Automatic detection of cardiac contours on MR Images using fuzzy logic and dynamic programming

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This paper deals with the use of fuzzy logic and dynamic programming in the detection of cardiac contours in MR Images. The definition of two parameters for each pixel allows the construction of the fuzzy set of the cardiac contour points. The first parameter takes into account the grey level, and the second the presence of an edge. A corresponding fuzzy matrix is derived from the initial image. Finally, a dynamic programming with graph searching is performed on this fuzzy matrix.

The method has been tested on several MR images and the results of the contouring were validated by an expert in the domain. This preliminary work clearly demonstrates the interest of this method, although a formal evaluation has to be done.

INTRODUCTION

Cardiac Magnetic Resonance Imaging (MRI) is a noninvasive imaging technique, that provides high-resolution images in any chosen plane of the heart. Extraction of significant parameters such as the ejection fraction and the wall thickening depends on a reliable determination of the cardiac contour.

In practice, the processing of cardiac images and the determination of the outlines are often manual or semi-automatic. Although manual contour tracing is accurate, there are several drawbacks: it is tedious, time-consuming and subjective. Moreover, there are inter observer variations[1]. To overcome these drawbacks, many attempts have been made to completely automatize the determination of the cardiac contours[2-5]. In cardiac cine-MRI, the spontaneous contrast between the blood pool (bright) and the myocardium (grey) defines the endocardial contour, and the spontaneous contrast between the myocardium and other thoracic structures defines the epicardial contours (figure 1-c). However, the presence of intra-cavity structures such as the papillary muscles or a poor image contrast may render contour definition ambiguous.

In cardiac cine-MRI, the heart is not an isolated structure, and so the use of the classical edge detection operators, such as Canny operator[6], or the Marr-Hildreth operator[7], is restricted. Some of the techniques for cardiac contour detection are based on geometric information on pixel groups. In particular, the dynamic contour models[8,9] must minimise energy functions. This method, based on the work of Terzopoulos et al.[10] , provides good results, but is not completely automatic. First, a coarse border is determined. This initialisation is often made manually. Then the border is deformed according to energy functions. Another family of techniques uses the fuzzy set theory in the processing and interpretation of medical images[11-13] .The particular form of the left ventricle allows the use of fuzzy clustering[14,15]. Fuzzy clustering consists of a classification of pixels into well-defined classes. It is based on objective function minimisation to generate a partition of data. An important preprocessing of the image including thresholding of the grey levels is needed to achieve data reduction. Graph searching has already been used in the detection of cardiac contours[2,5,16] .The aim of graph searching is to determine the best path between two sets of points. Each point is characterised by a value (or cost) that determines its relevance. Usually, this cost results from the use of a local edge operator.

The main objective of this work is to develop an automatic method for cardiac boundaries detection using graph searching. Each pixel cost is a fuzzy quantity depending on two distinct parameters, and represents the membership degree to the cardiac contour.

METHOD

The method we have adopted comprises two parts.

Firstly, two distinct parameters are defined for each pixel. The first parameter takes into account the pixel grey level value. Indeed, the pixels located on a cardiac contour have roughly the same grey level value, called **p**. Once the determination of **p** is done, the grey level

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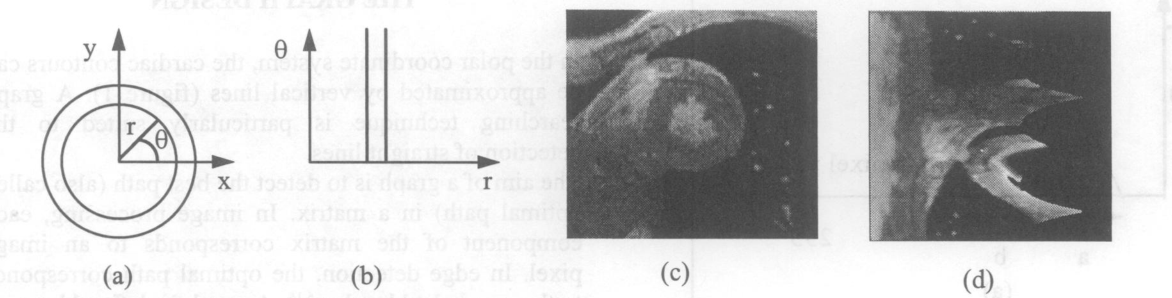


Fig. 1: Schematic representation of the heart in (a) cartesian coordinate system and in (b) polar coordinate system. Cardiac MRI in (c) cartesian coordinate system and in (d) polar coordinate system.

value of each image pixel is compared to **p**. The result of this comparison constitutes the first parameter. The second parameter takes into account the presence of edges. The definition of this parameter depends on the convolution between an edge operator and the image.
Secondly, the determination of cardiac contours is based on the use of fuzzy logic and dynamic programming. Indeed, from the two pixel parameters, the membership degree to the cardiac contours is calculated for each pixel. The image is then represented by a membership degree matrix. Finally, a graph searching is applied on this matrix in order to detect the cardiac contours.

GREY LEVEL VALUE OF THE CARDIAC CONTOURS

To determine the grey level value of the contour pixels, the user indicates a point near the centre of the cardiac left ventricle. Then, a series of radial lines is automatically drawn. Along each line, an edge operator (1) is used to detect the first edge between a high-intensity area and a low-intensity area (i.e. contour between the cardiac cavity and the heart muscle). This search is limited to the septum, because this edge is generally well-defined in this area. The operator used is derived from the Gaussian operator. The Gaussian operator being a smoothing filter, its definition is modified to form an edge detection operator as follows:

$$\forall x \in]-\infty;0[\,,\ f(x) = -\frac{1}{\sigma\sqrt{2\pi}}\, e^{\left(\frac{-x^2}{2\sigma^2}\right)}$$

$$\text{For } x = 0\,,\ f(x) = 0 \qquad (1)$$

$$\forall x \in]0;+\infty[\,,\ f(x) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{\left(\frac{-x^2}{2\sigma^2}\right)}$$

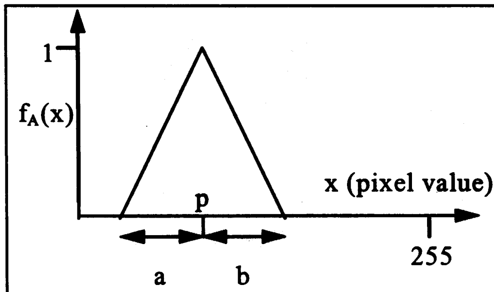
Along each radial line, we locate the pixel where the convolution provides the highest value, and the grey level value of this pixel is retrieved on the initial image. The extracted grey level value **p** of the endocardial contour is the maximum of the histogram of these local grey level values. The determination of the epicardial contour grey level is similar, except that we search for the first significant border met from the endocardial edge, and this search is restricted to the lateral wall of the heart.

DETECTION OF THE EDGES

We transpose the cardiac image into a polar coordinate system, taking the centre of the cardiac cavity as the centre of the initial cartesian coordinate system (figure 1). In practice, this is the point initially indicated by the user. To detect borders in an image, a gradient operator is often used. The operator we use is derived from the Kirsh operator[17]. In polar coordinates, cardiac contours are more or less parallel to the Y-axis (the angle axis) (figure 1). So, contrary to the Kirsh operator that privileges all the directions, our operator privileges the horizontal direction.

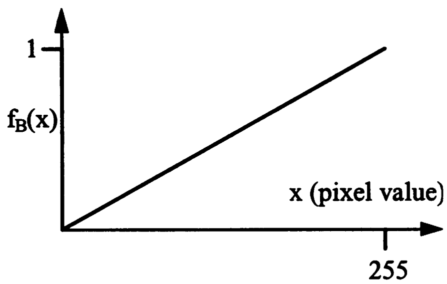
DETERMINATION OF THE CARDIAC CONTOUR POINT FUZZY SET

The possibility distribution associated to each parameter is graphically represented by a triangular function (figure 2) associated to a fuzzy set. For the grey level, the closer the value is to the extracted grey level, the greater the likelihood that the component belongs to the myocardium (figure 2-a). For the edge detection, the higher the value is (limited to 255), the greater the likelihood that the component belongs to an edge (figure 2-b). So, for each pixel, we determine its membership degree to each fuzzy set. From the initial image (figure 3-a) displayed in the polar coordinate system, the figure 3-b shows a representation of the membership degree of all the pixels for the grey level fuzzy set for the detection of the endocardial contour. The higher the intensity is, the higher will be the membership degree. Figure 3-c shows a representation



(a)

$f_A(x) = (x+a-p) / a$ if $p-a < x \leq p$
$f_A(x) = (b+p-x) / b$ if $p \leq x < p+b$
$f_A(x) = 0$ if not



(b)

$f_B(x) = x / 255$ if $0 < x \leq 255$
$f_B(x) = 0$ if not

Fig. 2: Definition of the membership functions. (a) Membership function associated with the grey level value, where p is the detected grey level (b) Membership function associated with the edge.

of the membership degree of all the pixels for the edge fuzzy set, calculated on the initial image.

We keep the minimum value between the two calculated membership degrees for each pixel. The new fuzzy set thus defined, is the fuzzy set of pixels belonging to the cardiac contour (figure 3-d). Indeed, this fuzzy set represents pixels with a grey level close to the extracted grey level, and located on a border.

A grey value for the epicardial contour has been determined, and another for the endocardial contour. The detection of both the epicardial contour and the endocardial contour is made separately. The first contour detected is the endocardial one. Afterwards, the fuzzy matrix associated with the epicardial contour is modified. The membership degree of the components located inside the area defined by the endocardial contour is set to zero. As the graph depends on this matrix, the contours cannot overlap one another.

THE GRAPH DESIGN

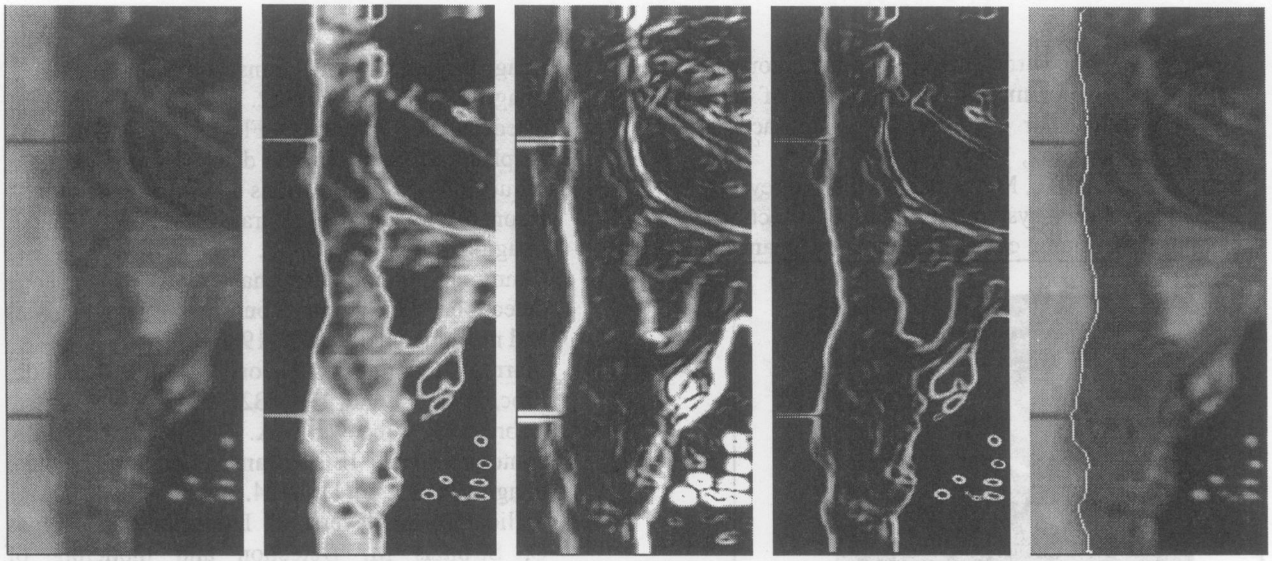
In the polar coordinate system, the cardiac contours can be approximated by vertical lines (figure 1). A graph searching technique is particularly suited to the detection of straight lines.

The aim of a graph is to detect the best path (also called optimal path) in a matrix. In image processing, each component of the matrix corresponds to an image pixel. In edge detection, the optimal path corresponds to the researched borders[5,16]. A graph is defined by a set of nodes joined together by links. There are two particular subsets of nodes: the start node, and the goal node. Each path is a possible solution to the problem. To detect the best path, we must evoke another parameter, called *cost*, and associate it to each node. In our system, the cost is the membership degree associated to each pixel. So, we get a cost matrix a_{ij}, where **i** is the number of the row, and **j** the number of the column. The start node and the goal node are the same, because we deal with a closed contour. It is easy to show that the choice of the row of the start nodes does not modify the final result. The total cost of a path is the sum of the cost of all the nodes that comprised the path. The best path is the path with the highest total cost. Here is the optimal path construction algorithm:

```
for j=start nodes to the goal nodes
    for i=0 to the width of the matrix
        prec = maxi ( a(i-1,j-1) , a(i,j-1) , a(i+1,j-1) )
        a(i,j)= a(i,j) + a(prec,j-1)
        link(a(i,j) , a(prec,j-1))
    endfor
endfor
research of the highest value between the goal node.
(i. e. The end of the best path)
```

maxi(a,b,c) is a function that determines the node with the highest cost between the nodes **a**,**b** and **c**, and returns the indice of this node. **link(d,e)** is a function that creates a link between the two nodes **d** and **e**. The path is then defined by all the links determined during the processing and the total cost. Figure 3-e shows an example of graph searching.

Although there is only one possible path, ambiguities can be encountered during graph searching. Two neighbouring nodes on the same row can have the same membership degree, so the search for the highest value fails. In that case, we keep the middle node of the three candidate nodes. The risk of error is therefore minimised because the two candidate paths are adjacent to this node. Moreover, we keep the theoretical linear form of the cardiac contour in a polar coordinate system.



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

Fig. 3: Detection of the endocardial border. (a) Initial image transposed in polar coordinates. (b) Membership degrees associated with the grey level pixel. (c) Membership degrees associated with the edges. (d) Initial fuzzy matrix. (e) Endocardial contour detected via graph searching

RESULTS

The method has been tested on images acquired by cardiac cine-MRI. The heart was presented in the anatomical short-axis plane. About forty images have been randomly chosen in a patient image database. The signal to noise and the contrast in the images vary considerably. A visual evaluation, by an expert in the domain, of the automatic contour plotting assured us that the automatic contour plotting was of quality. The figure 5 shows three examples. In some images, the difficulties arise from a lack of contrast between the blood pool and certain portions of the myocardium, and between the myocardium and the other thoracic structures, as show the arrows in the figure 5-b. Some anatomical structures present in the cardiac cavity, in particular the papillary muscles, are only enclosed in the endocardial contour detection when they are clearly seen to be connected to the myocardium, as shown by the arrow in the figure 5-a. In addition to the success of the technique in spite of the poor signal to noise ratio, the figure 5-c shows that our cardiac contour detection algorithm avoids following false contours (as shown by the arrow).

DISCUSSION AND CONCLUSION

In this paper, an original method to detect cardiac contours has been presented. This method is based on fuzzy sets and dynamic programming. The fuzzification of the parameters allows one to deal with the uncertainty often encountered in image processing. Moreover, other parameters, based for example on a priori knowledge, such as the cardiac anatomy, can be easily included. Indeed, once the fuzzification is done, intersection (or union) of parameters can be easily made. Moreover, the graph searching is a reliable technique to detect outlines. In particular, the graph deals with local and global information, and therefore, it is robust against local noise.

In cardiac cine-MRI, the cardiac contours are not always well-defined, due principally to the lack of contrast between the different structures. By testing the method on several images, it appears that the method is particularly robust.

A cardiac cine-MRI study allows one to obtain a series of images of the cardiac cycle for a given location. The next step is the automatic processing of a series of images using the same technique. The indication of the left ventricle centre is only needed for the first image. This central point does not move significantly from one image to another. Moreover, the information obtained on the processed image is used for the processing of the following image.

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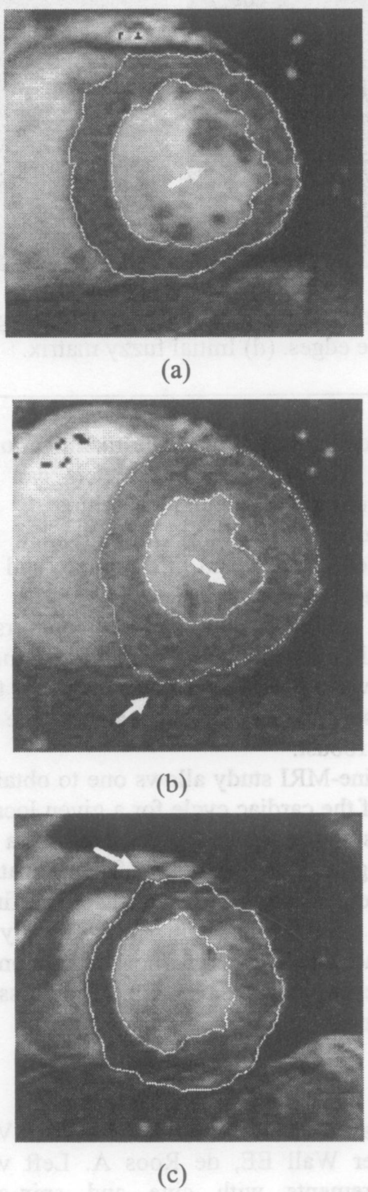

(a) (b) (c)

Fig 5: Examples of the automatic detection of cardiac contours.