EVALUATION AND IMPROVEMENTS OF THE LEVEL SET METHOD FOR RM IMAGES SEGMENTATION

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Abstract: We present a novel algorithm for the segmentation of bony tissues in MR images. Our approach is based on the level set algorithm. We introduce some pre-processing phases that improve image quality and segmentation performance. The technique requires no training and operates semi-automatically, requiring only the entry of a single seed point within the tissue to be segmented. The proposed approach is more robust than the other approaches present in the literature, with respect to the position of the initial seed point. The quantitative analysis of the results on a significant number of images demonstrate the effectiveness of our approach.

1 INTRODUCTION

Despite much effort and significant progress in recent years, image segmentation remains a notoriously challenging computer vision problem. In particular, segmentation of medical images is difficult because of several factors: the complexity of the images; the lack of anatomical models that fully capture all possible shape variations for each structure; poor image contrast, noise, and missing or diffuse boundaries. Furthermore segmentation of medical images is typically a semi-automatic process: human interaction introduces an instability in the results because the solution of most approaches depends considerably on the choices made by the user at the start of the process.
One of the most widely used methods for image and shape segmentation in medical images (as we will show in the next section) is based on curve or boundary evolution. Even though this approach presents effective solutions in terms of quality of the segmentation, it has some drawbacks that complicate its practical employment.
In this paper we present a new algorithm based on the level set approach that overcomes some of the well known problems of this kind of algorithms. In particular the proposed algorithm produces a solution that is more robust with respect to human interaction: the results of our algorithm are largely independent of the initial seed points.
The paper is organized as follows: in section 2 a review of the most used approaches for segmenting MR images is shown; the proposed algorithm is presented in section 3 while in section 4 the experimental phase together with the analysis of the results are described. Section 5 summarizes the conclusions obtained from our work.

2 RELATED WORKS

In medical imaging classical segmentation methods, like Thresholding or Region Growing, have been substituted with more effective approaches. A well known approach is to use some classifiers (k-nearest-neighbor (Vrooman et al., 2007), Bayes classifiers (Banga et al., 1992)) to segment an image. The process of segmentation with classifiers is computationally less expensive than the other approaches. However there are some drawbacks in the use of this approach: the first is that it is difficult to take into account spatial information in the features used for the classification; the second drawback is that this approach requires a supervised training phase. For this reason, some clustering algorithms (unsupervised classifiers) have been proposed for segmenting the images: the three most used algorithms are K-means ((Vemuri et al., 1995)), fuzzy c-means ((Ardizzone et al., 2007), (Foggia et al., 2006)) and expectation-maximization ((Clark et al., 1994)). One of the main disadvantage of standard clustering algorithms is that they depend solely on the intensities of the image

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and do not consider spatial context. Furthermore, these algorithms assume that the intensities of each class are stationary. This assumption is often incorrect in many images due to the intrinsic heterogeneity of a class, nonuniform illumination, or other imaging artifacts. To take into account spatial information, Markov Random Field (MRF) Models are often incorporated in this kind of algorithms (see (Pappas, 1992), (Krause et al., 1997)). MRF are very suitable for medical images analysis because in most cases the pixels belong to the same class of adjacent pixels; in fact, rarely, anatomical parts are composed by one pixel. Two critical points of MRF approach are the computational burden (due to the required iterative optimization schemes) and the sensitivity of the results to the model parameters.

The most used approach in segmentation of medical images is the level set method ((Cremers et al., 2005)). Level set is an optimization based method. A segmentation of the image plane Ω is computed by locally minimizing an appropriate energy functional $E(C)$ by evolving the contour C of the region to be segmented starting from an initial contour. In general, method based on this approach may use either an explicit (parametric) or implicit representation of the contours. In explicit representations ((Leitner and Cinquin, 1991), (McInerney and Terzopoulos, 1995)) – such as splines or polygons – a contour is defined as a mapping from an interval to the image domain: $C : [0,1] \rightarrow \Omega$. In implicit contour representations ((Dervieux and Thomasset, 1979), (Osher and Sethian, 1988)), contours are represented as the (zero) level line of some embedding function $\phi : \Omega \rightarrow \Re$:

$$C = \{x \in \Omega | \phi(x) = 0\}.$$

In the original level set algorithm, only gradient information is taken into account in the energy term $E(C)$. Some authors ((Osher and Santosa, 2001), (Chan and Vese, 2001), (Russon and Paragios, 2002)) have proposed improvements of the classical algorithm by introducing some priors information (e.g. shape, color or motion information).

Level set algorithms are widely used in medical images segmentation because they are very effective. However they present some drawbacks:

- The segmentations obtained by a local optimization method are strongly dependent to the initialization. For many realistic images, the segmentation algorithm tends to get stuck in undesired local minima (especially in the presence of noise) forcing the user to try with several seed points before obtaining a satisfactory solution.
- This approach lacks a meaningful probabilistic interpretation. Extensions to other segmentation criteria such as color, texture or motion are not straight-forward.
- This algorithm has a problem in finding correct contours of the regions when the region boundaries have corners or other singularities.

In this paper we present a novel algorithm based on level set that overcomes the first of the considered problems.

3 THE PROPOSED METHOD

To reduce the limits of level set standard algorithm we propose the follow improvements for the segmentation:

- an image smoothing filter is used to reduce the noise;
- an image pre-segmentation is performed to make the results independent of the chosen seed points;
- the final segmentation is based on the Laplacian level set, to enhance the contour of the tissue of interest.

In the following subsections, each of these steps is discussed in more detail.

3.1 Smoothing Filter

One of the main problems in MR image processing is the noise. To reduce this problem a 3D Gaussian filter, with a 3x3x3 kernel, is applied to the image before the segmentation step. The coefficients of the convolution mask are obtained according to the classical Gaussian distribution function. The size of the mask and σ have been empirically chosen. The latter value has been chosen by performing the mean of the variances among all the 3x3x3 sub images within a bone region of a set of training images. After this phase the resulting image is:

$$\begin{aligned} I_f(x,y,z) &= \frac{1}{\lambda}[I(x,y,z) * G_\sigma(x,y,z)] = \\ &= \frac{1}{\lambda}\sum_{i=-1}^{1}\sum_{j=-1}^{1}\sum_{k=-1}^{1} I(x,y,z)G_\sigma(i,j,k) \end{aligned}$$

where $\lambda = \sum_{i=-1}^{1}\sum_{j=-1}^{1}\sum_{k=-1}^{1} G_\sigma(i,j,k)$.

The smoothing filter has two positive effects: it reduces the image noise and the corners are less evident.

3.2 Image Pre-segmentation

The base level set algorithm strongly depends on the choice of the seed point. The reasons of this problem depend from the minimization of the energy functional; in fact it is possible to stop the process in a

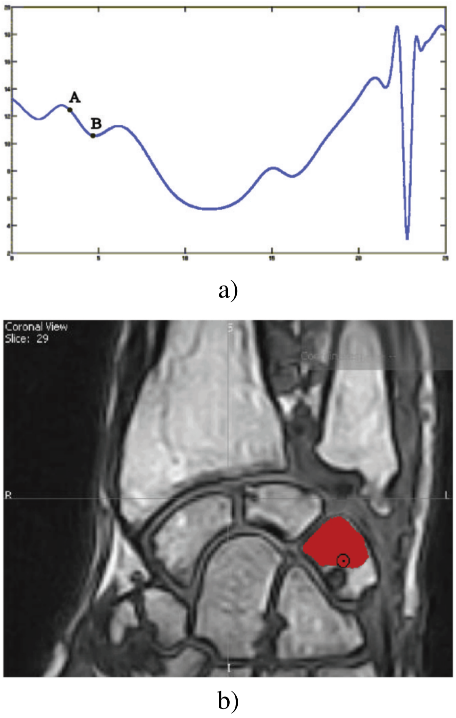


Figure 1: The effect of the seed point on the segmentation: a) Energy function diagram showing the energy of the seed point A and of the found (local) minimum B (the diagram is a 2D projection of the actual 3D diagram); b) Segmentation result.

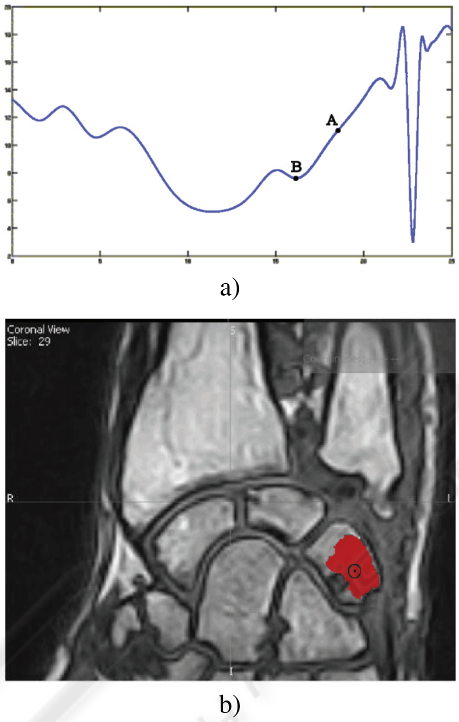


Figure 2: The segmentation obtained on the same image of fig. 1, starting from a different seed: a) Energy function diagram showing the energy of the seed point A and of the found (local) minimum B (the diagram is a 2D projection of the actual 3D diagram); b) Segmentation result.

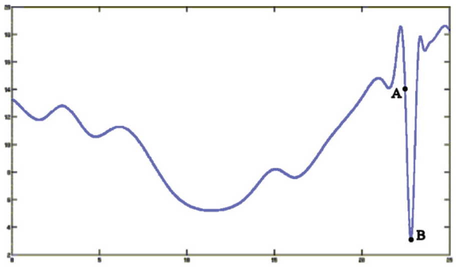
local minimum distant from a global minimum. The process start from a initial condition; in our application the segmentation with the base level set algorithm can evolve to very different solutions from different, but very close, seed points.
In figure 1 the point A indicates the initial condition of the energy function when we choose the seed in figure 1b , while the point B indicate the result of the minimization of the energy function. The point A and B in figure 2a have the same meaning for seed in figure 2b. We can note that choosing two close seed points we have two very different results of the segmentation process.
To reduce this dependence we introduce a pre-segmentation phase using a fast but not much effective algorithm which does not depend on the energy function. In this way we will use a larger region instead a single point for the initial condition. The created seed region produces an initial value of the energy function that is close to the global minimum independently from the point chosen by the user (see figure 3).
We tried two different algorithms for this phase: region growing (Adams and Bischof, 1994) and fast marching (Zhang et al., 2007). The results of both algorithms are similar, so we have chosen the first because of its minor computational cost. Moreover it has a small number of parameters with respect of fast marching algorithm.
In this phase, in order to avoid merging between regions of different tissues, the pre-segmentation algorithm parameters must be tuned so as to prefer over-segmentation to under-segmentation.

3.3 Laplacian Level Set

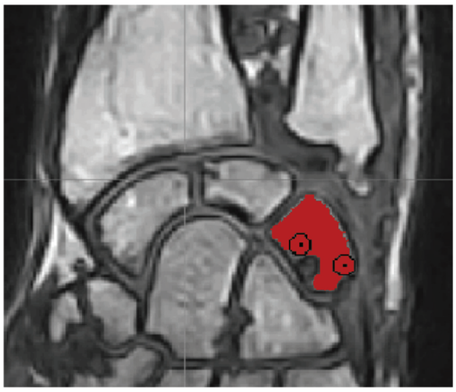
The smoothing filter reduces the corner problems, but at the same time it reduces the contrast of the image causing the loss of information for the contour of the tissue of interest. This effect generates the classic under-segmentation problem.
To avoid the under-segmentation problems a derivative filter is applied at the image to evidence the contours of the bone. The used filter is the Laplacian so defined:

$$\nabla^2 f(x,y,z) = \frac{\delta^2 f(x,y,z)}{\delta x^2} + \frac{\delta^2 f(x,y,z)}{\delta y^2} + \frac{\delta^2 f(x,y,z)}{\delta z^2}$$

The filtered image enhances the contours (see Fig. 4) and becomes the input image of the level set algo-



a)



b)

Figure 3: Minimum with pre-segmentation: a) Energy function diagram b) Segmentation result.

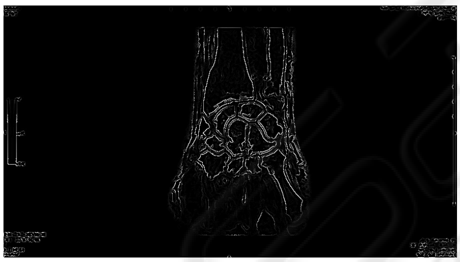


Figure 4: Output image of the Laplacian operator.

rithm. After the application of the filter, the energy term $E(C)$ to minimize (see Section 2) becomes the follow:

$$\begin{aligned} E(C) &= \int_{C_{inside}} (u(x,y,z) - \mu_{inside})^2 dxdydz + \\ &+ \int_{C_{outside}} (u(x,y,z) - \mu_{outside})^2 dxdydz \end{aligned}$$

where $u(x,y,z)$ is the intensity of the filtered image.

4 EXPERIMENTAL RESULTS

To evaluate the results of the proposed algorithm we used the *precision* and *recall* index so defined:

$$precision = \frac{TP}{TP+FP}$$

$$recall = \frac{TP}{TP+FN}$$

where TP is the number of correctly detected objects of interest, FP is the number of wrongly detected objects of interest and FN is the number of missed objects of interest. These indexes are directly usable for applications where the objects of interest are either completely detected or completely missed. In our application, instead, the objects of interest are not atomic regions, so we need to consider also partial recognition of the tissue of interest. For this reason TP, FP and FN are so defined:

$$TP = \frac{|g \cap d|}{|g \cup d|}$$

$$FP = \frac{|d| - |d \cap g|}{|d|}$$

$$FN = \frac{|g| - |d \cap g|}{|g|}$$

where g is the set of voxels actually belonging to the region of interest (ground truth), d is the set of voxels detected by the algorithm and $|\cdot|$ denotes the cardinality of a set. It is simple to show that when the object of interest is perfectly detected $precision = 1$ and $recall = 1$; instead when the detection is totally incorrect $precision = 0$, and $recall = 0$.
The algorithm has been tested on 11 MRI of wrists acquired at low field for a total of 762 bi-dimensional slices. The ground truth has been manually traced by medical experts.
We compare the proposed algorithm (LLS) with basic level set algorithm (BLS) and with basic level set with pre-segmentation module (PLS). We also compare our algorithm with another algorithm: Geodesic Active Contours (see (Caselles et al., 1997) and (Yan and Kassim, 2006)). Geodesic Active Contours (GAC) based algorithms are similar to Level Set based algorithms, but the first are motivated by a curve evolution approach and not by an energy minimization one. Comparison between GAC and our algorithm is more suitable than comparison with only Level Set based algorithms because GAC are less sensitive to initial parameters. Also for GAC algorithm we present both basic algorithm and algorithm with pre-segmentation module (PGAC).

In the following table we report the results:

Table 1: Experimental Results.

	Precision	*Recall*
BLS	0.81	0.89
PLS	0.92	0.94
GAC	0.95	0.89
PGAC	0.99	0.90
LLS	**0.99**	**0.94**

For the algorithm BLS we have manually searched the best seed point and we have often changed the calibration parameters. The results shown in table 1 are performed considering the best segmentation obtained for any image. It is important to note that we are not sure that the chosen seed is really optimal in the mathematical sense.
Even if the algorithm could in theory produce better results, in practical use it is not possible to proceed in this way because of the high effort in the calibration phase and because of an uncertainty factor on the results. So we apply the pre-segmentation step also to the BLS algorithm, to compare this latter with our proposal independently of the chosen seed.
In conclusion it is important to remark that the idea of the pre-segmentation phase is necessary for the result repeatability. Furthermore the Laplacian operator improve the precision of the results (see table 1).
Under-segmentation problem is present in an algorithm with a low value of precision. This is the case of BLS: the basic algorithm is not able to recognize blurred contours (often presents in RM images). With our pre-segmentation module all algorithms improve their results with respect of the precision index.
The algorithms with a low value of recall present over-segmentation problems. Table 1 shows that BLS, GAC and PGAC are over-segmenting.
We can conclude that Geodesic Active Contours based approaches are very effective to find tissues contours, but they often present missing voxels within the tissue: these approaches are very sensitive to brightness variability. Level Set based approaches are not able to find blurred contours: in these approaches local information give weak contribution to the final solution.
In any case, Table 1 shows that our approach is more effective than all others. To have a visual idea of the effectiveness of our proposed algorithm, in Fig. 5a and Fig. 6a, Fig. 5b and 6b, Fig. 5c and Fig. 6c results of the application of Basic Level Set with pre-segmentation phase, Geodesic Active Contours with pre-segmentation phase and Laplacian Level Set are respectively shown. Note that the images result of the PLS algorithm, obtained after a difficult calibration phase, is not able to avoid the under-segmentation

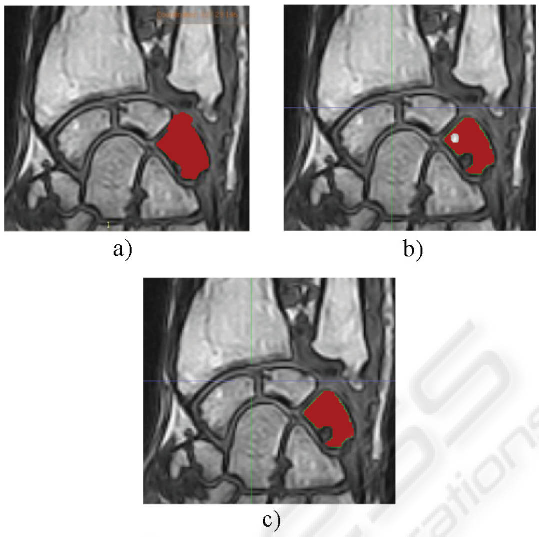


Figure 5: a) Basic Level Set with pre-segmentation; b) Geodesic Active Contours with pre-segmentation; c) Laplacian Level Set.

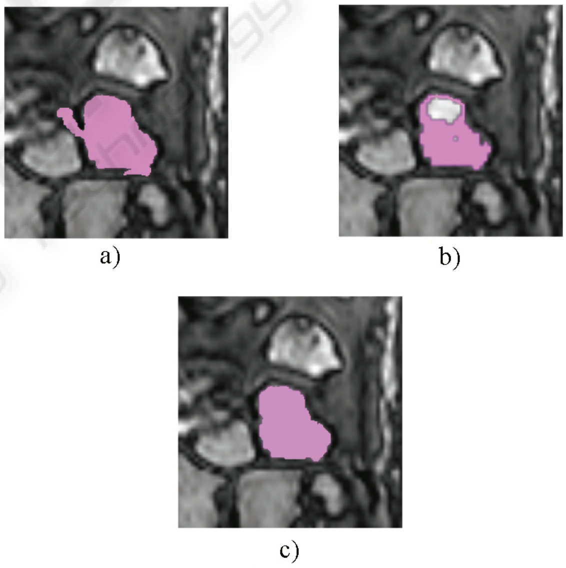


Figure 6: a) Basic Level Set with pre-segmentation; b) Geodesic Active Contours with pre-segmentation; c) Laplacian Level Set.

problem and the images result of PGAC algorithm presents some holes within the tissue.

5 CONCLUSIONS

A new algorithm for segmenting MR images is proposed. The algorithm is based on the level set approach and is conceived to overcome some of the difficulties of the original level set method: the solution is repeatable as regard as changes in initial conditions and the precision of the result is very high. This algorithm can be used for many applications in the field of Computer Aided Diagnosis.
Currently we are working on the extension of the experiments to assess the results. Then we will analyse the new results to find other improvements to the described method.

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