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Scintilogram Image Pre-Segmentation using Neural Network

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Abstract

One of the difficulties in gated blood pool images is to identify the left ventricle and calculate the ejection fraction. In this work an automatic image segmentator has been developed using a Self Organized Feature Finder (SOFF) neural network. Fifty and nine images have been used for the training and fifty nine for testing. First the program is trained to recognize the heart's pattern and second it searches the image looking for the pattern. Once it is found a box is drawn around it.

Recognition raises 69% which can be maximized with re-training of the misclassified patterns.

The next step will be the automatic edge detection of the selected area and the determination of the ejection fraction.

1. Introdution

Gated blood pool imaging of the heart is a commonly used nuclear medicine diagnostic imaging procedure intended to visualize and quantify cardiac function during rest, exercise, or other interventions [2].

The gated blood pool images are obtained by the injection of radiopharmaceuticals (like Technetium99m) in the patient. These radiopharmaceutics have high energy emissions that are detected by a gamma camera. Since the amount of radioactivity within the blood pool of the heart is quite small, counts of gamma rays must be collected over many cardiac cycles to obtain a usable image. To achieve this the gamma camera is gated to the patient´s electrocardiogram using a computer[1].

Once the intensity of the pixels in a gated blood pool image is proportional to the volume of blood in the heart, it is possible to calculate the ejection fraction (EF) which is given by: EF = (ED-ES)/ED, where ED = end-diastolic activity and ES = end-systolic activity. This is a measure of the capacity of the heart to pump blood.

The end-diastolic activity is obtained by segmenting the ventricle (Fig. 1) of the heart during maximum diastole e summing the intensities of the segmented region. The same is done to obtain the end-systolic activity (during the maximum systole) and the EF can be calculated.

This paper presents the first step in the segmentation of the heart's left ventricle.

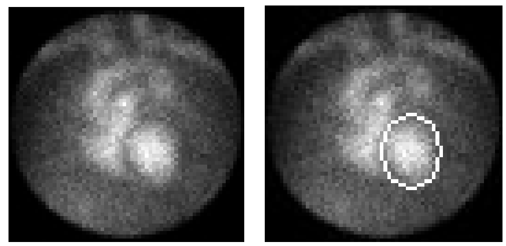

Figure 1 – a)Gated Blood Image
b)Segmented image

2. Image Segmentation

One of the most used techniques to segment images of scintilogram is through the watershed algorithm, which is done inverting the intensity of the image and generating a "watershed" that is filled and determines the boundaries of the region of interest [3].

Another technique is the use of region growing, which consists in the use of a seed which grows using neighborhood and connectivity.

Other methods can be used that consider characteristics like the gradient and the intensity of the pixel.

All this methods depends on the direct treatment of the pixels and depends very much on the type of image being considered, the level of noise and a priori information.

The advantage of using neural networks is that it can be easily adapted to different images (just training them) with the same algorithm. Unfortunately, a more precise segmentation is difficult to be done using artificial neural networks.

3. Methodology

There are several ways of segmenting images and many of them depend on an initial guess to start the segmentation (like region growing, snakes, etc.). The purpose of this work is to give this first step in segmentation through the use of an artificial neural network.

Our set of training data is composed of 59 segmented images of the heart similar to the ones shown in Fig. 2, which are normalized to 21 by 21 pixels.

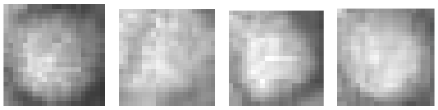

Figure 2 – Training set

The training set was obtained segmenting manually the images with different sizes varying from 16x16 pixels to 25x25 pixels, not necessarily in squared size (some were 20x25 pixels and so on). This variation occurs because most of the images are from diseased people and there are dilated hearts (i.e., Chagas' disease), small hearts and deformed hearts.

The neural network used was the Self-Organized Feature Finder, which considers that the training set is representative of the data space. On the SOFF, each image is used to help the calculation of the best representant of a cluster.

Supposing that each pixel of the image represents one dimension we would have 441 (21x21) dimensions. Once the images are similar, these points form a cluster in the space R441. If the training images are representatives, all images of the heart will also be located near the cluster. But instead of using one representant of this cluster, we can choose several representants given that the images have differences between each other. So we can group them according to their similarity.

Then we have:

1. Find the maximum output $\eta^* = \max(\eta(n))$ in the layer where

$$\eta(n) = \frac{\vec{w}(n).\vec{x}}{\|\vec{w}(n)\|.\|\vec{x}\|} \qquad (1)$$

x is the input signal and w is the weight of neuron n.

2. If ($\eta^* > \varepsilon$), w*(n) represents the closest cluster to the entrance and is improved to get closer to x by:

$$\vec{w}^{\,\mathrm{mod}\,ified} = \vec{w}^{old} + c.(\vec{w}^{old} - \vec{x}) \qquad (2)$$

3.If ($\eta^* \leq \varepsilon$), w*(n) is too far and is created a new neuron that $\vec{w}^{new} = \vec{x}$.

To recognize an image already stored, an input vector is presented to the net which is compared with all weight vectors. But, as we want that any image that is close to some weight vector to be classified as correct, we consider a recognition when any weight vector is closer than a threshold ε to the input vector x.

Finally, we can segment our image going through the same selecting subsets (in this case a sub-image of 19x19 pixels resized to 21x21 pixels) and comparing it to the patterns in the network.

4. Results and Discussion

Figure 3 shows some of the results of the segmentation of data. The rectangles bolded mean that the image was detected more than once. the red rectangle shows the iteration passing through the image.

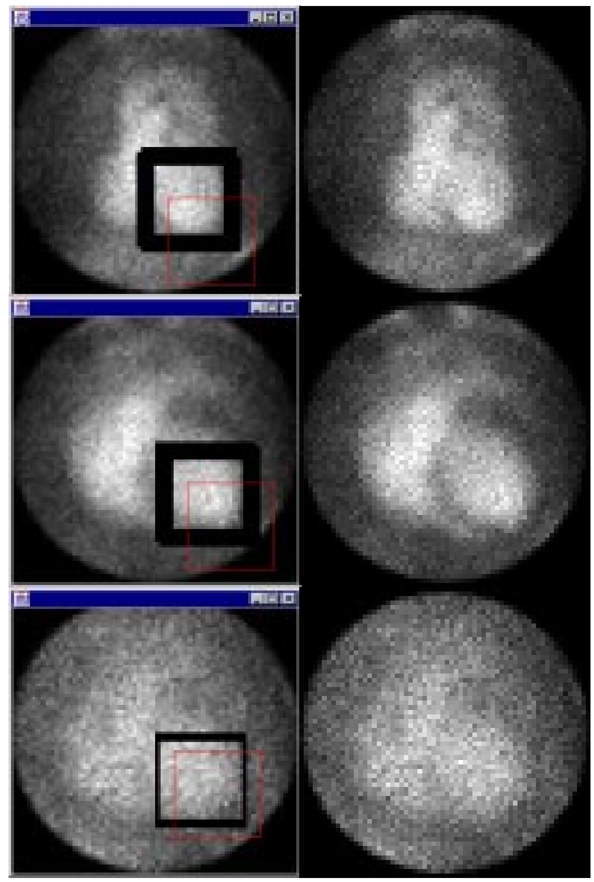

Figure 3 – Segmentation of images; Original (Right) and Segmented (Left)

A correct classification rate of 69% (41/59) of the data was obtained with the net which must be improved but reveals the good efficiency of the SOFF as a feature extractor of raw data.

This rate can probably be improved by changing the size of the sub-image taken for testing, once that the size of the heart varies a lot depending on the person.

Another parameter is the epson used to classify the clusters. It was used 0.82, which is low, but gave a good classification.

Certainly the use of parameters encoding for the image will improve the classification rate, but it is useful to know the results of the SOFF network on raw data.

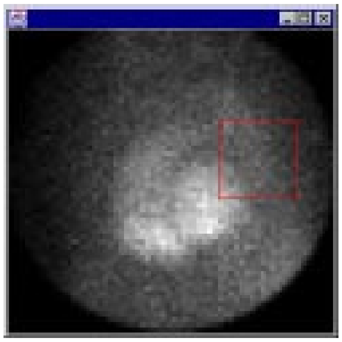

Figure 4 – Misclassified image

Despite this technique has been used here to segment scintilogram images, it also can be used to segment any kind of image like ultrasound images, computed tomography, and others where is necessary the automatic selection of part of the image.

5. Future Work

This is the first step in the automatic segmentation e calculating of the ejection fraction.

The next steps will be the improvement of the correct classification rate and the use of a segmentation algorithm like snakes.

6. References

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