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Medical Image Segmentation Using Modified Active Contour Method

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Abstract: Image data is of major practical importance in medical informatics. Accurate segmentation of medical images largely determines the final result of image analysis, which provides significant information for 3D visualization, surgical planning and early detection of diseases. In this paper, a modified segmentation approach based on the active contour method is proposed to extract parts of bones from MRI data sets. The efficiency of the method is verified on real MRI slices. Good results are shown in comparison with existing approaches of segmentation of medical data.

Keywords: Magnetic Resonance Imaging (MRI), Segmentation, Anisotropic Gradient, Active Contour, Region-based Active Contour, Medical Images.

1 Introduction

Medical imaging is currently at the forefront of diagnostics. Improved health care policy and increasing availability of medical equipment lead to increased use of computer imaging (CT) and magnetic resonance imaging (MRI) for diagnosis, treatment planning and clinical research. In many cases, CT and MRI are compulsory procedures for establishing the correct diagnosis and treatment. The current progress in the development of mathematical methods in medicine and computer technology is characterized by an increase in the number of global methods for processing digital images. Nevertheless, despite the fact that modern imaging devices provide exceptional views of internal anatomy, the use of computers to quantify and analyze the embedded structures with accuracy and efficiency is limited. The accuracy of clinical diagnoses depends critically upon image quality, the higher is the quality, the more accurate is the diagnosis [1, 2].

Medical imaging is the production of visual representations of tissues, parts or functions of certain body organs using high-energy modalities (for example,

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X-rays, ultrasound, magnetic resonance, and tomography) for clinical diagnosis. This technique is aimed at non-invasive detection of internal structures hidden by the skin and bones. Medical imaging also establishes a database of normal anatomy and physiology making it possible to identify abnormalities [3]. Magnetic resonance imaging (MRI) – is a medical imaging technique that uses a powerful magnetic field to align hydrogen atoms in the body, radiofrequency fields and magnetic field gradients are then used to build up images from the signals retuned by rotating hydrogen nuclei [4]. Magnetic resonance imaging (MRI) provides information about the body cavity in a special form, which allows identifying problems that in many cases cannot be detected by other modalities of X-ray, ultrasound or computed tomography (CT). This type of medical imaging makes images of slices of the human body in three projections (sagittal, frontal, and axial).

The eventual result of image analysis is largely determined by the quality of segmentation, and the degree of detail of the extracted characteristics depends on the specific task. Thus, segmentation of images is the most important process for most medical analysis tasks. Such a process is difficult because of the huge size of the data sets, the complexity and variability of the anatomical structures of interest. Also, obtaining these musculoskeletal models from sets of MRI slices requires manual segmentation, which is an extremely labour-intensive and time-consuming process; for example, segmentation of the hip bone can take up to several hours. The challenge of segmentation is to extract boundary elements belonging to the same structure. Automatic segmentation will benefit to create a variety of musculoskeletal models. The accuracy of segmentation is very important; as it provides significant information for three-dimensional visualization, surgical planning and early detection of diseases, as well as for various applications in medical field, particularly for 3D printing [5].

To extract areas of interest in the image, there are many segmentation methods based on the following dimensions: color, grey values, depth, motion, texture, discontinuity, and similarity.

Main methods of region segmentation are: edge detection, region growing, clustering, split and merge and active contour methods. The techniques available for segmentation of medical images are specific the application, imaging modality and type of body part to be studied; this should be taken into account. For example, requirements of brain segmentation are different from those of thorax.

Snakes or active contour methods have become very popular in recent years, and have found applications in a wide range of problems including visual tracking and image segmentation [6 – 8]. Active Contour Model first introduced by Kass, Witkin, and Terzopoulos [9]. The basic idea is to allow a contour to deform to minimize a given energy functional to produce the desired segmentation [10 – 12].

The basic steps of snakes are:

– A higher-level process or a user initializes any curve close to the object boundary;

– The curve is deformed until it reaches the boundaries of the object;

– The resulting curve is completely "compressed" around the object.

The advantage of the active contour is the segmentation of the shape of various objects, which are not easily represented by rigid primitives. When segmenting medical data, it is difficult to obtain accurate representations of the same structures. An example is the representation of a vein, which cannot be accurately represented. The active contour is divided into two main types: edge-based and region-based (Fig. 1).

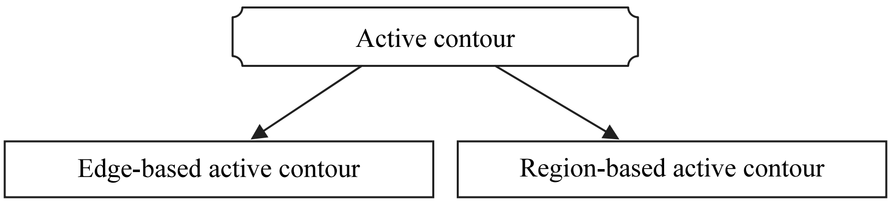


Fig. 1 – *Key active contour methods classification.*

Edge-based active contour models proposed in [13 – 14] utilize image gradients to identify object boundaries. This type of highly localized image information is adequate in some situations. The main drawbacks of this method are the considerable sensitivity to image noise and indistinguishable edges. Modern researches, inspired by the region-competition work Zhu and Yuille [15], describe the active contour method based on regional flows. These approaches model the foreground and background regions statistically and find an energy optimum where the model best fits the image. There is an energy optimum where the model is best fits in the image. The most well-known and widely used region-based active contour models set a constant intensity to different areas [16 – 17].

Region-based image segmentation is considered as a division of the image into regions or categories, which is similar to different objects or parts of the objects. This method attempts to partition or group regions according to common image properties, i.e. intensity values of the original image, or values computed based on an image operator. Chan and Vese [18] proposed the active contour model using a variation level set formulation. By incorporating region-based information into their energy functional as an additional constraint, their model has larger convergence range and flexible initialization.

In comparison with edge-based methods, region-based methods have resistance to the initial placement of the curve and insensitivity to image noise. These methods use the statistical information inside and outside the contour to control evolution. However, for segmentation of heterogeneous objects, such modelling of the region is not entirely suitable. From global statistics, region-based methods can lead to segmentation errors [19]. Heterogeneous objects frequently occur in the natural and medical imagery. To obtain accurate segmentation results, a new class of active contour energies should be considered, combining both local information and the advantages of regional methods.

The limitations of the traditional Snakes are:

– The Snakes algorithm is parametric, so it is extremely sensitive to parameters.
– It is very sensitive to the location of the original boundaries. The desired convergence depends on this. It is necessary to manually define a curve near the boundary of the object of interest, which leads to poor interactivity;
– Fails to detect the object contour with sunken regions;
– Sensitivity to noise, the curve can go over the edge (Fig. 2a);
– Smoothing miss edges in the presence of noise (Fig. 2b);
– Detects only objects with sharp edges defined by gradients (Fig. 2c).

(a) (b) (c)

Fig. 2 – *Weakness of traditional snakes.*

Images obtained by magnetic resonance imaging (MRI) introduce additional complexity for the exact automatic extraction of 3D components. This is described for the following reasons [20 – 22]:

– Objects of interest are usually of small size and low contrast compared to the surrounding background;
– Complex heterogeneous representation of anatomical structures;
– Inconsistencies: the external difference of bone tissue from each other is greater than from the surrounding muscle tissue;
– Presence of artefacts;
– Intensity inhomogeneity: highly inconsistent lighting in the MRI scanning workspace;
– Sophisticated identification of various tissue with weak contrast: low signal-to-noise ratio of MRI scans;
– Closeness in the grey level of different soft tissue.

The purpose of this work is to develop a segmentation algorithm to extract parts of bones from a set of magnetic resonance imaging (MRI) data with noise and boundaries, undetectable gradient.

2 Proposed Method

In this work, we use a novel active contour segmentation algorithm to extract the parts of bones from magnetic resonance imaging (MRI) data sets in the presence of noise and blurred edges. This is achieved using anisotropic gradient based on LPA-ICI (local polynomial approximation – intersection of confidence intervals).

We summarise the algorithm in the following scheme (Fig. 3):

Step 1: Define the initial contour.

Step 2: Define the anisotropic gradient.

Step 3: Define the energy function E.

Step 4: Derive the curve to minimise the energy (calculus of variations).

Step 5: Propagate the curves (gradient descent) to reach the minimum using level set (easier to implement in reality).

A snake is defined by a set of n points where $i=\overline{0,n-1}$, the internal elastic energy term, and the external edge-based energy term $E_{external}$. The purpose of the internal energy term is to control the deformations made to the snake, and the purpose of the external energy term is to control the fitting of the contour into the image. The external energy is usually a combination of the forces due to the image itself E_{image} and the constraint forces introduced by the user E_{con}. We use standard active contour definition of Energy Function. Contour possesses energy E_{snake} defined as the sum of the three energy terms [9]:

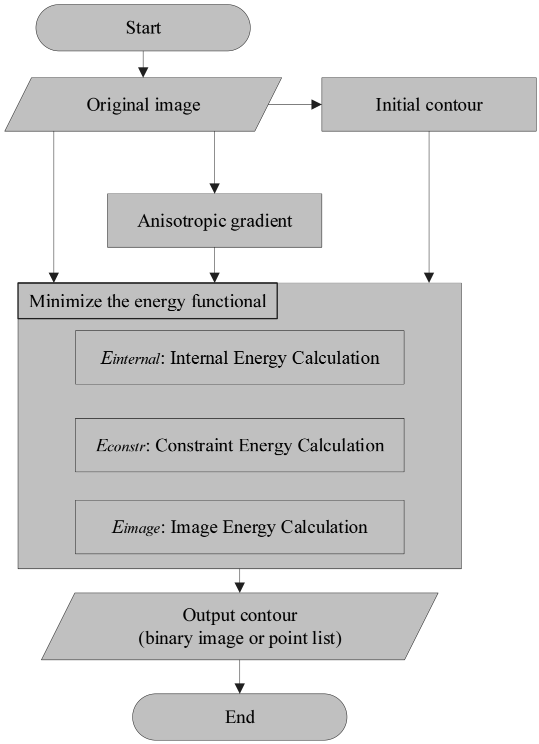


Fig. 3 – *Flowchart of the proposed method.*

$$E_{snake} = \int_0^1 E_{snake}\left(v(s)\right)\mathrm{d}s = \int_0^1 \left(E_{internal}\left(v(s)\right) + E_{image}\left(v(s)\right) + E_{con}\left(v(s)\right)\right)\mathrm{d}s\,. \quad (1)$$

The image energy is derived from the image data as follows:

$$E_{image} = \omega_{line}E_{line} + \omega_{edge}E_{edge} + \omega_{term}E_{term}\,, \quad (2)$$

where ω is an appropriate weighting function.

The edge functional is defined by:

$$E_{edge} = \left|\nabla f\left(x,y\right)\right|^2. \quad (3)$$

The edge pixels obliterate the details in the case of medical imaging. Therefore, edge-based segmentation techniques using Sobel's filter derived from Gaussian and Laplace of Gaussian are difficult to segment thin areas, they cannot detect the details of the edges of objects in medical images.

We propose to use LPA-ICI (local polynomial approximation – intersection of confidence intervals) anisotropic gradient [23]. Often medical image contains a noise at the boundaries and surfaces of objects, as well as fuzzy and not smooth contours. In this connection, to eliminate these drawbacks as a method of reducing the noise level an adaptive filtering based on the local polynomial estimations with ICI rule (LPA-ICI) is used.

The LPA-ICI technique combines two independent ideas [24]:

– Local polynomial approximation (LPA) to design a bank of linear filters of various bandwidth that perform pixel-wise polynomial fit on a certain neighbourhood.
– The intersection of confidence interval rule (ICI) is an adaptation algorithm, used to define the most suitable neighbourhood where the polynomial assumptions fit better the observations.

We use the LPA-ICI method to build the 'ideal' neighbourhood ω in the discrete image domain using LPA filters having directional supports for the image $f(x, y)$ (Fig. 4).

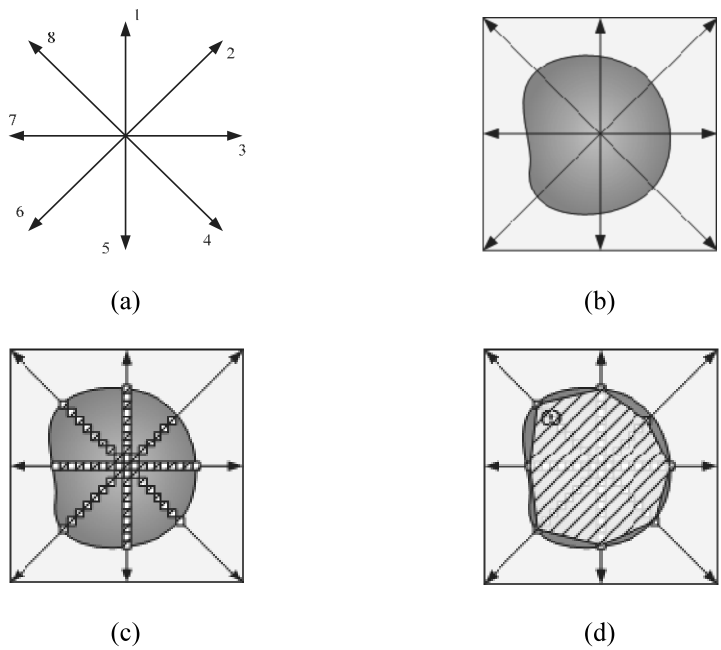


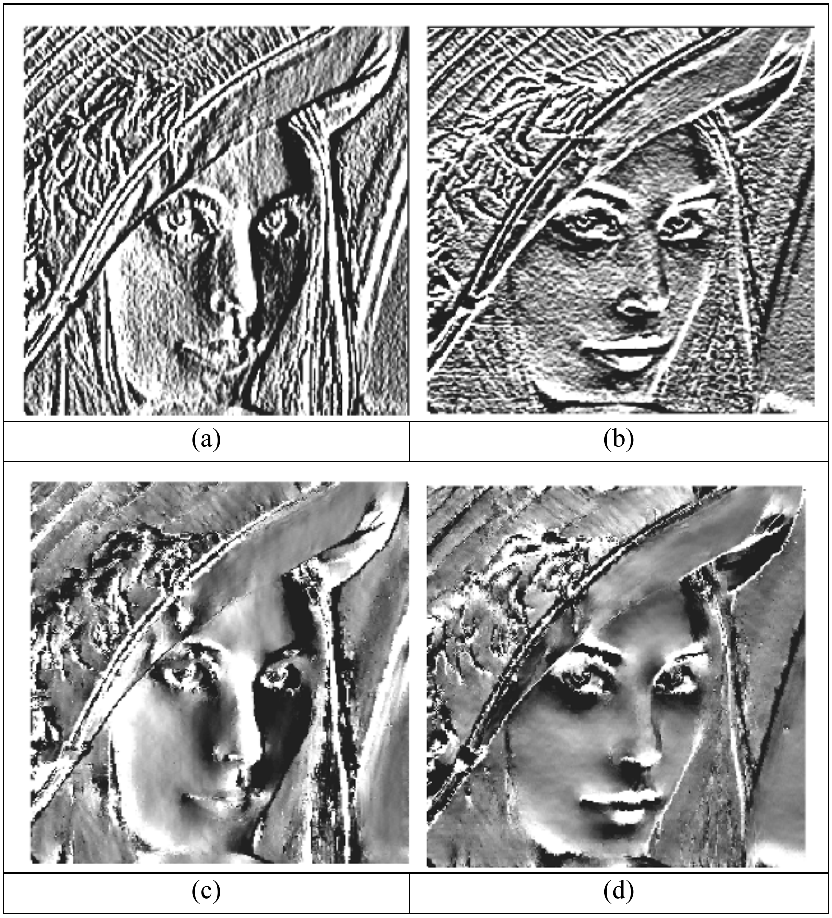
Fig. 4 – *Building neighbourhoods using LPA-ICI method.*

The anisotropic gradient concept allows the existence of a few neighbourhoods V_i at the pixel p with the corresponding a few possible different vectors $(\nabla f(p))_l$ such that

$$f(p+\nu)-f(p)-\nu^T(\nabla f(p))_l = o(|\nu|), \quad \nu \in V_l . \tag{4}$$

The ICI adaptive anisotropic differentiation is aimed at estimating simultaneously both the gradients $(\nabla f(p))_l$ and the neighborhoods V_l.

The examples of gradient calculation for different direction are given on Fig. 5 (a, b – Sobel derivate; c, d – LPA-ICI anisotropic gradient).



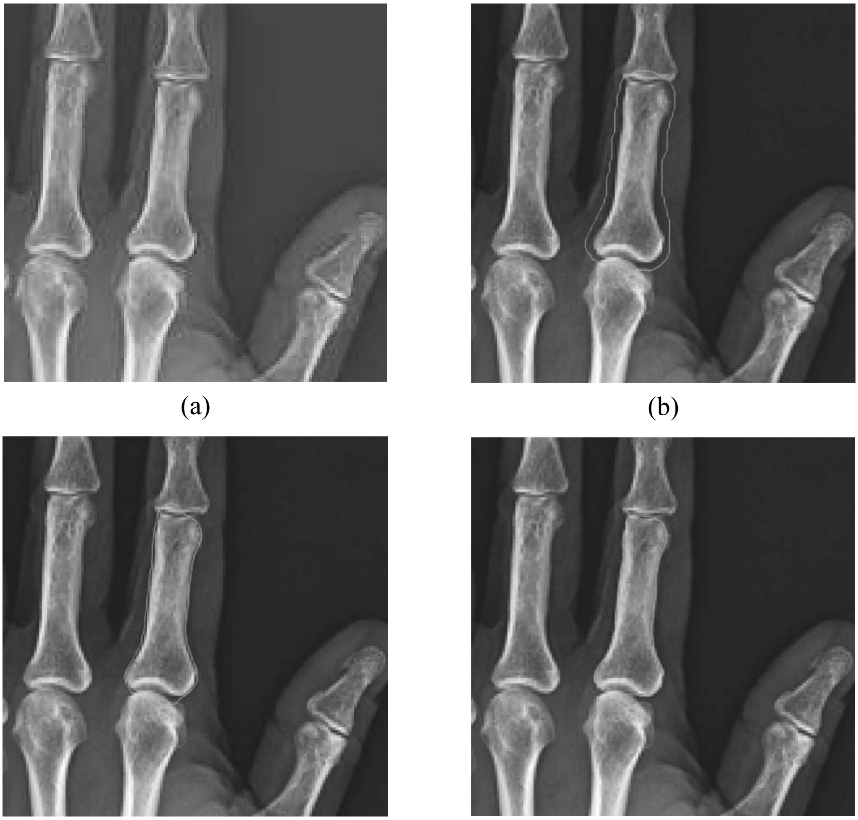
(a) (b) (c) (d)

Fig. 5 – *The examples of gradient.*

3 Experimental Results

To demonstrate the effectiveness of the proposed approach, MRI data segmentation results were compared with edge-based active contour segmentation method [25].

In Figs. 6 and 7 examples of segmentation (a – the noise-free image; b – initial contour; c – edge-based active contour segmentation method on noise-free image; d – the proposed segmentation method on noise-free image) are given.



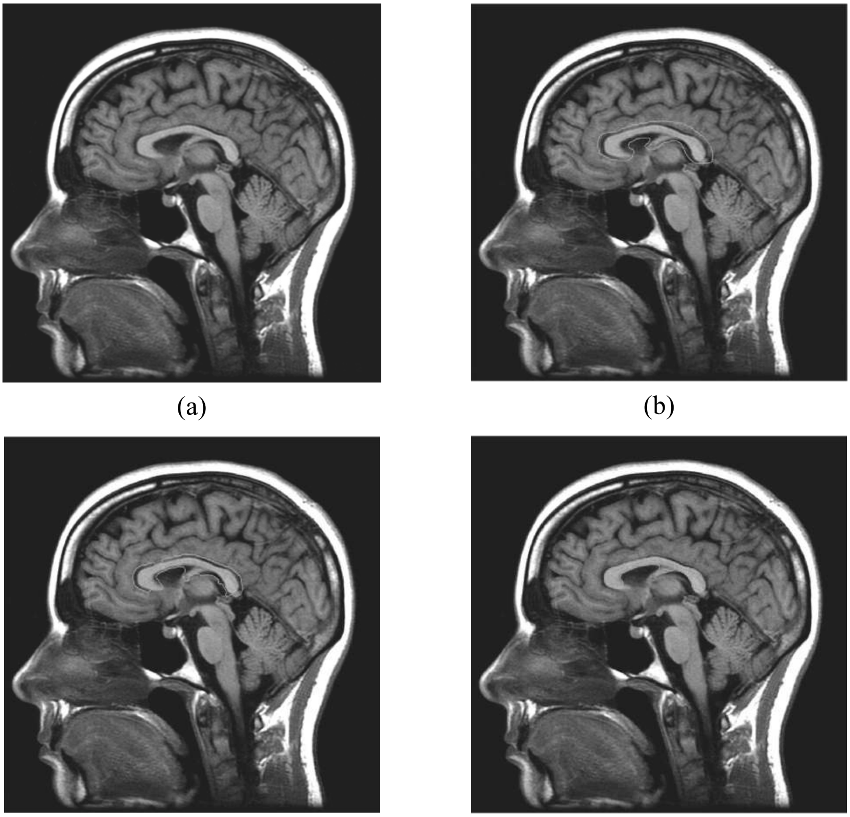
(a) (b)

(c) (d)

Fig. 6 – *Result of MRI data segmentation.*

The results show that anisotropic gradient can significantly improve the quality of the segmentation for MRI images. As we can see, some parts of the boundaries of the bones are quite blurry. We use these images to demonstrate the robustness of our method in the presence of weak object boundaries. As shown in Figure 6, this initial straight line successfully evolved to the object boundaries, and their shapes are recovered very well. This result demonstrates the desirable performance of our method in extracting weak object boundaries, which is usually very difficult for the traditional level set methods to apply.

In Figs. 8 and 9 examples of segmentation (a – the noisy image; b – initial contour; c – edge based active contour segmentation method on the noisy image, d – proposed segmentation method on noisy image) are given.



(a) (b)

(c) (d)

Fig. 7 – *Result of MRI data segmentation.*

(a) (b)

Figs. 8 – *Result of MRI data segmentation.*

(c)

(d)

Figs. 8 – *Result of MRI data segmentation.*

(a)

(b)

(c)

(d)

Fig. 9 – *Result of MRI data segmentation.*

Some images have noise and low signal-to-noise ratio, and therefore it is very difficult to apply traditional methods to extract the object boundaries. The proposed method demonstrates the performance of the proposed algorithm and its robustness to the presence of weak boundaries and strong noise.

The proposed method is useful if the user is interested in separating a selected object from the rest of the image (background). Analyzing Figs. 8 and 9, we can observe that the bones are perfectly extracted from the background.

4 Conclusion

We present a novel segmentation algorithm to extract the parts of bones from Magnetic Resonance Imaging (MRI) data sets. The proposed method is based on LPA-ICI (local polynomial approximation – the intersection of confidence intervals) anisotropic gradient. The proposed segmentation algorithm is resultative and compare favourably to other state-of-the-art methods on MRI images in the presence of noise and blurred edges.

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