

Potential Contour Ensembles

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Abstract. In the paper a contour ensemble image segmentation concept is presented. It bases on the previously observed relationship between contours and classifiers. Because of the specificity of the active contour segmentation the method requires a special procedure to obtain ensemble members with desired properties. In this work it is achieved by early stopping of randomized optimization algorithm. The results of the method are illustrated with a practical problem of heart ventricle segmentation by means of active potential contours. Automatically found contours may be of use in a process of pulmonary embolism diagnosis.

Keywords: active contours, classifier ensembles, information fusion, potential contours.

1. Introduction

Active contour methods are popular techniques of image segmentation. There exist a wide variety of approaches that can be included in this group like: snakes, geometric active contours or active shape models [1–3]. Their main virtue, distinguishing them from other classic groups of segmentation methods, is their ability to utilize almost any kind, even very imprecise, knowledge about objects that are sought in the images. In particular it need not to be only the knowledge contained in those images but also any kind of other external, domain knowledge. This feature is of special importance in case of medical diagnosis where without the experience of the physicians proper interpretation of image content is usually impossible.

Classifier ensembles are methods that more and more successfully compete with classic approaches to classification problems. The main idea in this group of techniques is to use a set of simple and weak classifiers instead of one that is potentially very complex. Of course such a procedure requires additional steps to obtain final result as it must be somehow aggregated from the responses given by ensemble members. The most famous methods belonging to that group of classifications techniques are: bagging, boosting or random forests [4–6].

The idea described in this paper bases on the observation, presented among others in [7], that contour c , which separates object from a background in the image, can be considered as pixel classifier that with a pixel (x, y) binds its label $c(x, y)$: object or background (contour corresponds with a decision boundary). This relationship can be further extended since contour evolution can be treated as a classifier training. The main difference lies usually in the kind of knowledge exploited during the optimization. In classification it is mainly a training set used for construction of objective function while in active contours the energy function usually tries to express any available, heuristic knowledge. This kind of knowledge does not consider individual pixels separately but it can also take under consideration groups of them or even the whole image. In classification techniques similar concept is noticeable in case of regularization or margin maximization.

In the paper the approach joining ideas known from contour based segmentation and classifier ensembles is presented. It is organized as follows: the second section describes a practical problem of heart ventricle segmentation for which the proposed method will be applied, in the third section the contour ensembles are discussed whereas in the fourth section the obtained results are presented, finally the last section contains a short discussion and summary of the those results.

2. Heart ventricle segmentation

Theoretical concepts presented in this paper are illustrated with a problem of heart ventricle segmentation. This may be an important element of diagnostic process of pulmonary embolism as arteries obstruction by the emboli increases blood pressure in the right ventricle changing the shape of the whole heart. Manual process of endocardial and epicardial contour drawing is time-consuming as it requires hundreds of images to be analyzed. It cannot be avoided since the geometrical changes of heart shape structure need to be evaluated. That is why automatic or semi-automatic method of determining of those contours would be a great simplification of that work.

The used image data were gathered using 64-row computed tomography scanner. It was ECG-gated which allowed to acquire 4D chest sequences (3D sequences in 10 phases of heart cycle). Those sequences were further processed to obtain two chamber short axis view (the workstation software was used for this purpose) of the heart. As a result a set of 80 images, 10 phases with 8 slices, was generated for each patient. To limit the amount of data further in this work only 2 such patients and the endocardial contour of left ventricle are considered. In both cases the expected

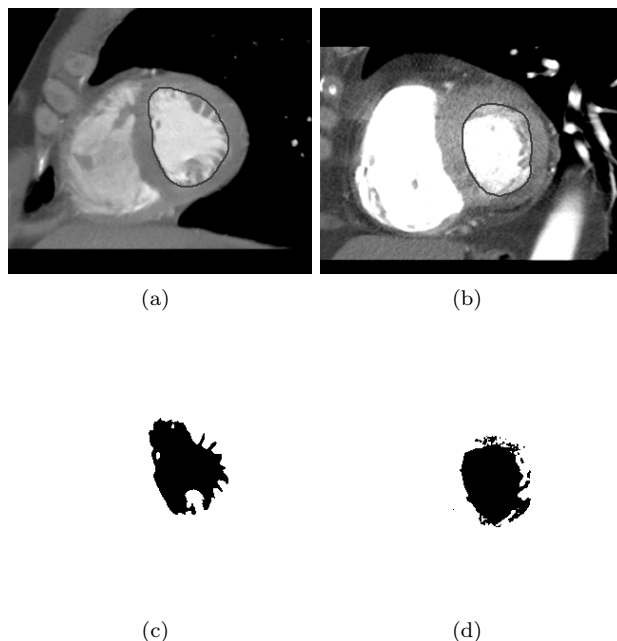


Figure 1. Sample heart images considered in this work: (a), (b) – images with contours manually drawn by a physician; (c), (d) – detected regions representing blood with contrast inside the left ventricle.

contours were drawn manually by a radiologist (Fig. 1a, Fig. 1b). It allows not only to evaluate the segmentation results by their visual examination but also enables the usage of more formal methods described further.

In previous works devoted to the solution of this problem potential active contours were used [7]. Potential contour is a contour located in the image there where the summary potentials of two types of potential sources, representing object and background, are equal. In other words those pixels where the summary potential of object sources is greater than summary potential of background sources compose the interior of the contour, the rest of them belongs to the contour exterior. This idea comes from the concept of potential function classifier [8]. That type of contour was chosen because of several reasons. It allows to describe contour shapes that are typical for medical applications (smooth and rounded). Moreover, not too many parameters need to be found in evolution process (only position of the potential sources and parameters characterizing strength and distribution of potential field). Both those reasons causes that the search space of the optimization process is reasonably limited. It is important in the situation where the objective function expresses the heuristic expectation about the resulting contour and consequently it has no properties required by most of the classic methods of optimization (it may not be continuous or differentiable). In image segmentation it is usually the case as the knowledge required for training is not available in the the form of training set. In this work the information about image acquisition process as well as medical knowledge were used instead.

The computed tomography images were acquired after intravenous injection of contrast media. It causes that blood inside heart ventricles is represented by bright pixels which significantly distinguishes it from the heart muscle. It does not mean, however, that endocardial contour can be easily found. The problem is that fragments of heart muscle grows into the ventricle interior making its image to be non-uniform. Consequently the simplest expectation about the best contour describing ventricle can be formulated as follows: *it should be the smallest, smooth contour containing all pixels representing blood inside the ventricle.* The energy function which describes this expectation can have the following form:

$$E = wE^o + E^a, \quad (1)$$

where E^o measures how many pixels representing blood inside the ventricle lies outside of the contour and E^a measures the area of the contour. The weight $w > 0$ allows to control the trade-off between those two components. To find pixels representing blood the procedure described in [9] can be applied (Fig. 1c, Fig. 1d). As an optimization technique for that kind of energy function simulated annealing algorithm was proposed. Its main advantage is its ability to avoid local minima and fact that it does not impose any special constraints on objective function. It has, however, also its drawbacks. The most important is that it requires, as a randomized algorithm, a large number of iterations to obtain satisfactory and repeatable results. In [7] this approach was discussed in details and its crucial parameters were identified. For the purpose of this work the one that is essential is the number of iterations between the changes of the temperature in the annealing process. It can be expressed as a multiple $v \in \mathbb{R}$ of the some basic constant number of iterations.

3. Potential contour ensembles

A consequence of treating contours as classifiers is that the concepts usually connected with classification tasks can be easily imported into image segmentation problems. One of such concepts are classifiers ensembles. The main assumption standing behind those methods is that classifiers composing ensemble should be trained independently using slightly different type of knowledge. In practice it is achieved for example by selecting random subsets of a training set. In case of active potential contours and the problem described in previous section this approach cannot be transferred directly as the training knowledge has a form of specific energy function. However, the similar goal can be gained in some other way. As an optimization algorithm simulated annealing was chosen. It is a randomized algorithm which if is run many times and stopped early should give different and independent results. The hypothesis of this work is that instead of performing a long evolution of single contour the better or comparable results can be obtained by combining the set of significantly shorter trained contours. Those contours will constitute a potential contour ensemble.

Many methods of contour aggregation may be considered here. Some of them may utilize the value of energy function for each member of the ensemble. Denoting c_i and

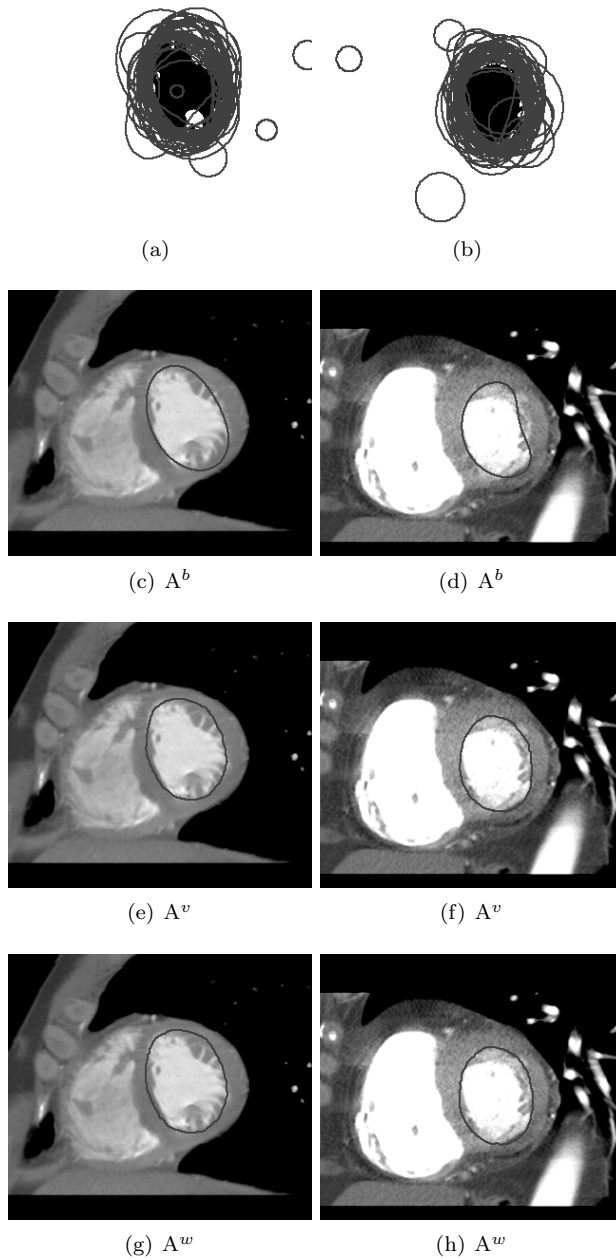


Figure 2. Sample results of potential contour ensemble for $w = 10$, $N = 50$, $v = 0.1$ and different types of result aggregation: (a), (b) – ensemble members; (c), (d), (e), (f), (g), (h) – ensemble aggregation results.

E_i as ensemble member contour and its energy, respectively, for $i = 1, \dots, N$ where the N is the cardinality of the ensemble, the following sample contour aggregation methods A can be considered:

- Best member A^b – the resulting contour is a contour with a lowest energy function:

$$c(x, y) = c_{\arg \min_{i=1, \dots, N} E_i}(x, y).$$

- Votes of members $A^v(t)$ – the resulting contour is such a contour according to which each pixel belongs to the object if more the t fraction of member contours treats this pixel as an object pixel:

$$c(x, y) = \begin{cases} \text{object} & \text{if } \sum_{i=1}^N I(c_i(x, y) = \text{object}) > tN, \\ \text{background} & \text{otherwise.} \end{cases}$$

- Weighted votes of members $A^w(t)$ – the resulting contour is a contour obtained in the similar way as the previous one but this time the weights $e_i \in \mathbb{R}$ of the votes depending on energy function values are considered:

$$c(x, y) = \begin{cases} \text{object} & \text{if } \sum_{i=1}^N e_i I(c_i(x, y) = \text{object}) > t \sum_{i=1}^N e_i, \\ \text{background} & \text{otherwise,} \end{cases}$$

where:

$$e_i = 1 - \frac{E_i - E_{\min}}{E_{\max} - E_{\min}},$$

for $i = 1, \dots, N$, E_{\min} and E_{\max} denote minimum and maximum energy of the ensemble members, respectively.

Above I is an indicator function which value is 1 if the specified condition is true and 0 otherwise. The method A^b is not a typical ensemble aggregation method. It is used and compared further with other methods as it was used in previous work. There, however, the motivation for its usage was different as it was simply considered to increase a chance of obtaining better results in case of short potential contour evolution.

4. Results

To verify the hypothesis several experiments were performed for $w = 10$. For each image two segmentation methods were considered: a potential contour ensemble trained with $v = 0.1$ and $N = 50$ and traditional potential contour trained with $v = 5$. Training in both cases required the same number of iterations. The choice of the parameters was imposed by a reasonable time of computations.

The first experiment was supposed to check what is the repeatability of the results produced by those two methods. In order to compare them for a chosen images the

Table 1. Results illustrating how often the values of the considered scores are better for potential contour ensemble than for standard potential contour (better column). average value of the score for an ensemble (value column) and the change of the score in comparison with the standard method (change column): (a) – the best of 10 experiments. (b) – the worst of 10 experiments. (c) – the average of 10 experiments.

(a)

	F_1			P			R		
	better	value	change	better	value	change	better	value	change
A^b	92.5%	0.917	+0.088	93.8%	0.895	+0.146	44.4%	0.944	+0.001
$A^v(0.5)$	87.5%	0.896	+0.067	88.8%	0.870	+0.122	47.5%	0.931	-0.012
$A^w(0.5)$	87.5%	0.892	+0.063	84.4%	0.836	+0.087	70.0%	0.961	+0.018

(b)

	F_1			P			R		
	better	value	change	better	value	change	better	value	change
A^b	80.6%	0.917	+0.049	83.8%	0.895	+0.087	40.0%	0.944	-0.004
$A^v(0.5)$	67.5%	0.896	+0.028	74.4%	0.870	+0.062	45.0%	0.931	-0.017
$A^w(0.5)$	65.6%	0.892	+0.024	60.6%	0.836	+0.028	65.6%	0.961	+0.013

(c)

	F_1			P			R		
	better	value	change	better	value	change	better	value	change
A^b	86.3%	0.917	+0.067	87.7%	0.895	+0.115	42.4%	0.944	-0.003
$A^v(0.5)$	76.6%	0.896	+0.046	82.1%	0.870	+0.091	46.2%	0.931	-0.016
$A^w(0.5)$	75.6%	0.892	+0.042	72.8%	0.836	+0.056	68.4%	0.961	+0.014

same method was executed 20 times and for each pixel the probability of assigning it a label of object or background was calculated. Basing on these probabilities as a measure of the repeatability the sum of entropies for all pixels in the images was considered (the lower value the better). It is worth to emphasize that in this case it was not important whether the contours correspond with expert results but how much they differ among trials. The obtained results revealed that the values for contour ensemble are at least two times lower than for traditional potential contour.

In the second experiment the results of both segmentation methods were compared for all the 160 images. As contours can be treated as classifiers and there are available reference contours drawn by physicians to evaluate objectively segmentation results the measures used in classification tasks like precision P and recall R can be adopted. First of them evaluates how many background pixels was incorrectly classified as pixels of the sought object. Second checks how many object pixels was incorrectly assigned to the background. Additionally, also the F_1 score, combining precision and recall, is used. In Table 1 the summary of the experiment is presented illustrating among others how often, for a given aggregation method, the contour ensemble has better values of those scores than traditional potential contour. As the results of the standard method are not sufficiently repeatable the comparison was performed 10 times. The results

reveal that contour ensemble is a promising alternative for a standard approach. An interesting result was obtained for A^b . In some cases it gives even better outcomes than other aggregation methods. It can be, however, easily explained. Since it is a randomized algorithm among N members of the ensemble it may happen that a good solution will be found. The problem is that in general it is not guaranteed and that is why A^w seems to be a better choice. In Fig. 2 the sample ensembles as well as the aggregated contours are presented.

5. Summary

In this work a new approach to image segmentation was presented. It joins concept known from active contour based segmentation and classifier ensemble training. Because of the specificity of the image segmentation a non-standard procedure had to be undertaken to ensure the proper diversity of contour ensemble members. It was possible thanks to the nature of the optimization algorithm which is a non-deterministic technique. Instead of randomizing the knowledge used while training the early stopping procedure was used to gain the similar goal. The presented results show that such an approach allows usually to achieve better results in comparison with previously used approaches. The objection that can be raised is that traditional classifier (obtained for $v = 5$) has the same complexity as ensemble members (obtained for $v = 0.1$ and $N = 50$) and consequently a simple reference classifier is compared with potentially complex ensemble classifier. The results, however, suggests that this procedure allows to obtain more stable results and just for that reason it is undoubtedly useful in the presented form. To sum up two main conclusions can be drawn from the presented work:

- The concept of classifier ensembles can be extended to contour ensembles and applied for image segmentation.
- Contour ensemble may increase stability of the results if the objective function used for training requires heuristic, randomized methods of optimization.

It should be also emphasized that the presented approach need not to be applied for potential contours only. Any other contour model may be of use here well. Moreover the similar approach can be also of use in classification tasks that require heuristic methods classifier training. The author is also aware of the fact that for the described problem only the simplest form of the energy function was considered and that the experiments should be verified also in other cases. All those aspects are under further investigation.

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