Contouring Blood Pool Myocardial Gated SPECT Images with a Neural Network Leader Segmentation and a Decision-Based Fuzzy Logic.

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Abstract

We have developped an algorithm to extract ventricular contours in Gated Single Photon Emission Computed Tomography (G-SPECT) images of the blood pool. In this kind of images, we have to deal mainly with three problems. First of all, there is a superposition of nuclear emission sources within the epicardium making difficult the separation of the two myocardial ventricles. Secondly, due to the great variety of ventricular forms, the process is hard to automate and, thus, human participation is required although it is time consuming. Third, we have to deal with noise and diffusion resulting from the nature of the technique itself. Our algorithm employs wavelets filters to overcome the first and third difficulties. A neural network leader type algorithm, combined with a decision-based fuzzy logic system, enables to segment the G-SPECT images and to recognize the left ventricle. This way, the endocardial contour is extracted and the second problem can be solved. Experimental results and a comparison with other methods, among them the one used in our laboratory in clinical routine, show that the performance of our algorithm is very high.

1. Introduction

Analysing quantitatively the cardiac function in blood pool myocardial Gated Single Photon Emission Computed Tomography (G-SPECT) images requires knowledge of the contours of the ventricular heart cavities. This is particularly important if we employ these features to calculate the left ventricular ejection fraction (LVEF). Extraction of the myocardial contours may not be so easy due to a series of reasons : we have, indeed, first to deal with noise; secondly, there is a large variety of irregular ventricular forms and lastly we have to cope with the diffusion and superposition of nuclear emissions sources within the body tissues. Often, these superpositions are very strong at the septum and, usually, we cannot easily separate the two ventricles. Consequently, a completely automated detection of the contours of the myocardial ventricles is very difficult to achieve.

One can, however, find in the literature some apparented developments, as the approach for analysing myocardial perfusion images proposed by Germano et al. [1], that find in an automated way the contours of the myocardium. These authors threshold the entire SPECT image volume to 50% of the maximum pixel value. If the left ventricle is still connected to other organs in the image, then a series of erosions and dilations are performed in order to isolate it. Use of fuzzy logic Theory [13,14] has also been proposed for myocardial segmentation. Ouahab et al. [2] have constructed a left ventricle detection system for planar gated blood pool images based on the so-called fuzzy ISODATA algorithm. The method is however limited to the cases where the left and right ventricles are well separated. Otherwise, an overlapping region may invalidate the approach.

In this paper, we propose a new automated method for extracting the left ventricle in blood pool G-SPECT images. Our method combines three techniques to overcome the problems mentioned in the first paragraph, in particular the superposition of nuclear activity within the septum. This special problem will be introduced in more details in section 2. For our approach, we employ wavelet based filter, as introduced by Mallat [15,16,17], to approximately localise the myocardial contours. However, the wavelet filters themselves are not able to extract completely the organ of interest. Thus, we further use a neural network [3,9] acting as established in the leadership algorithm proposed by Carpenter and Grossberg [4]. A fuzzy logic based decision system finally recognizes the left ventricle in the neural network segmentation result and extracts accurately the desired contours. In section 3., we present the details of the proposed algorithm, giving first a brief description of the wavelet approach before explaining how we use it in overlapping regions. The last part of section 3. is aimed at exposing the object recognition procedure using neural networks and the fuzzy logic decision system.

We have also applied our method to a series of real patient images. In order to validate our method, we have compared our results with MRI data and with results obtained with the nuclear medicine method used routinely in our laboratory on the same set of patients. These results

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are exposed in section 4. We end our contribution with a short conclusion in section 5.

2. Anatomy of the G-SPECT images

Gated blood pool SPECT images are obtained after radiolabeling red blood cells with technetium 99m. During twenty minutes, scintigraphic electrocardiogram gated projection images, corresponding to half a tour, are acquired with a gamma camera. Three sets of ventricular cavities images are then obtained by a filtered back projection algorithm. These sets are called horizontal short axis, vertical long axis and horizontal long axis images. The short axis images are of particular interest because they are used to calculate the left ventricle ejection fraction. This is the ratio between the difference of the diastolic and systolic heart volumes divided by the diastolic heart volume. Due to the nature of the technique itself, we are able to detect radioactivity beyond the limits of the organ. The counting statistics measurements are, of course, stronger at the center of the organ and weaker at its boundaries. However, these organ boundaries are not well defined. In clinical routine, the analysis is carried out considering that the endocardium of the ventricles corresponds usually to 50% of the maximum intensity found in the image, that is at the center of the cavities [1].

The most difficult problem to solve, using this method, is to separate the two adjacent myocardial cavities when the septum is too thin. In this case, the radioactivities from the two cavities are added over the septum region, leading to a strong intensity value in the image which makes the problem unsolvable by this conventional method. This latter phenomenon is what we call organ overlapping. As a consequence, the septum is a critical region. Figure 1 shows a typical image in which the conventional algorithm has failed when trying to separate the two cavities.

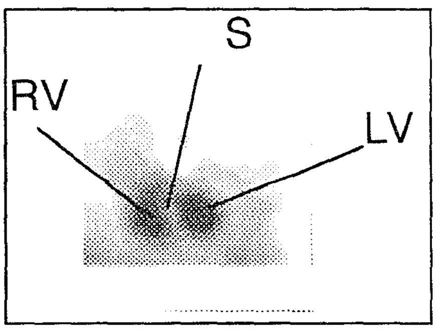

Figure 1. Typical blood pool heart image from the horizontal short axis set. RV : right ventricle, S : septum , LV : left ventricle. 64*64 pixels.

3. Basic strategy of suggested method

We have developed our image processing procedure to work with the horizontal short axis set of ventricular images. Our main objective is to recognize in this set of images the left ventricle in order to calculate its ejection fraction. Many recognition systems perform their task not from the original image but from an image of contours [5,8]. In our case, recognition of the left ventricle takes place using a segmented image to obtain later a contour image.

The algorithm is composed of three steps : A wavelet image processing step, a neural network segmentation and a fuzzy logic based decision procedure. We use the wavelet transform, which is normaly used to get the contours in an image, to initialize a neural network based segmenting algorithm. In order to deal with the great variety of irregular forms observed, we make also use of a technique using artificial intelligence, and based on fuzzy logic, to achieve pattern recognition in the segmented image.

The wavelet processing step is aimed to detect approximately the endocardium of the left ventricle. We use the smoothing and contour detection properties of the wavelets to enhance the borders of the image organs, enabling this way the separation of the organs, principally those situated in the critical region. Detected points belonging to the endocardium will be used in the second step to initiate the segmentation algorithm. For that purpose, we have implemented the so-called leadership algorithm [4,10,11] with neural networks. If the clustering process starts with a point located on the endocardium or near to it, then we are certain to generate a class of points which can be associated with the region defining the left ventricle.

Actually, after segmentation, the left ventricle may be represented by different classes forming some kind of level lines. We have thus to determine the level line defining the endocardium and then to merge the other classes to completely extract this ventricle. We have for that purpose developed a procedure to extract information such as length, area, position, etc. from each level line. These parameters are inputs of the Fuzzy-logic decision system used in order to choose the most appropriate level line and to recognize at the same time the left ventricle. After thresholding the image using the chosen level line, we can get the left ventricle contours and thus calculate the ventricular left ejection fraction LVEF. The outline of our algorithm is given in figure 2.

3.1. Dealing with critical regions

We have chosen to work with wavelets in order to decrease, on one hand, the pixel intensity value in the septum

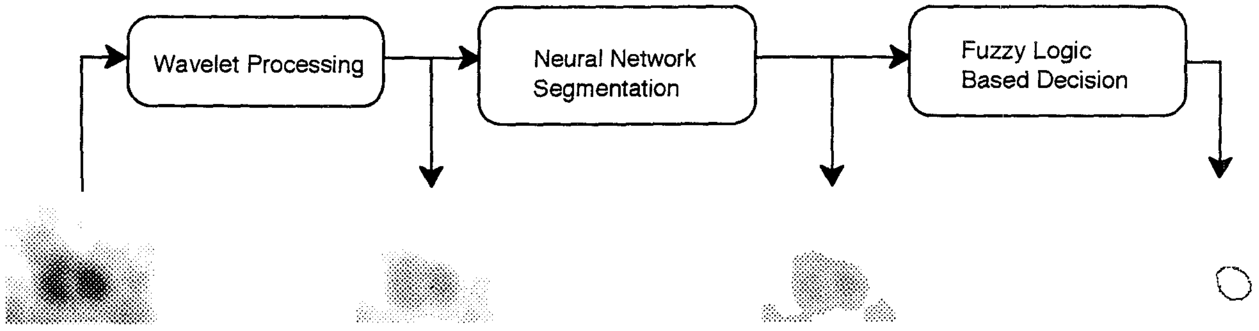

Figure 2. Steps of the whole SPECT image processing algorithm.

region and, on the other hand, to enhance the endocardial contour in this critical zone. Wavelets are well known for their ability to recognize contours in images with weak intensity variations and/or in noisy images [17].

A wavelet is a function Ψ with compact support able to generate the space of square integrable functions f (i.e. with their integrals $\int f^2(x)\, dx$ being bounded). Usually noted $L^2 \in R$, this space is obtained through dilations and translations of Ψ over R. A wavelet has also to be an oscillating function having a fast decay. A dilated and translated version Ψ_s of a basic wavelet Ψ can thus have the form :

$$\Psi_s = \Psi\left[(x-b)/s\right] \tag{1}$$

where b is the translation factor and s the dilating factor (changing the value of s modifies thus the resolution).

The computation of the wavelet transform WT_s is implemented as the convolution of the image $I(x)$ (here supposed to be of dimension 1 for simplicity) with a dilated wavelet function Ψ_s :

$$WT_s[I(x)] = I(x) * \Psi_s(x) \tag{2}$$

Edge detection is fulfilled through analysis of the wavelet transform of the variations in the image of the pixel intensity. For reasons of adequate image processing, $\Psi_s(x)$ should also have a smoothing property. In order to fulfil this requirement, we have chosen to use the gaussian function for generating the wavelet functions. Defining $\theta(x)$ as the gaussian function, we thus have designed a filter which uses the first derivative of a gaussian function as the wavelet. According to [16], the wavelet chosen for implementation in our work (i.e. the first derivative of the gaussian function) can then be written as :

$$\Psi_s^1(x) = \frac{1}{s\sqrt{2\pi}}\left(\frac{-x}{s^2}\right) e^{\left(\frac{-x^2}{2s^2}\right)} \tag{3}$$

If we note s the dilation factor of the wavelet $\Psi_s(x)$, then eq. (2) can be rewritten as :

$$WT_s^1[I(x)] = \frac{d}{dx}\int_{-\infty}^{+\infty} I(u)\,\theta\left(\frac{x-u}{s}\right) du \tag{4}$$

Due to the critical septal regions described in section 2., we thought that taking the second derivative of the gaussian function as the wavelet function would be more appropriate. We based our decision on the fact that the second derivative of a gaussian function, also known as the "mexican hat", is an even function with a central positive peak and negative lobes on each side. Changing the dilation factor of the gaussian function, we can use different peak amplitudes. Making use of the three coefficients of the mask used for convolution, we can correct for the influence of adjacent values the central value of the convolution result (i. e. WT_s^2) associated with the part of the image being convolved. In the image, for the critical septal region, this is equivalent to eliminate the influence of the diffusion arising from two adjacent nuclear sources. In that latter case, we have :

$$\Psi_s^2(x) = \frac{-1}{s\sqrt{2\pi}} e^{\left(\frac{-x^2}{2s^2}\right)}\left(\frac{s^2-x^2}{s^4}\right) \tag{5}$$

Eq. (5) leads straightfowardly to an expression for WT_s similar to eq. (4).

We have thus used these two derivative wavelet functions in our image processing step. First, the second derivative of the gaussian function is applied to decrease the pixel intensity level in the critical regions and to enhance the borders, then the first derivative of the gaussian function is employed in order to determine the maximum gray level points associated with the endocardial contour for which the contrast in the image is stronger.

The coefficients $g\ (n\ )$ for the discrete filters are calculated according to formula (6) and applied as proposed by Mallat [16]. We first process the lines of the images and then the columns. For each step, in a direction orthogonal to the wavelet function, a neighbourhood averaging filter (in our case, a spatial lowpass filter with constant coefficients (0.2)) is applied.

$$g^{1\ \mathrm{or}\ 2}(n) = \frac{1}{2}\int_{-\infty}^{+\infty} \Psi_s^{1\ \mathrm{or}\ 2}\left(\frac{x}{2}\right)\theta(x-n)\,dx \qquad (6)$$

3.2. Left ventricle pattern recognition

In order to segment the image, we employ a neural network leader algorithm similar to the one described by Carpenter and Grossberg [4]. The various classes that may appear in the image are not known a priori. For each gray value of a pixel in the image, the network performs clustering into distinct classes depending on the evaluation of similarity criteria. A representative pixel, known as the leader, is defined for an initial class. If an input pixel is found to be similar to the existing leader, it is classified under the corresponding class. If the input data has not enough similarity, it becomes a new exemplar or leader for a new class. Thus, as all the inputs are fed to the network, several leaders are created, each one representing a class or cluster.

The final clustering result can be represented as gray value level lines. The distribution of these level lines in the image depends on the pixel value of the first chosen leader. If the first leader is chosen randomly, it may happen that the level line considered for finding the ventricle area has a gray value above the actual gray value defining the endocardium. To overcome this difficulty, we initialize this processing step with one of the points found during the wavelet processing step which approximately identify the endocardium.

To ensure a good segmentation, the starting neural network is defined with two layers : an input layer or comparison layer and an output layer or recognition layer. Each layer is composed of four neurons, at the start of the process. We use a radial gaussian function (with a sigma value equal to 1) as the transfer function for the input layer neurons. One transfer function is centered at the gray level value given by the wavelet processing step, and the three others are translated by multiples of seven from this first point value. In this way we just guide the network to find a correct solution, but we do not label the whole image. This kind of clustering is often called clustering with partial supervision, as defined by Bensaid and Bezdek in [12]. The output layer performs its task in a competitive way between neurons and with lateral inhibition.

Finally, to analyse properly the segmented image regions and to recognize the left ventricle, we have implemented a decision based fuzzy system. However, the input of this system is not the segmented image but a series of parameters which have been extracted from the image using the public domain NIH Image processing Program [18]. For that purpose, we analyse the image areas defined by the set of level lines to obtain spatial properties of the objects they define. The parameters obtained this way are area, length, x-center, y-center, major axis of the ellipses enclosing the regions and number of regions in the image.

To recognize the left ventricle, we have generated a set of rules in linguistic form. Using this set, we can deduce or infer using the fuzzy logic approach. Deduction of a result relies on a logic scheme based on the well-known modus ponens law :

Implication : if fuzzy_antecedent then fuzzy_consequence
Premise : fuzzy_antecedent has degree_of_truth
Conclusion : consequence has certainty_value

We have defined the following fuzzy antecedents sets : member of the acquired first images in the sequence, in the middle range of images and at the end of the slices defining the short axis set of images; small to medium number of regions in the image; small size , slightly larger size, big and very big sizes for the area of each region; circularity criterion for the perimeter of each region and quality of positioning with respect to an expected center for the x-y position of each region. All the membership functions are of triangular or trapezoidal nature and the coefficients of the associated equations have been established heuristically. There are 35 rules in the fuzzy-base which enable us to recognize the left ventricle. An example of such a rule is as follows : "If the image is member of the acquired first images and the number of regions is small and the area is small and the region is circular and the region is well centered, then the region is the left ventricle". Once pattern recognition has been achieved, then the corresponding level line gray value is retained as threshold value. The contour of the ventricle is obtained by substraction of the region of interest from a version dilated by one pixel.

4. Application to medical test cases

We have applied our procedure to a series of images from 12 patients. The results obtained were compared to results obtained with the nuclear medicine method used routinely in our laboratory and with MRI data. The set of patients were selected without a particular criterion although all of them presented cardiac troubles leading to a wide range of ventricular volumes. Table 1 summarizes the results and allows comparison between the different methods.

PATIENT number	LVEF (%) MRI method	LVEF (%) Routine method	LVEF (%) Proposed method
1	53	59	52
2	59	57	64
3	68	68	60
4	59	59	57
5	58	61	54
6	77	74	62
7	55	53	55
8	53	46	47
9	67	70	70
10	7	13	22
11	62	73	62
12	43	44	41

Table 1. LVEF Results obtained with the 3 methods.

In order to compare our method with the other approaches, we have calculated the linear regression coefficient between our results and those of the other two techniques (see figure 3.).

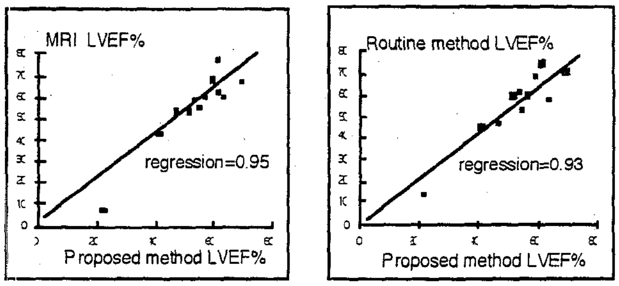

Figure 3. Comparison between results obtained with proposed algorithms with those obtained using standard approaches.

This leads to a coefficient of 0.95 between the MRI method and our method. The comparison with the method used in clinical routine leads to a coefficient of regression of 0.93. The greatest variation of our results, when compared to the other two methods, can be observed when the left ventricle is very small. Our algorithm has a tendency to overestimate the endocardium and this modifies slightly the results. It is thus hard to state if our method offers more or less accurate results than the other two where the contours are obtained interactively with the help of an operator. Further, these two techniques are not a standard for image contouring. Most important is however the fact that we manage to isolate and extract the left ventricle in an automated way. Statistics show that the proposed algorithm gives results almost equivalent to that used presently for diagnostic and obtained manually. This fact validates therefore our recognition and contouring system for G-SPECT images.

5. Conclusion

We have presented an algorithm for contouring automatically blood pool myocardial gated SPECT images in order to calculate the LVEF. Our method processes the images sequencially in three steps. The first step implies a wavelet based processing which enables to separate properly the myocardial ventricles and to enhance the images. The second step relies on a neural network leader segmentation. The clustering result of the images can be represented as level lines. This level lines agree with the enhanced borders obtained after the wavelet processing. For the third step, to recognize the left ventricle among the different segmented regions in the images, a decision based fuzzy logic system has been created. The set of rules enables to analyse the geometric and spatial properties of the different regions in the segmented image for each level line. The left ventricle is then obtained and isolated using the most appropiate level line. The calculated left ventricule ejection fractions are consistent with those computed using either MRI data or the results of the nuclear medicine method used routinely in our laboratory. Our method has the appreciable advantage over the two others of being completely automated. We hope to be able to separate the ventricles and find the contours even in the most complex cases where currently only an operator is capable of doing this task manually. This would result in a substantial saving of operator time, together with elimination also of the variability of execution from operator to operator.

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