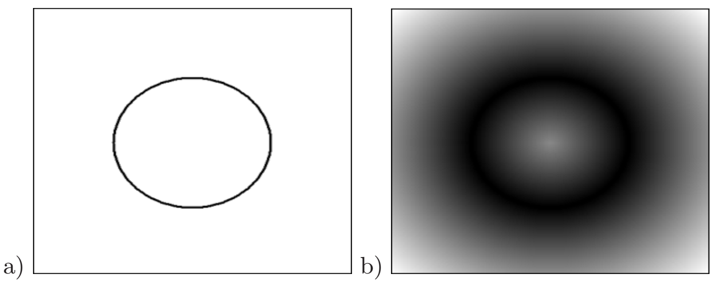


Fig. 1. (a) Test image of a circle consisting of black pixels. (b) Image of a circle during a preparation process (blurring of black contours).

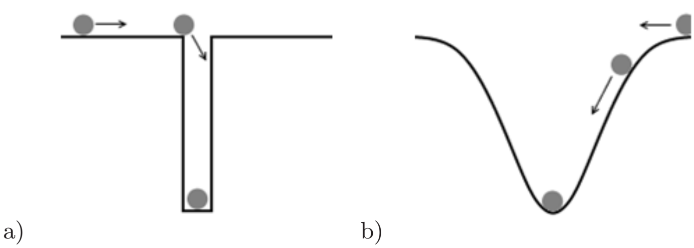


Fig. 2. (a) An image without blurring. The horizontal line represents high energy value. In search of low energy value, the contour should "fall into" a steep gap. (b) Blurred image, the energy value changes smoothly.

assigns each pixel a color in a greyscale, depending on the distance between the pixel and the nearest black point of an image, as illustrated by the formula:

$$P(x, y) = \frac{255\rho(x, y)}{\rho_{max}} \tag{1}$$

where $P(x, y)$ - the resultant intensity of light at a pixel specified by coordinates (x, y), $\rho(x, y)$ - Euclidean distance between point (x, y) to the nearest black point of an object, ρ_{max} - the longest distance between the point of the image and the nearest black point of the object. The result is shown in Fig. 1b. The blurring of contours enhances the method's efficiency, because the contour behaves similarly to a sphere rolling down a slope into a valley, that is the lowest point - Fig. 2. Blurring of contours can be implemented in external energy function. However, energy value is calculated at every step of the algorithm, which means that an image is blurred with each iteration. During segmentation, the image does not change. Thus, it is more useful to blur the image only once during the preparation phase and then use the image processed in this way. The preparatory phase saves processor time.

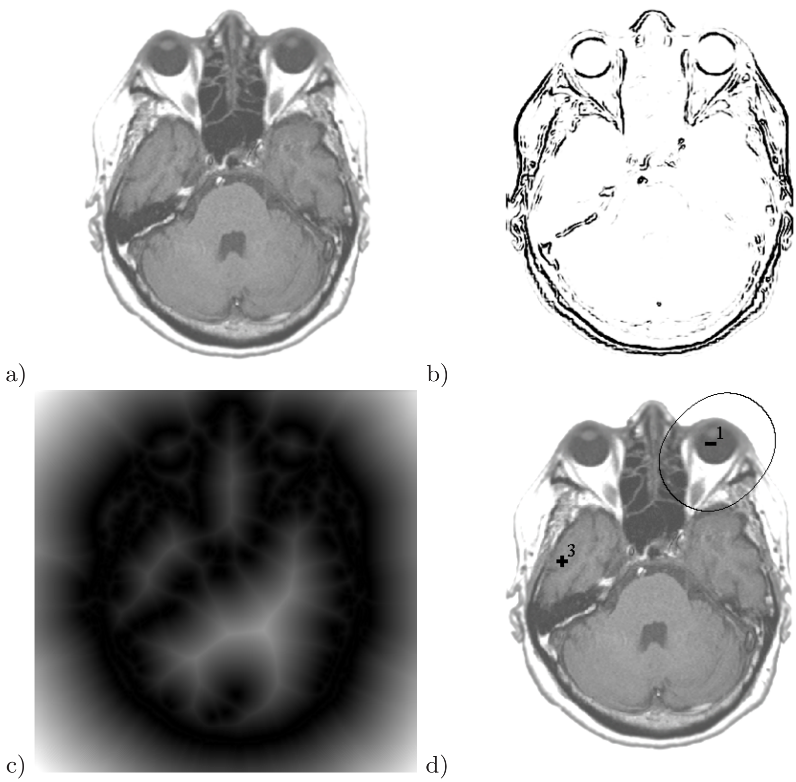


Fig. 3. (a) Cross-section of human skull. (b) Contours detected on the image of a skull. (c) Contour image after blurring. (d) Initial contour against a medical image.

3 Detection of an Eyeball

In the work, potential active contours in the form described in [8] have been applied. This experiment is based on a medical image showing a cross-section of human skull (Fig. 3a). The contours have been detected, as shown in Fig. 3b, which has subsequently been blurred (Fig. 3c). The method was initialized with one object source and four background sources, according to Fig. 3d. Method parameters are given in Table 1 – for their detailed description see [8]. The steps of the experiment are shown in Fig. 4. The experiment was repeated ten times,

Table 1. Adjusting of a contour to a human eyeball - parameters of the method

Simulated annealing	
Initial temperature T_0	-
The calculation of initial temperature T_0	YES
The number of iterations L needed to calculate initial temperature T_0	100
Maximum number of iterations M	3000
Temperature change interval L_T	30
Cooling schedule factor α	0.95
Normalization	NO
Markov process	YES
Markov chain length L_M	30
Move generator	
Position disturbance radius r	1.0
Charge disturbance factor γ	0.02
The probability of source number change p_z	0
Source chance equalizing	YES
Internal energy	
Desired area S_z	1300
Desired length L_z	-
Punishment for lack of consistency	NO
Internal energy weight w_{int}	4.0
Shape energy weight w_s	-

Table 2. Selected energy and temperature values for the process shown in Fig. 4

Initial temperature	3.04e10
Initial energy:	54342.0
Final temperature:	1.80e8
Final energy:	633.0

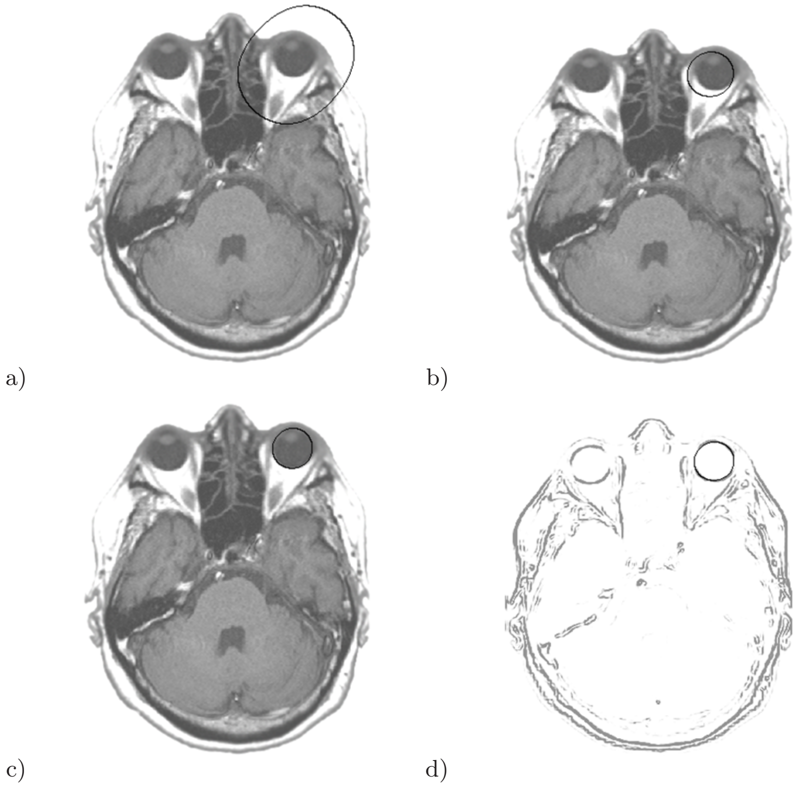


Fig. 4. The process of human eyeball retrieval: (a) Start, (b) 1000th iteration, (c) Final (3000th iteration), (d) Final contour against the contour image

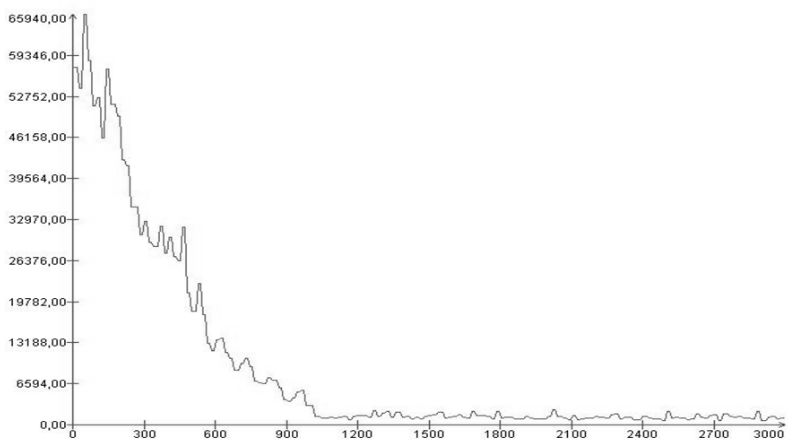
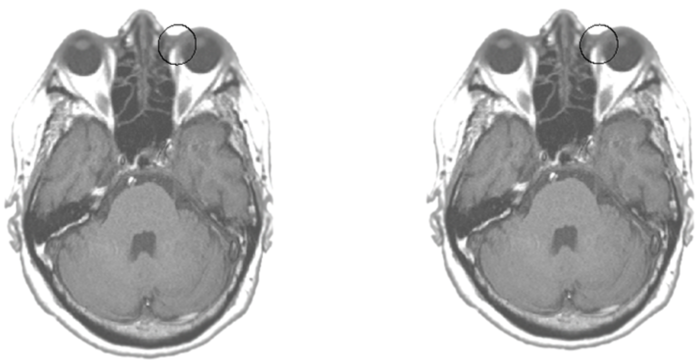


Fig. 5. Diagram of contour energy changes in function of number of steps in the algorithm

Table 3. Results of successive iterations. High standard deviation value is a result of two unusually high final energy values.

Test number	**Final energy**
1	642
2	647
3	1862
4	630
5	649
6	638
7	641
8	1853
9	631
10	649
Minimum	630
Maximum	1862
Average	944.5
Standard deviation	513.02



a) b)

Fig. 6. The resultant contour against the image. (a) The final position of the contour for test 3 in Table 3 ($E = 1862$), (b) the final contour for test 8 ($E = 1853$).

in order to check the repeatability of the result - Table 3. Images Fig. 6a and Fig. 6b show unsuccessful attempts to adjust a contour to a particular fragment of an object. In these two cases, the final energy value is much different from those obtained in the other tests. So high a value is a result of an unsuccessful annealing process. As shown in Fig. 7, the method is able to find many objects simultaneously.

a) b) c)

Fig. 7. Simultaneous detection of both eyeballs. (a) Initial contour ($E = 3902$). (b) The result after 100 iterations ($E = 2916$). (c) The result obtained after 2000 iterations ($E = 562$).

4 Summary

The experiments carried out in the present paper show how useful the potential active contour method can be for the segmentation of medical images. As proved by the majority of tests conducted here, the method is able to perform a correct segmentation of an eyeball. Both eyeballs have been detected on the image, although only one contour was used at the start. Moreover, the experiments are characterised by high repeatability of results. It is worth mentioning that a potential contour is based on a probabilistic optimisation algorithm. Therefore, the results depend to a large extent on a random factor. The algorithm has to be reiterated a few (or many) times and the best result is considered to be the final one. The method is more efficient if it is preceded by a preparation phase, during which the contours are found and the image is blurred.

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