

Application of Active Contours with Expert Knowledge to Heart Ventricle Segmentation

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Abstract. *Automatic heart ventricle segmentation in CT heart images can be an element of system supporting pulmonary embolism diagnosis. To solve that problem in this paper an application of two classical active contour models, snakes and geometric active contours, is proposed. The prepared implementation uses the unified model of those techniques which allows to define forces acting upon a contour only once. The nature of the images causes that the process of force construction requires additional expert knowledge since using only the information visible in the image satisfactory results cannot be obtained.*

Keywords: *active contours, snakes, geometric active contours, expert knowledge.*

1. Introduction

Image segmentation is a crucial element of almost any system automatically analysing image content. There are many segmentation techniques such as: thresholding, edge based techniques or region based techniques. Their shortcoming is that decision how a single pixel should be treated depends only on local characteristic of the image in the neighborhood around. The alternative approach are active

contour techniques. In the literature there many different variants of active contours starting from snakes ([1, 2, 3, 4, 5, 6]), from which that group of methods originates, through geometric active contours, ([8, 9, 10, 11, 12, 13]), active shape models ([14, 15, 16]), up to Brownian Strings ([17]) and others ([18, 19, 20]). All of them share, however, the common scheme which requires three elements to be defined:

- contour model - it determines the space of regions that can be segmented
- energy function - it contains a domain knowledge and evaluates contours
- evolution process - it allows to find an optimal contour within contour model and with respect to a given contour energy

The most commonly used techniques are snakes and geometric active contours which, as it was shown in [7], are closely related. That relationship allows to define domain specific contour energy (or directly contour forces in the evolution process) only once and use them with both those approaches. These are the main reasons why those methods were selected for implementation. Moreover, the described experiments allow to compare them with a new method proposed by the author of this work in [22].

This paper is organized as follows: in section 2 the theoretical background of chosen active contour methods and their unified model are presented, section 3 describes the problem to be solved, the required expert knowledge, evaluation methodology and obtained results, finally section 4 contains a summary of the research.

2. Active contours

2.1. Snakes

Snakes are representatives of parametric active contours and were firstly described in [1]. Contour, in this method, is defined as a function $c : [a, b] \rightarrow \mathbb{R}^2$ for $a \in \mathbb{R}$, $b \in \mathbb{R}$ and $a < b$. It means that for each value of parameter $s \in [a, b]$ that function defines a point in the image plane $c(s) = (x(s), y(s)) \in \mathbb{R}^2$. The basic energy function proposed in [1] is defined as follows:

$$E(c) = \int_a^b \frac{\alpha(s) \|c'(s)\|^2}{2} + \frac{\beta(s) \|c''(s)\|^2}{2} + V(c(s)) ds \quad (1)$$

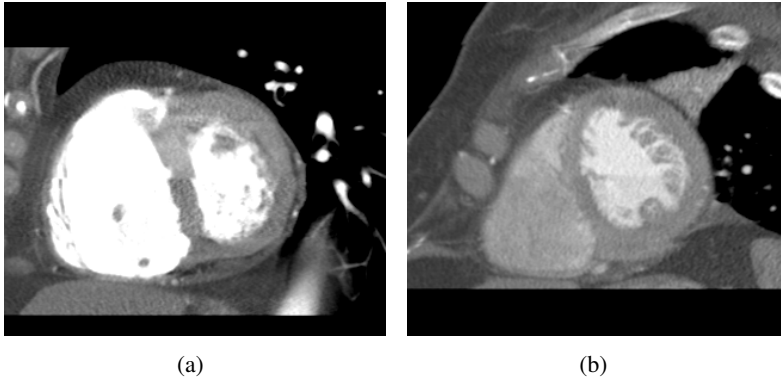


Figure 1. Sample CT heart images.

The first two components of that energy (respectively elasticity and rigidity components) depend only on the shape of the contour and therefore represent an internal energy, the third evaluates the position of the contour in the image and is called an external energy. It is worth noticing, which is not a rule, the value of the internal energy for a given contour point depends only on the characteristic of parametrization c . It is important since two contours that are visually the same can have different parameterizations and consequently different energy. The external energy needs not to consider only the information in the form of potential field $V : \mathbb{R}^2 \rightarrow \mathbb{R}$ defined by some image characteristic. It can use any other available information.

To find an optimal contour Euler-Lagrange method must be applied which leads to the following contour evolution scheme:

$$\frac{\partial c}{\partial t} = (\alpha c')' + (\beta c'')'' + \mathbf{F} \quad (2)$$

where $\mathbf{F} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ is a force that corresponds to potential V and $\mathbf{F} = \nabla V$. This equation has an intuitive interpretation. One can consider the search for an optimal contour as an iterative process in which optimal trade-off between energy components must be found or equivalently in which the corresponding forces are balanced.

There are numerous modifications of the presented basic approach. In [2, 3] the additional pressure force was proposed which acts in a direction \mathbf{N} normal to

the contour:

$$\mathbf{F} = F\mathbf{N} \quad (3)$$

where $F : \mathbb{R}^2 \rightarrow \mathbb{R}$. That pressure can be constant or depend on the characteristic of image regions which leads to the concept of region energy and region force.

The evolution scheme presented above requires solving of system of two partial differential equations in one dimension which can be effectively solved using numerical schemes presented in [1].

2.2. Geometric active contours

In parametric active contours the resultant energy forces can act not only in direction \mathbf{N} normal to the contour but also in a direction tangent to the contour and have an influence on contour parametrization. In geometric active contours during evolution force can be only normal to the contour. Consequently, the contour evolution can be described as:

$$\frac{\partial c}{\partial t} = F\mathbf{N} \quad (4)$$

Since parametrization is not important, contour can be described in an implicit form as a set of points $c = (x, y) \in \mathbb{R}^2$ such that $C(x, y) = 0$ for some $C : \mathbb{R}^2 \rightarrow \mathbb{R}$ and contour evolution can be expressed then as:

$$\frac{\partial C}{\partial t} = F \|\nabla C\| \quad (5)$$

Here, it is a surface C that evolves and not contour parametrization c . Such an implicit representation is called a level set representation and allows to describe contours of different topology which without any additional modifications was not possible in explicit snakes approach.

The basic variant of geometric active contours was proposed in [8, 9] where the equation of evolution had the following form:

$$\frac{\partial C}{\partial t} = V(F + f(\kappa)) \|\nabla C\| \quad (6)$$

The force having an influence on the contour is a sum of constant component $F \in \mathbb{R}$ and component $f : \mathbb{R}^2 \rightarrow \mathbb{R}$ depending on contour curvature κ . The potential field V was used to stop the contour close to the desired image features.

The above formulation does not specify the energy function explicitly. In [10] that inconvenience was overcome by geodesic active contours where the energy function was defined as:

$$E(c) = \int_a^b V(c(s)) \|c'(s)\| ds \quad (7)$$

which leads to the following evolution equation:

$$\frac{\partial c}{\partial t} = (V\kappa - \langle \nabla V, \mathbf{N} \rangle) \mathbf{N} \quad (8)$$

and which, using level set approach, can be expressed as:

$$\frac{\partial C}{\partial t} = V\kappa \|\nabla C\| + \langle \nabla V, \nabla C \rangle \quad (9)$$

Adding additional constant force and generalizing the curvature force the following equation, similar to geometric active contours, can be derived:

$$\frac{\partial C}{\partial t} = V(F + f(\kappa)) \|\nabla C\| + \langle \nabla V, \nabla C \rangle \quad (10)$$

The evolution scheme presented above requires solving of a partial differential equation in two dimensions which can be effectively solved using numerical schemes presented in [7].

2.3. Unified model

The results presented further in this paper were obtained using a model proposed in [7] where the relationship between the above methods was described. Within that model contour evolution can be expressed for snakes as:

$$\gamma \frac{\partial c}{\partial t} = (\alpha c')' + F\mathbf{N} + \mathbf{F} \quad (11)$$

and for geometric active contours as:

$$\gamma \frac{\partial C}{\partial t} = (\alpha\kappa) \|\nabla C\| + F \|\nabla C\| + \langle \mathbf{F}, \nabla C \rangle \quad (12)$$

Assuming that $\alpha : \mathbb{R}^2 \rightarrow \mathbb{R}$, $F : \mathbb{R}^2 \rightarrow \mathbb{R}$ and $\mathbf{F} : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ change in the image plane, this model, which was proved in [7], can be transformed to many of the existing variants of the discussed methods. The $\gamma > 0$ parameter controls the speed of contour evolution and is crucial for numerical stability of the used algorithms. In the presented work the rigidity component β was not considered and consequently was omitted in the above equations.

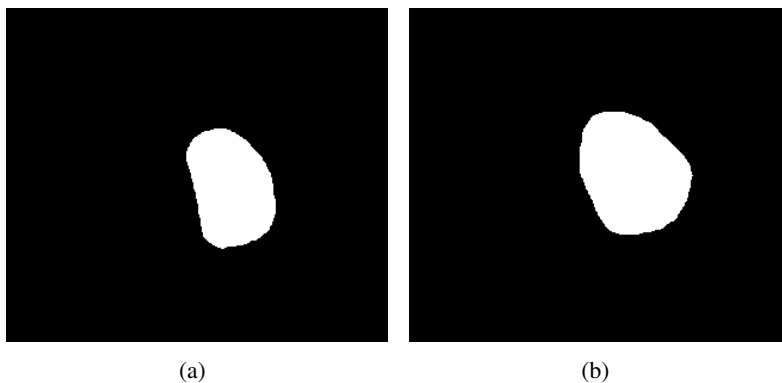


Figure 2. Sample mask images representing ground truth information provided by a radiologist (white pixels - left ventricle interior, black pixels - background).

3. Application

3.1. Problem

The discussed active contour methods within the implemented unified model were used for heart ventricle segmentation. Heart images were obtained using CT scanner connected with ECG device which allowed to acquire 3D video sequences of working heart. From each sequence 8 slices perpendicular to long heart axis at 10 different moments during one heart cycle were selected. Having 7 video sequences this procedure allowed to prepare 560 image set that was later divided into training set with 28 examples and testing set with 532 examples. The low number of training examples was motivated by a time consuming training process described further in this paper.

Heart ventricle segmentation can be of use during diagnostic process of pulmonary embolism which is a frequent cause of death in developed countries. The presence of emboli in the arteries can be indirectly detected while observing the changes of heart ventricle shape during heart contraction cycle. So far the process of heart shape detection was performed manually which, taking into account the number of images for one patient, was a very tiring process. Automatic detection of heart ventricle contours could be a significant convenience in this procedure. Of course, the automatic detection will not eliminate radiologists. It should be



Figure 3. Sample masks M representing blood inside left ventricle (black pixels - blood, white pixels - background).

considered only as an assistance - there should be a possibility to manually correct automatically located contours.

This paper focuses on detection of contours describing the interior of left heart ventricle. Sample regions that were drawn by a radiologist are presented in Fig. 2. The similar procedure can be used to detect contours for right ventricles.

3.2. Knowledge

To automatically find a proper contour an additional expert knowledge about image content must be incorporated in segmentation process. The interior of a heart ventricle can be easily distinguished from the rest of heart tissues since before patient examination the contrast was injected into the blood vessel which results in very bright pixels representing blood in CT image. There are, however, two problems with direct exploitation of that information. Firstly, in the considered images the blood is visible in both ventricles as well as in other veins and arteries. Moreover, bone tissue results also in pixels with the similar brightness which can constitute a problem if there are some ribs visible after image reconstruction. Secondly, heart muscle can grow into the ventricle interior which causes that there is no difference between pixels representing heart interior and heart wall. Both those problems are evident in Fig. 1.

In the unified model described above that knowledge can be encoded in α , F and \mathbf{F} parameters. To overcome first of the mentioned problems the preprocessing

procedure described in [21] can be used. The proposed solution in a first phase is able to remove additional bright pixels (vessels, bone tissue) analysing the whole video sequence and detecting those regions that change during heart contraction. The second phase locates a parabola that approximates the shape and localization of interventricular septum. Finally, in a third phase the mask $M : \mathbb{R}^2 \rightarrow \{0, 1\}$ containing only pixels representing blood inside a selected ventricle is generated. Sample results of that approach are presented in Fig. 3. That mask can be used to define the first force component F having an influence on contour evolution:

$$F = w(1 - M) \quad (13)$$

where $w \in \mathbb{R}$ determines the strength of this component. That force represents a constraint preventing contour from crossing the interior of the sought ventricle. The second problem can be overcome using elasticity component controlled by $\alpha \in \mathbb{R}$ parameter. In experiments described further this parameter had a constant value in the image plane. This component should guarantee that during evolution the contour will shrink (it will be always initialized outside the searched ventricle) and that it will not try to penetrate the ventricle interior even if heart muscle grows inside. To sum up, the proposed approach should assure that optimal contours will contain the whole blood inside the ventricle and it will be smooth as well. To find a proper trade-off between parameters w and α a training procedure was used as described below.

3.3. Evaluation

To perform training as well as to assess the final results a method of segmentation evaluation is required. In this work for each analysed image there existed ground truth information about ventricle localization which was provided by a radiologist. It allowed to prepare an objective measure of the results. The proposed measure bases on the observation, described among others in [22], that contour can be treated as binary a classifier of pixels. In consequence measures used for classifier evaluation can be of use also in case of image segmentation. The measures used in this work are precision:

$$P = \frac{TP}{TP + FP} \quad (14)$$

and recall:

$$R = \frac{TP}{TP + FN} \quad (15)$$

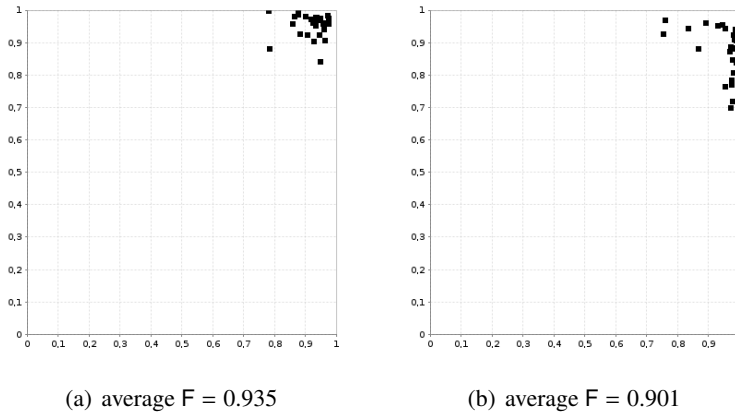


Figure 4. Optimal parameter selection results - 28 images (horizontal axis - P, vertical axis - R): (a) - snakes - $\alpha = 1.5$, $w = 0.5$, $n = 24$, , (b) - geometric active contours - $\alpha = 1.4$, $w = 0.4$.

where:

- *TP* - true positive - the number of pixels that should be inside the contour and in fact they are there
- *FP* - false positive - the number of pixels that should not be inside the contour but they are there
- *FN* - false negative - the number of pixels that should be inside the contour but they are not there

Both those measures give values in the interval $[0, 1]$ and their interpretation is quite obvious. Precision is equal to 1 if nothing that is outside a heart ventricle is inside a contour. Recall is equal to 1 if the whole ventricle is inside the contour. It can happen that one of those measures has the best value while the other has the worst one. That is why during optimal parameter selection both of them should be maximized. To not consider a multi-objective optimization task a measure combining precision and recall must be chosen. The most popular is F-measure defined in the following way:

$$F = 2 \frac{PR}{P + R} \quad (16)$$

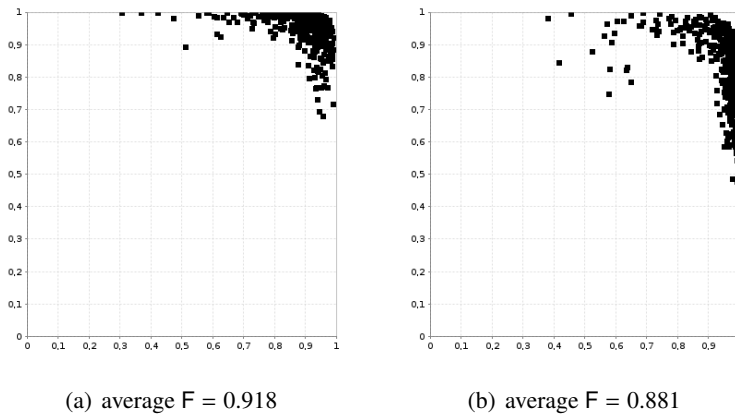


Figure 5. Test results - 532 images (horizontal axis - P, vertical axis - R): (a) - snakes, (b) - geometric active contours.

The last thing worth mentioning is a fact that the above approach should be used carefully in case of geometric active contours since the resulting contour can have different topology. In this paper only the most outer contour is considered during evaluation which means that if there are any holes in the object that are detected by the contour they will be omitted.

3.4. Training

As it was mentioned above to select optimal parameters w and α a training set containing 28 images was selected. Using those images the search for optimal combination of parameters was performed separately for snakes and geometric active contours. For snakes the additional parameter $n \in \mathbb{N}$ was considered. This parameter controlled the number of contour vertices which is required by numerical implementation of contour evolution. In geometric active contours the discretization parameter was constant - its value was limited by the efficiency of the implementation. The optimal parameters were sought in a brute force process where for a combination of parameters for each training image the contour evolution was performed and an average F-measure was calculated. The analysed combinations were chosen from a regular grid in parameter space. In Fig. 4 the best selected parameters are presented as well as the distribution of precision and recall values for images in a training set.

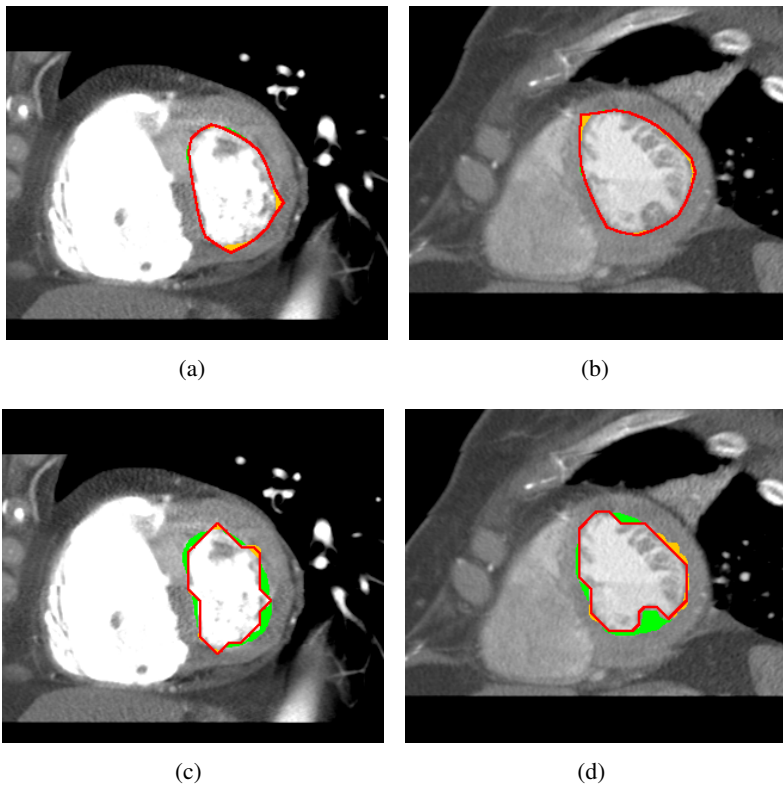


Figure 6. Sample results: (a), (b) - snakes, (c), (d) - geometric active contours.

3.5. Results

Using the selected parameter values the method was evaluated using 532 images. In Fig. 5 the distribution of precision and recall values for those images is presented and in Fig. 6. sample segmentation results are depicted.

The analysis of the obtained results reveals that the proposed approach can be of use for radiologists since in most of the cases the contours require only a slight manual modification. The second observation is fact that geometric active contours ususally give results with very high precision and lower value of recall. In this case it means that contour describes precisely blood inside a ventricle but has problems with that part of heart muscle that grows into the heart interior. The reason of that can be the implementation which allows to use only limited precision

of contour approximation and which consequently may cause problems with taking into account the sufficient influence of elasticity force component. To overcome that problem a better implementation, using for example a narrow band, approach should be used.

4. Summary

In this paper two classical variants of active contour models were used to automatically localize left heart ventricle in CT images. The results allow to draw a conclusion that the proposed approach can be useful in diagnostic practice since it can speed up the process of contour delineation. Those results can be also compared with potential active contour approach proposed by the author of this work in [22]. Such a comparison reveals that a potential contour model seems to give better results because its natural ability to describe smooth shapes of medical organs. In case of snakes and geometric active contours to achieve contour smoothness additional operations were required (elasticity force). Of course it does not mean that described methods are useless. Perhaps additional parameter tuning, for example depending on heart contraction phase or patient-specific morphology, could improve results. Also taking into additional expert knowledge about the width of heart wall could be of use here. These ideas will be the objective of further research.

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