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An Enhanced Level Set Algorithm for Wrist Bone Segmentation

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1. Introduction

In the last decades there was a growing interest in designing CAD devices for medical imaging: the main role of these system is to acquire the images, generally TAC or RMI, and to display the parts of interest of human body on suitable visual devices, after some pre-elaboration steps aimed to improve the quality of the obtained images. A TAC or a MRI sequence, obtained as a result of a scan process of the interested parts of the human body is a generally wide set of 2D gray-level images, seen as the projection of the body into three different coordinate planes. Starting from these sequences it is rather difficult, for the radiologist, to imagine the whole appearance of the body parts, since without a 3D model of each part it is only possible to browse the images in the three planes independently.
In this framework, the most challenging task remains that of extracting, from the whole images, a 3D model of the different parts; such a model would be important not only for visualization purposes, but also for obtaining quantitative measurements that could be used as an input to the diagnostic process.
Even if the pre-processing step of the acquired images plays a key role in the achievement of a good visualization quality, the literature is today so rich of papers describing procedures aimed to increase the signal/noise ratio that this problem can be now considered as definitely solved. So, the attention of researchers is nowadays concentrated on the definition of robust methods for the 3D segmentation. In the case of Magnetic Resonance Images (MRI), the segmentation is made complex by the unavoidable presence of inhomogeneity in the images, as well as the presence of image distortions.
Despite the research efforts and the significant advances achieved in recent years, the image segmentation problem still remains a notoriously known challenging problem, especially in the case of poor quality images. In particular, the segmentation of MR images is made even more complex, by the complexity of the shapes of the parts to be segmented, and by the lack of suitable anatomical models able to fully capture all the possible shape variations for each of them. These models can provide, if suitably exploited, important information: for bone tissues it is relevant the knowledge about the shape and the size of the synovial parts, devoted to connecting bones: their characterization allows the scientist to choose the most appropriate technique for a correct segmentation. Namely, synovia appears in the images as a darker surface surrounding the bones; its presence is fundamental for the correct segmentation, since often the bone tissues and the adjacent cartilagineous tissues have similar intensity levels, and would be indistinguishable without the synovia.

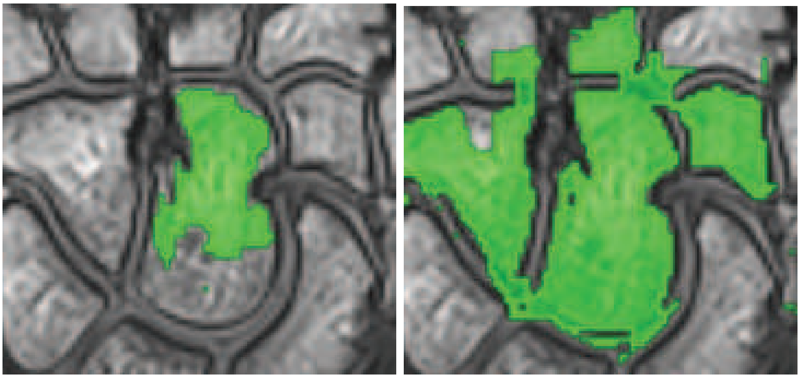


Fig. 1. The effect of the similarity threshold on region growing segmentation. a) A threshold too low produces an over-segmentation. b) A threshold too high produces an under-segmentation.

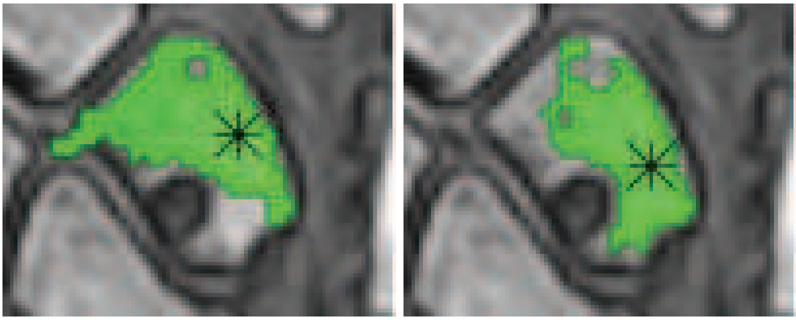
The simplest segmentation approaches are those based on a thresholding applied to each pixel (or voxel) on its intensity values: they result to be generally uneffective in the case of an MR image: the segmentation results are in fact very poor, as the intensity levels of the pixels of bones and the synovia are quite similar, so causing the undersegmention of some regions contemporarily to oversegmented areas. A threshold, appropriate for reaching the solution all over the image is practically impossible to be determined. More complex solutions, based on partitioning of the image in different parts, on which different values of the thresholds, in the experience of the authors, can perform better but the results are far from satisfying the radiologist.
An other class of segmentation algorithms are those based on the well known region growing paradigm. A point, surely belonging to the area to be segmented, is given as input by the user, and considered as a seed: the pixels adjacents to the seed are considered as belonging to the region to be segmented, if their intensity values are similar to that of the seed: the similarity is suitably defined on the application domain and generally a threshold is applied to determine wether two pixels are similar or not. The process is iterated for the last added pixels until, at the given step, no further pixel is added to the region. Although different variants of this class of algorithms have been developed along the years, their rationale is that of expanding the regions on the basis of their homogeneity. Their application in all the cases in which foreground and background have little gray level differences can results in over-segmentation problems. Figure 1 highlights these effect on a wrist bone, with two different similarity thresholds, so demonstrating the difficulty of obtaining effective results in a practical case.
More recently, some approaches, based on the attempt of facing the segmentation approach by a classification system, have been proposed. The rationale of these methods is aimed to obtaining algorithms able to work without the interaction with the radiologist: they perform the training of the classifier on a suitably built training set of pixels and, once adequately trained, classify the pixels of the image as belonging to a foreground area or to the background. In this way, the interaction with the radiologist, if any, is required in the training phase. The simplest implementations of this class of methods is based on the k-nearest-neighbor, as

in Vrooman et al. (2007), where brain tissues are segmented; the k-NN classifier is trained automatically using an a priori model of the brain provided by a brain atlas. Another approach of this kind is based on Bayes classifiers Banga et al. (1992); in particular in the cited article the segmentation of the retina is performed using an unsupervised Bayesian classifier whose parameters have been estimated using the Expectation-Maximization algorithm. In spite of their simplicity and their low computational cost, their intrinsic nature does not allows them to take into account spatial information, so making them unprofitable in all those cases in which the latter information is crucial for the final result, as in the case of bone tissues.
A further class of segmentation algorithms are those based on (unsupervised) clustering techniques. The three most used clustering techniques are the K-means, the Fuzzy C-means and the Expectation-Maximization algorithm. An example of the use of K-means is Vemuri et al. (1995), that performs the segmentation of brain MR images by clustering the voxels on the basis of wavelet-derived features. Two papers using the Fuzzy C-means clustering are Ardizzone et al. (2007), that is also applied to brain MR images, and Foggia et al. (2006), that is applied to mammographic images. Finally, in Wang et al. (2005) a clustering method based on the Expectation-Maximization algorithm is used for segmenting brain images showing a greater robustness with respect to the noise due to field inhomogeneity.
The algorithms discussed so far assume that the intensities of each voxel class are stationary: this assumption does apply only on limited sets of images, due to the intrinsic heterogeneity of a class, the nonuniform illumination, or other imaging artifacts. So, to take into account spatial information, recently some approaches based on the use of the Markov Random Field (MRF) Models have been used, as in Ruan & Bloyet (2000) and Krause et al. (1997). The idea behind them is that, in the case of biomedical images, the probability of a pixel to belong to a class is strongly related to the values of the surrounding pixels, as rarely the anatomical parts are composed by just 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 (Cremers et al. (2005)), based on an optimization apprach. 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 & Cinquin (1991), McInerney & 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 & Thomasset (1979), Osher & 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 & Santosa (2001), Chan & Vese (2001), Russon & 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



a) b)

Fig. 2. The effect of the seed point on Level Set segmentation. Between a) and b), a slight change of the seed point determines a different segmented region shape (the seed point in the image is indicated by the star-like cursor).

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 Ű such as color, texture or motion Ů 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 a recent paper (Conte et al. (2009)) we presented a new algorithm that overcomes the first of the considered problems. In this paper we propose a significant improvement, especially with respect to the last problem (that is still an open problem in the literature).
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. Important

Manuscript must contain clear answers to following questions: What is the problem / What has been done by other researchers and where you can contribute / What have you done / Which method or tools you used / What are your results / What is new and good, what is not good / Future research

3. The proposed method

As we have seen, every segmentation approach has its strenght and its weak points. Our proposal is to base the segmentation on the integration of two complementary approaches: region growing and level set segmentation.
Region growing has problems with local noise, especially on the boundary of the region to be segmented, and has a strong dependency on a similarity threshold, leading to either over-segmentation (if the threshold is chosen conservatively) or under-segmentation (if the threshold is chosen to capture as much as possible the shape of the region). But neither of those problems affect the level set algorithm.

On the other hand, level set has a strong dependency on the choice of the seed point, as shown in fig. 2, and also may have problems where the region boundary has some singularity (e.g. a sharp corner). Region growing instead is fairly immune to both those problems. So, region growing and level set segmentation appear to complement each other with respect to their strenght, and this is the reason why we have chosen to combine them into a technique that should overcome the limitations of both.
Basically, our method is composed of the following steps:

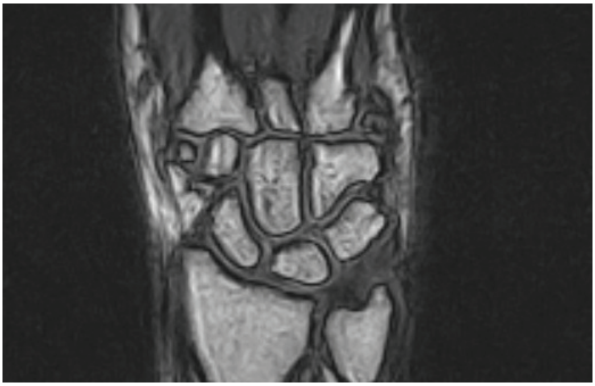
- first, a smoothing of the image is performed using a low pass filter; this step is related to the use of the Laplacian Level Set variant of the level set technique, as we will discuss later;
- then a pre-segmentation is realized using region growing, to obtain a rough, conservative estimate of the region;
- the result of the pre-segmentation is used to initialize the proper segmentation, performed by means of a level set algorithm; in this way the result of the level set algorithm is not dependent on the choice of the seed point;
- finally, a local contour refinement, based again on region growing, is applied in order to better fit the contour to sharp corners and other singularities.

Each of these steps will be described with more detail in the following subsections. As an illustration of the different steps, we will present their effect on an example image, shown in figure 3.

3.1 Smoothing filter

The region growing technique used for the pre-segmentation step is highly sensitive to pixel-level noise. So it is important to remove this kind of noise before the pre-segmentation.
Moreover, for the proper segmentation step, we have used a variant of the level set technique called Laplacian Level Set (LLS), introduced in Conte et al. (2009). The LLS algorithm performs a Laplacian filter on the image to enhance the boundaries of the regions; but a side effect of the Laplacian filter is a magnification of the high-frequency noise components. Hence, the denoising is important also for the LLS segmentation.
In order to remove the noise we have used a Gaussian smoothing filter, which is a well known low-pass filter widely used in the image processing field.
The use of a low-pass filter may seem contradictory with the goals of a segmentation algorithm: if the algorithm has to determine the sharp edges that form the boundary of the regions, it may be thought that by smoothing those very edges should make the task of the algorithm more complicated. However, the following factors should be considered:

- by carefully choosing the filter cutoff frequency, the filter can cancel out only the intensity variations that are due to noise, while the ones due to the boundaries between regions will only be a little bit blurred
- the pre-segmentation process needs only to find a reasonable approximation of the region, so it can easily be tuned to be unaffected by the blurring of the region boundary; on the other hand it greatly benefits from the reduction of the pixel level noise achieved by the low-pass filter
- the proper segmentation process will apply a laplacian filter to the image; the net effect of the combination of the low-pass and laplacian filter is that of a band pass filter that, by virtue of the choosen cutoff frequency, will preserve exactly the variations whose spatial frequency correspond to the boundaries between the regions.



a)

b)

Fig. 3. An example image, that will be used to illustrate the different steps of the proposed algorithm. What is actually shown is a 2D slice of the 3D MR image. a) The original image. b) A zoomed image of the bone that will be the target for the segmentation.

Fig. 4. The result of the application of the Gaussian filter to the image of fig. 3b.

The Gaussian filter introduces a parameter σ, related to the cutoff frequency, that needs to be tuned for obtaining an adequate performance. However the optimal value of σ depends only on the resolution of the image and the size of the smallest features of interest in the segmented region. Hence, for a given MRI machine and anatomical district, the tuning of σ has to be performed only once.
Figure 4 shows the effect of the gaussian filter on our example image.

3.2 Image pre-segmentation

The level set technique starts with a tentative contour of the region to be segmented, and makes this contour evolve so as to reach a (local) minimum of a suitably defined energy function. The usual approach for initializing the contour is to choose a small sphere around the user selected seed point.
However, especially if the shape of the target region is complex, starting with a contour that is so different from the desired one may easily lead the algorithm to a local minimum that does not correspond to the ideal segmentation. Furthermore, this local minimum strongly depends on the choice of the seed point, making it difficult to have a repeatable result for the segmentation process.
On the other hand, if the level set algorithm starts from a tentative contour that is reasonably close to the true boundary of the region, it usually converges without problems to the desired minimum of the energy function.
In order to provide such an initial contour, our method performs a pre-segmentation step. In this step, our system attempts to segment the region of interest using a region growing technique Adams & Bischof (1994). In region growing, basically, the algorithms starts with a

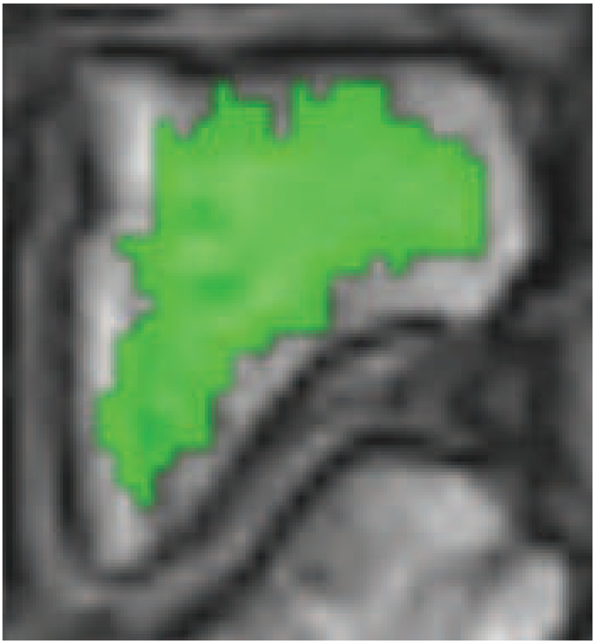


Fig. 5. The result of the pre-segmentation on the image of figure 3b

tentative region formed by the seed point alone; and then repeatedly add adjacent voxels as long as their intensity is within a threshold θ from the average intensity of the region built so far.
The tuning of θ is one of the most delicate aspects of region growing, since a value too tight will not make the algorithm cover the whole region (over-segmentation), while a value too loose would cause extra parts to be included in the region (under-segmentation).
However, since we are using region growing only as a pre-segmentation step, we do not need to find the optimal value for θ. We just need to be sure to "err on the safe side", in the sense that the algorithm should not produce an under-segmentation. This is necessary because the level set algorithm can expand the contour, but cannot contract it.
So, also the tuning of θ can be done once for a given MRI machine/anatomical district combination, instead of adjusting this parameter for each different image.
As an alternative to region growing we have also tried the fast marching technique Zhang et al. (2007) for pre-segmentation. The results of both algorithms are similar, but fast marching is slower than region growing, and has more parameters to be tuned. Hence, we have decided to adopt region growing.
The pre-segmentation of our example image is shown in figure 5.

3.3 Laplacian Level Set

The current trend in MR imaging is towards the reduction of the intensity of the magnetic field to which the patient is exposed, in order to obtain a reduction in the costs but also in the weight and and space occupied by the MRI machines. At the same time, the acquisition time

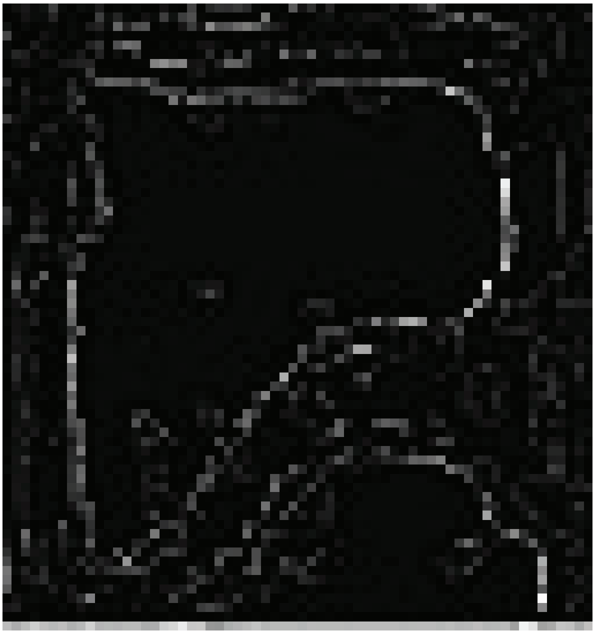


Fig. 6. The result of the Laplacian filter applied to the example image of figure 3b.

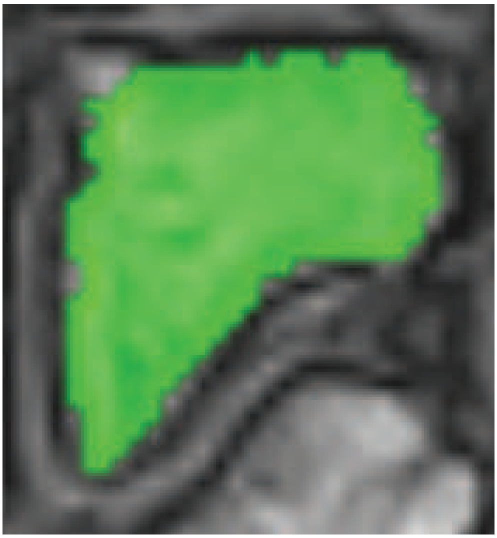


Fig. 7. The result of the Laplacian Level Set segmentation applied to the example image of figure 3b.

has to be kept short, since during the scan the patient has to remain still, and so the MRI exam would be too uncomfortable if it were too long.
As a result, the contrast between different tissues is often quite low, and this can cause problems to any segmentation algorithm. In order to overcome this issue, in Conte et al. (2009) the so called Laplacian Level Set (LLS) algorithm has been proposed. The LLS algorithm is based on the use of the Laplacian filter, defined as:

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

where $f(x,y,z)$ is the intensity of the voxel at position (x,y,z). Actually, a discrete approximation of the filter is used. The filtered image enhances the contours of the regions, as exemplified (on a 2D slice of the image) in Fig. 6.
The algorithm operates on the filtered image, starting with a contour surface C that is initialized as the contour of the region found in the pre-segmentation step, and evolving it in order to minimize an energy function $E(C)$ which is defined as:

$$\begin{aligned} E(C) = &\int_{V_{in}(C)} (u(x,y,z) - \mu_{in}(C))^2 dxdydz + \\ &+ \int_{V_{out}(C)} (u(x,y,z) - \mu_{out}(C))^2 dxdydz + \\ &+ k\frac{|C|}{|V_{in}(C)|} \end{aligned} \tag{1}$$

where

- $V_{in}(C)$ is the region inside C
- $V_{out}(C)$ is the region outside C
- $u(x,y,z)$ is the intensity of the filtered image
- $\mu_{in}(C)$ and $\mu_{out}(C)$ are the average value of $u(x,y,z)$ over $V_{in}(C)$ and $V_{out}(C)$ respectively
- $|C|/|V_{in}(C)|$ is the ratio between the area of C and the volume of $V_{in}(C)$, that acts as a regularization factor for the contour; this factor is weighted by the parameter k: a larger value for k makes the algorithm oriented towards smoother contours and more robust to noise, but also less able to follow sharp corners on the region boundary

The result of the LLS algorithm on our example image is presented in figure 7.

3.4 Local contour refinement

The last step of the algorithm starts with the contour C found by the Laplacian level set and tries to refine it to better fit the sharp corners that are usually smoothed out by the level set.
Namely, this refinement is performed using a limited form of region growing, that has no problem in following sharp corners. Since region growing is prone to under-segmentation, especially in low contrast images such as the ones produced by MRI, special care is taken in the definition of the stopping criterion to ensure that only small corrections to the contour C are performed.
More formally, the voxels adjacent to C are examined and are added to the contour iff:

$$|f(x,y,z) - f(n(x,y,z,C))| < \theta'/d(x,y,z,C) \tag{2}$$

where:

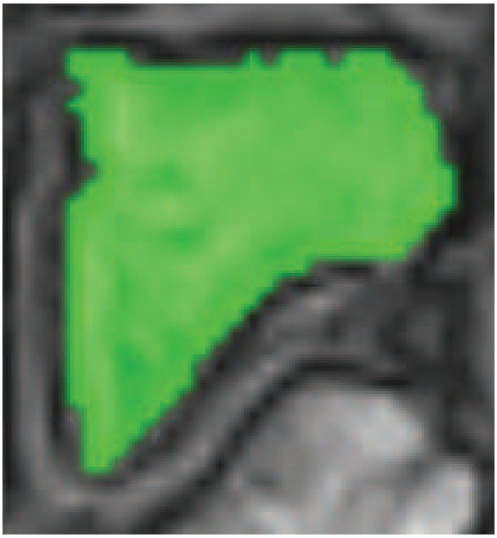


Fig. 8. The result of the local contour refinement applied to the segmentation shown in figure 7.

- $f(x, y, z)$ is the intensity value of the considered voxel of coordinates (x, y, z)
- $n(x, y, z, C)$ is the position of the voxel in C that is the nearest to (x, y, z); so $f(n(x, y, z, C))$ is the intensity of this voxel
- $d(x, y, z, C)$ is the Euclidean distance between (x, y, z) and $n(x, y, z, C)$
- θ' is a suitably defined threshold

The division of the threshold θ' by $d(x, y, z, C)$ ensures that this refinement step will never extend too much the initial contour C. In particular, this extension is performed on a local basis, only where the adjacent pixels are very similar to the ones already in C.
Figure 8 shows the effect of the local contour refinement algorithm on our example image, starting from the segmentation presented in figure 7.

4. Experimental results

The algorithm has been tested on 11 MRI sequences of wrist bones acquired at low magnetic field, for a total of 762 bi-dimensional slices. The ground truth has been manually traced by medical experts.
We compare the proposed enhanced laplacian level set algorithm (ELLS) with the following algorithms:

- our previous algorithm (Laplacian Level Set, LLS);
- the basic level set (BLS)
- the basic level set with pre-segmentation module (PLS)
- Geodesic Active Contours (see Caselles et al. (1997) and Yan & Kassim (2006)); Geodesic Active Contours (GAC) algorithms are similar to Level Set algorithms, but the first are motivated by a curve evolution approach and not by an energy minimization one;

- Geodesic Active Contours with pre-segmentation module (PGAC).

The choice of Geodesic Active Contours for the comparison is motivated by the fact that also this family of algorithms, like our method, is fairly robust with respect to the choice of the seed point.
To evaluate the results of the proposed algorithm we used the *precision*, *recall* and *f-index* indices so defined:

$$precision = \frac{TP}{TP + FP}$$
$$recall = \frac{TP}{TP + FN}$$
$$f\text{-}index = \frac{2 \cdot precision \cdot recall}{precision + recall}$$

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.
The most commonly used definition of these indexes is directly usable for applications where the objects of interest are either completely detected or completely missed. In our application, however, the objects of interest are not atomic regions, so we need to consider also partial recognition of the tissue of interest. For this reason we have redefined TP, FP and FN in a fuzzy sense as follows:

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

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 (in the sense that all the voxels in the ground truth are detected, and no voxel outside of the ground truth is detected), then $precision = 1$ and $recall = 1$; on the other hand, if the algorithm detects voxels that do not belong to the ground truth, it will have $precision < 1$, and if the algorithm misses some of the voxels in the ground truth, it will have $recall < 1$.
In the following table we report the results, averaged over the 11 MRI sequences:

	Precision	*Recall*	*f-index*
BLS	0.81	0.89	0.85
PLS	0.92	0.94	0.93
GAC	0.95	0.89	0.92
PGAC	0.99	0.90	0.94
LLS	**0.99**	**0.94**	**0.96**
ELLS	**0.98**	**0.97**	**0.97**

Table 1. Experimental Results

Notice that for the BLS algorithm we had to perform the test changing both the seed point and the value of the parameter k of the Level Set energy function, since the algorithm did not provide adequate results for all the images with a single choice of these parameters. The other algorithms did not have this problem. It is important to remark that the idea of the pre-segmentation phase allows also the level set algorithm to overcome this problem.
Furthermore, the results presented in table 1 show that the Laplacian operator provides an important contribution to the improvement of the performance. Indeed, the two algorithms based on this operator (LLS and ELLS) achieve the best overall performance.
Algorithms that exhibit an under-segmenting behavior can be expected to obtain a low value of the precision index. This is indeed the case of the BLS algorithm, as it is evident from table 1.
On the other hand, algorithms with a tendence to over-segmentation attain a low value of the recall index. As shown in table 1, this happens for BLS, GAC and PGAC. Notice that the BLS algorithm can yield (depending on the input image) both an under-segmentation and an over-segmentation.
Table 1 shows that Geodesic Active Contours based approaches have a relatively low recall value. From a detailed analysis of the images it can be concluded that the while the boundary of the region is usually well approximated, the low recall is due to the fact that often these algorithms miss voxels that are internal to the region.
In conclusion, Table 1 shows that our approaches are more effective than all the others. In particular, the ELLS algorithm shows a significant improvement in the recall index. A good recall index (together with a good precision) is important for applications that use the segmentation as the basis for quantitative measurements, e.g. for diagnostic purposes.
To have a visual idea of the effectiveness of our proposed algorithm, in Fig. 9 the results of each segmentation algorithm are shown.
Note that the result of the PLS algorithm, even after a difficult calibration phase, is not able to avoid the under-segmentation problem. Also notice that the result of the PGAC algorithm presents some holes within the tissue.
The comparison between fig. 9f and fig. 9g, and between fig. 9f and fig. 9g, demonstrates how the new ELLS algorithm is able to segment correctly the sharp corners of the tissue, overcoming the problems of our previous method.

5. Conclusion

In this paper we propose a novel segmentation method for MRI images, that is based on the integration of two complementary techniques: region growing and level set segmentation. Each technique is used at a different stage of the segmentation process, and the results are combined in such a way as to obtain a final segmentation that is not affected by the problems and limitations of both techniques when used alone.
The new method is robust with respect to the choice of the initial seed and to the setup of the (few) parameters, yielding repeatable results; furthermore, its performance is high in terms of both the precision and recall indices, as we have demonstrated experimentally, resulting appropriate for Computer Aided Diagnosis applications that need accurate quantitative measurements.

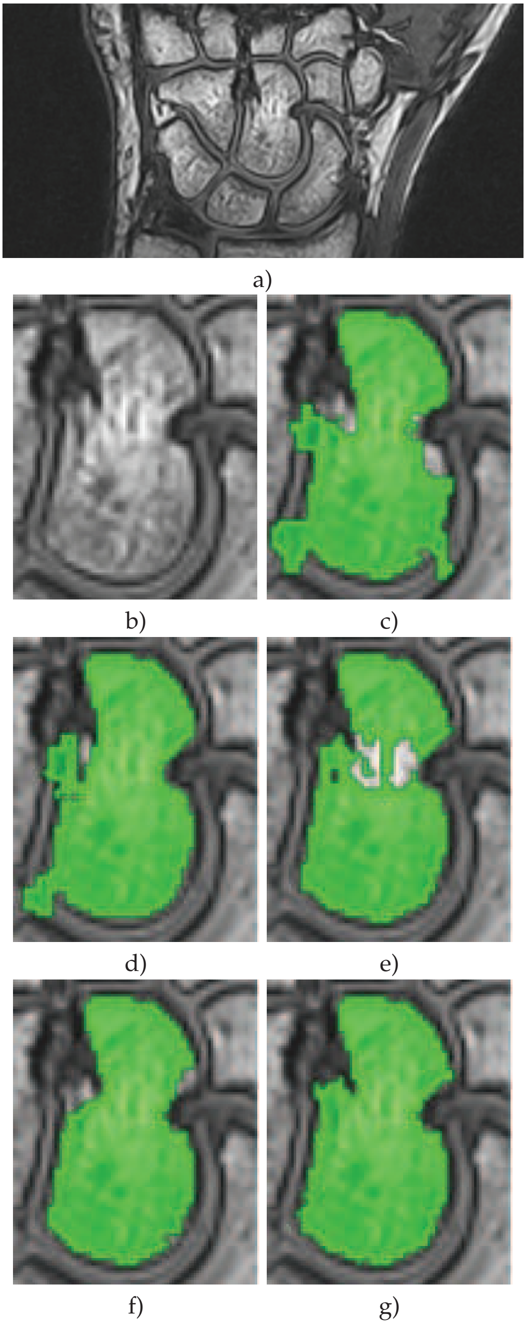


Fig. 9. An example of the segmentation obtained by the tested algorithms (only a 2D slice is presented). a) Original image. b) A zoomed image of the region of interest. c) Basic Level Set segmentation (BLS). d) Level Set with Pre-segmentation (PLS). e) Geodesic Active Contours (GAC). f) Laplacian Level Set (LLS). g) Extended Laplacian Level Set (ELLS).

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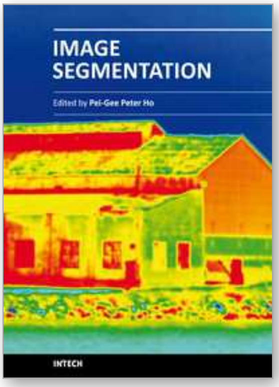

Image Segmentation

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It was estimated that 80% of the information received by human is visual. Image processing is evolving fast and continually. During the past 10 years, there has been a significant research increase in image segmentation. To study a specific object in an image, its boundary can be highlighted by an image segmentation procedure. The objective of the image segmentation is to simplify the representation of pictures into meaningful information by partitioning into image regions. Image segmentation is a technique to locate certain objects or boundaries within an image. There are many algorithms and techniques have been developed to solve image segmentation problems, the research topics in this book such as level set, active contour, AR time series image modeling, Support Vector Machines, Pixon based image segmentations, region similarity metric based technique, statistical ANN and JSEG algorithm were written in details. This book brings together many different aspects of the current research on several fields associated to digital image segmentation. Four parts allowed gathering the 27 chapters around the following topics: Survey of Image Segmentation Algorithms, Image Segmentation methods, Image Segmentation Applications and Hardware Implementation. The readers will find the contents in this book enjoyable and get many helpful ideas and overviews on their own study.

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