Original Article

Diagnosis of Cardiovascular Disease Using Fuzzy Methods in Nuclear Medicine Imaging

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Abstract

The study used fuzzy logic to extract information and analyze nuclear medicine imaging. Data were extracted for accurate and rapid diagnosis of left ventricular cavity volume (LVV), which is very effective in rapid and accurate diagnosis of left ventricular disease. The proposed method has three steps: First, a wavelet-based analysis was performed on existing medical imaging to reduce the noise in them and improve image resolution. The brighter image of this step was used as the second step input. Image segmentation was performed using a neural network algorithm. At this stage, image classification was performed using the Gaussian function. Finally, in the third step, the area corresponding to the left ventricle was selected, and fuzzy logic was used for this selection.

Keywords: Medical Imaging, Cardiovascular Disease, SPECT, Fuzzy Method

Introduction

Today, medical imaging is performed in a variety of ways. Although each method has specific application areas, all of them pursue a common goal, namely an accurate diagnosis of the disease after analyzing the obtained data. Usually, the obtained medical images include incomplete information for various reasons. In such cases, comprehensive information is obtained using mathematical analysis. One way to analyze these images is by fuzzy logic, which can be used to obtain complete information. In recent years, various reports of the application of this method in various engineering and medical fields have been presented [1]. An online computer-aided diagnosis system based on fuzzy logic has been developed for use in radiology imaging. The application of this method to orthopedic data analysis has been shown [2]. Research has also been conducted on the ability of fuzzy logic to diagnose liver disease by different researchers and teams [3]. In the field of MRI, image segmentation has been investigated in various references [4] and [5] for achieving tissue differentiation and extracting useful and efficient information. To measure cerebrospinal fluid volume and brain white and gray matter, a report is presented [6] that illustrates the performance of fuzzy logic in this area. In addition to the above, in recent years, numerous interesting articles have been presented on fuzzy c-means clustering that has been useful in analyzing data in medical imaging [7].

The present study was designed and implemented to present a new method based on fuzzy logic to extract essential information and accurate diagnosis of cardiovascular diseases from medical imaging.

Materials and Methods

1. Proposed Method Strategy

The proposed algorithm used in this research consists of three processing steps that are performed continuously. The first stage is called Wavelet-based pre-processing [8] and [9]. At this point, it is attempted to eliminate the noise in the images as much as possible and separate the right and left ventricles, thus defining the approximate border of the left ventricle in the image. In the second step, the image is segmented [10] and [11] by applying a neural network implementing the Adaptive Resonance Theory (ART) algorithm. Finally, at the last stage, it is possible to detect and draw a left ventricle using a fuzzy nervous system. At this stage, a learning process is required to formulate the rules of the fuzzy nervous system.

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2. Wavelet-based Image preprocessing

Wavelets are a set of mathematical tools that allow for the breakdown of a signal by considering some issues. The main advantage of these tools is that they are capable of performing signal analysis with the same precision in both time and frequency domains. This accuracy is not present in some conventional analysis methods, such as Fourier analysis, so using them can lead to reduced overall system accuracy. In other words, in this method of analysis, increasing the accuracy of the analysis in one area leads to a decrease in the accuracy of the other. Also, wavelets have the desirable ability to accurately and appropriately identify the evaluated signal changes [12] and Holliday et al., (2019). This study aims to analyze images with two high-pass filters designated with two different frequency bands. For this purpose, the first and second-order derivatives of the Gaussian function are used as wavelet functions. The filter coefficients are obtained after sampling both functions at a specified frequency.

Initially, a second derivative based filter is applied to enhance the gray level variations between the endocardium and the wall. As a result, the second derivative of the Gaussian function makes a filter known as the Mexican hat filter [13]. This filter has a positive peak point and a negative lobe on each side of the peak value. This special form allows you to modify filtered values to reduce values close to the center point of the convolution. As such, the image density (as a result of the nuclear radiation emitted from the heart cavities) decreases in the image and especially in the wall area. In the second step, the first derivative-based Gaussian filter is applied to identify the contour points.

First, all image lines are processed and then columnized (tabulated). After each filtering step, the low-pass filter is applied in a separate direction from the high-pass filter. Choosing the right resolution for which the image should be analyzed is a function of the inherent resolution of the system and the amount of detail in the image.

3. Image Segmentation Using A Neural Network

By mimicking biological neural networks, neural networks are nonlinear detection systems that are capable of storing and learning new models and can be used to identify and classify subsequent operations. These systems are often used in parallel to enhance performance in complex and heavy computing.

This research has chosen a neural network method for pre-processed image segmentation that is similar to the one presented [14]. As such, each defined category is associated with a specific region of the image upon completion of the process. The level corresponding to the primary class is defined as the corresponding area of the left ventricle. The dimension characteristics of each area are strongly dependent on the pixel gray level, which is selected as a Class I leader. According to surveys, if a class leader is selected at random, there will be no criteria that can determine the dimensions of the area corresponding to the left ventricle. To increase the accuracy of measurements, a wavelet-based filtering step is first performed on the image density value of a given pixel. This study defines the desired pixel as the contour point in the image at the boundary between the area of the left endocardium and the area of the septum. With this selection, the gray intensity of the class I surface can be set to be used as the starting point for the classification of the neural network and the segmentation stage.

Neural network implementation is achieved using two layers: the first layer, i.e., input or comparison layer, and the second layer, output, or classification layer. Each layer is made up of five neurons in which the conversion functions are defined as Gaussian functions. Of the five functions mentioned, the third function has a central value in the gray level w region, which is specified by the contour point output and is determined at the wavelet-based processing stage. Other values of the center peak are determined by a factor of 7 with a distance. Therefore, the central values of the Gaussian functions are placed at w-14, w-7, w, w + 7, w + 14. It should be noted that the value 7 is empirically obtained to obtain a good segmentation resolution around w. This classification method is based on the method of Mantero et al. (2005) [15]. Although initial class and gray level resolution are both important parameters in segmentation and quality control of results, it should be noted that early leaders acting as some sort of core point correspond to the significant points derived from wavelet-based analysis. Implementation and use of other methods, such as the k-means method, have more analytical steps and lower quality of results. Figure 1 shows an example of the segmentation result for the HSA region.

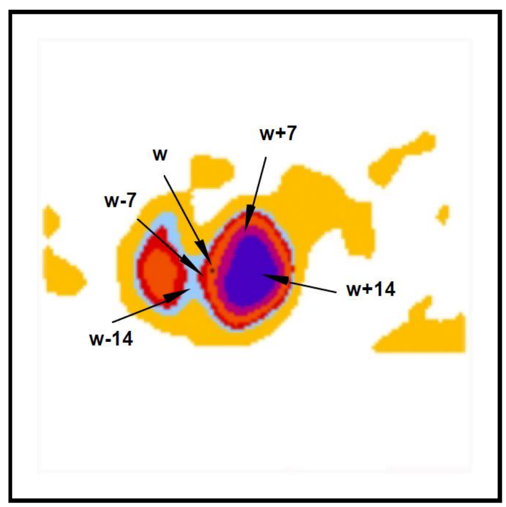


Figure 1. Sample image segmented after analysis with neural network

4. Fuzzy logic-based detection

One of the most difficult and complex steps in medical imaging evaluation systems that automatically detect organs (such as ventricles in G-SPECT images) is to distinguish the target organs (in this study, the left ventricle) from other organs shown in the image, such as vessels, etc. The left ventricle is difficult to detect even when only the right and left ventricles are present in the image. This is especially difficult to change from one patient to another or even from one segment to another. To better communicate and examine a specific area in the images of the left ventricle, it can be assumed that the cavity should be within the range defined in the image and between the two regions of minimum and maximum. This range is to determine the tolerance for subsequent ventricular imaging. The neural network-based segmentation step output provides portions of the image that have roughly the same gray level, and the borders are marked by lines in the original gray-level images. It is possible to identify each of these areas as a left ventricle. Considering each of the surface lines separately, several hypotheses have been put forward for the relationship between the left ventricle and the region created to determine the corresponding confined area and its relation to the myocardium. Figure 2 shows the different species after the segmentation step of an image sample. We call this series of images, "extensive images." The first image above is skipped right because of its shape and dimensions in the first step and the desired image will be selected among the other four images.

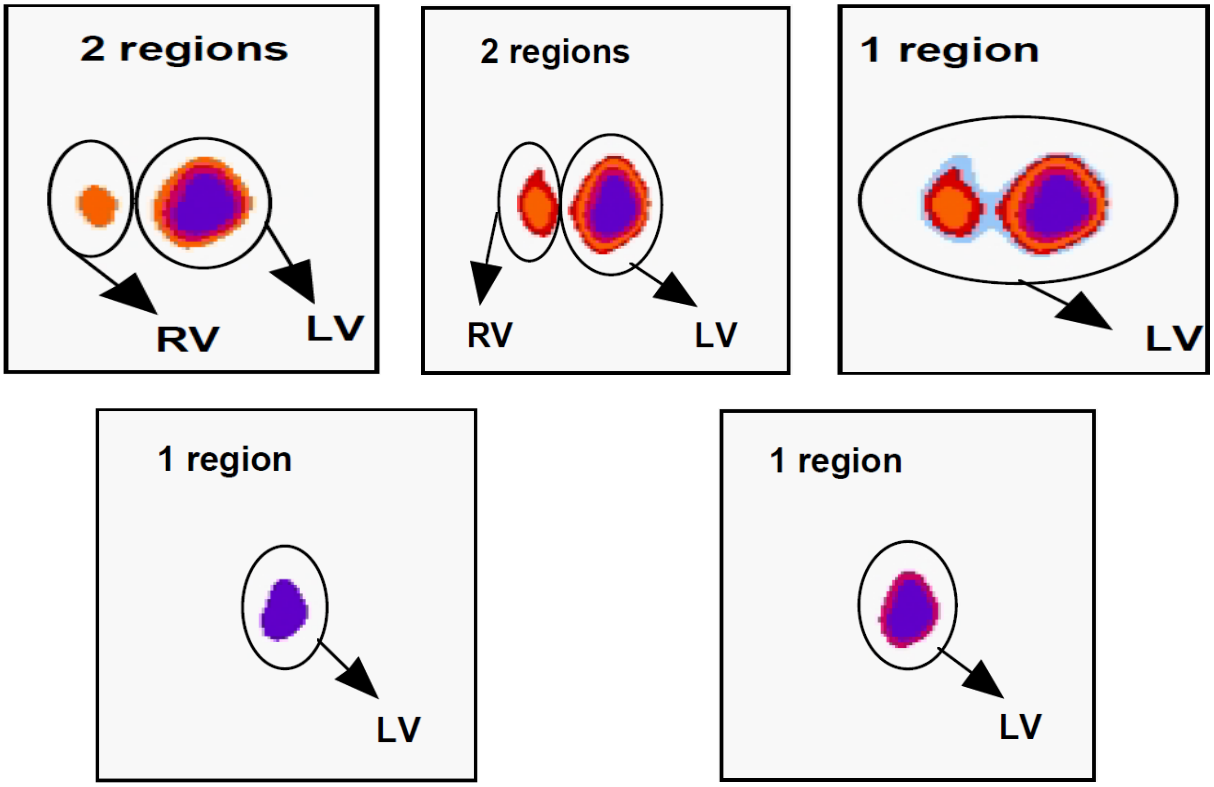


Figure 2. The left ventricle and various post-segmentation hypotheses related to Figure 1

To allow for the automatic identification of the left ventricle in the later stages, each area is described by a set of measured parameter values. Table 1 shows the main input of the processing step using the fuzzy algorithm method. To normalize the data in the fourth column, the first image is obtained from the set cut, the area level is captured as a left ventricle and a reference; in the other image available, the zone area is divided by this reference value. As such, a relationship between the created image fragments and the growth coefficient is easily obtained from the first segment to the last segment. Columns 6 and 7 are normalized to the maximum value obtained in each column.

Table 1. An example of heart info corresponding to the figure

Slice Number	Exploded Image	Number of Regions	Are of Possible LV	Circularity of Possible LV	x Position of Possible LV	y Position of Possible LV
1.0000	1	1	1.0000	1.8066	0.7143	0
1.0000	2	1	0.3613	1.9333	0.7143	-0.2000
1.0000	3	1	0.2514	1.9450	0.7143	-0.2000
2.0000	1	1	0.7948	1.8963	0.7143	-0.1000
2.0000	2	1	0.4306	1.9669	0.7143	-0.2000

2.0000	3	1	0.3006	1.9541	0.5714	-0.2000
3.0000	1	1	0.9480	1.8883	0.5714	0.1000
3.0000	2	1	0.4249	1.9536	0.5714	-0.1000
3.0000	3	1	0.2659	2.0001	0.5714	-0.1000
3.0000	4	1	0.1474	2.0253	0.5714	-0.2000
4.0000	1	2	2.0318	1.8612	0.5714	0.3000
4.0000	2	2	1.6936	1.8860	0.4286	0.3000
4.0000	3	2	1.4017	1.8588	0.4286	0.3000
4.0000	4	2	1.1705	1.8530	0.4286	0.3000
4.0000	5	2	0.7081	1.8192	0.4286	0.2000
5.0000	1	1	2.3555	1.9094	0.5714	0.2000
5.0000	2	2	2.0058	1.8866	0.4286	0.3000
5.0000	3	2	1.6792	1.9201	0.4286	0.3000
5.0000	4	1	1.3671	1.9036	0.4286	0.3000
5.0000	5	1	0.8873	1.8541	0.2857	0.3000

Since there is no clear pattern of the myocardium in the normal course of practice for physicians and professionals, fuzzy logic can be used to circumvent this deficiency. The existence of databases is one of the requirements of the fuzzy system in each application; in this particular case, it is used in various interpretive fields to evaluate the cut-off sequences and identify the appropriate values for the parameters to accurately identify the left ventricle among the available regions. This is possible using fuzzy logic, which allows us to analyze the available data and information in a set of comparative rules. These rules form the inference engine of the fuzzy system according to the famous law of modus ponens:

Implication: IF previous_fuzzy THEN Next_fuzzy
Premise: previous_fuzzy has degree_of_truth
Conclusion: Result has Specified_Amount

Using this mechanism, we can formulate rules that describe the system in question. For example:

IF Are_of_the_region is Big THEN Region is The_left_vent

In these definitions, Big and The_left_vent are members of fuzzy sets. By combining different parameters in heart info and building a rule, you can find the right tool for analyzing images. In this research, the parameters are combined as follows:

IF Ns is Mf, and Np is small,
and Ar is Big,
and Cr is High,
and Xcr is Well_horizontally_centered,
and Ycr is Well_vertically_centered
THEN Region is The_Left_ventricle

where N_s is the number of segments in the image, M_f is the number of similar images, N_p is the number of image components, A_r is the area level, C_r is the degree of circularity of the area, X_{cr} is the coordinate of area X, and X_{cr} is the coordinate of area Y. Above, new fuzzy sets are introduced, such as Small, Big, Ms, Well_horizontally_centered, and Well_vertically_centered.

5. Combining Neural Methods and Fuzzy Logic Systems

Figure 3 shows the structure used in this study. In this structure, the last three layers of the neural structure described above combine to form a new layer called the output layer. This layer is located at the bottom of the network and uses a fixed node, which is called the "max operation associated" conversion function. This is because we simply want to use fuzzy rules to identify the left ventricle. In operation considered in this study, on the one hand, if a region in the image is not corresponding to the ventricle, if the input to the fuzzy-neural detection system is input, it will not produce a rule. On the other hand, we need several rules to define the various situations in which the left ventricle must be identified. Given this, when an area that truly corresponds to the left ventricle is fed into the system input, the neural network selects one or more rules from the database, and the remainder corresponding to the outputs of a "different type of left ventricle" is not selected. These other choices may be larger or have different shapes. As such, we create a set of rules and place them in databases, which describe the left ventricle.

In doing so, membership functions that define fuzzy sets for the assumptions used in the first layer nodes are considered triangular, and their parameters are obtained during the learning phase of the recognition system. During the learning process, the number of membership functions corresponding to each input and the number of corresponding rules is also determined.

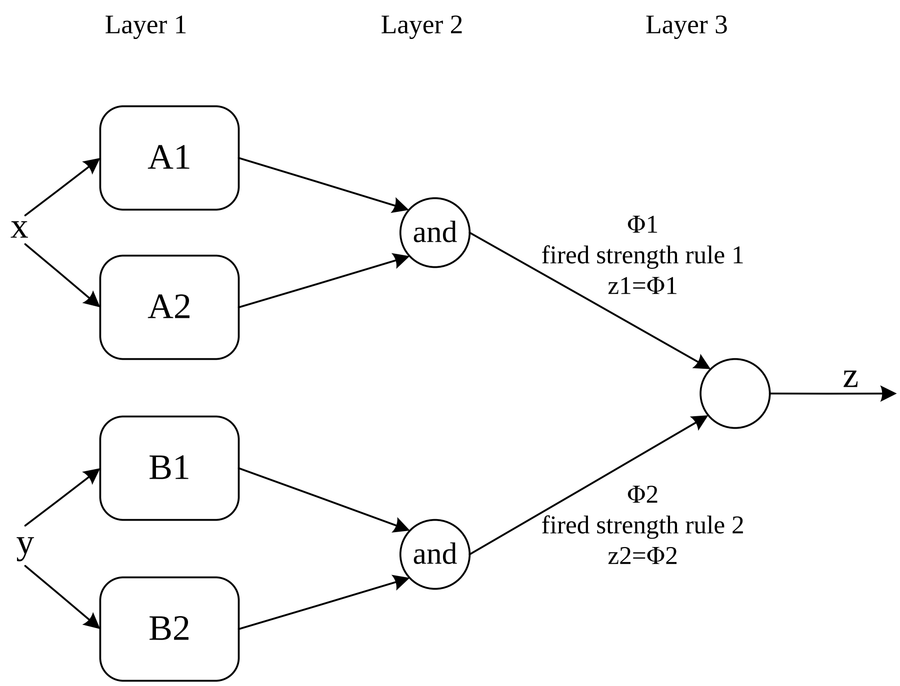


Figure 3. The equivalent system used in this study

Results and Discussion

- ### Used membership functions

One of the important parameters in using fuzzy logic is the selection of membership functions. A membership function must be chosen for each of the parameters and variables in the problem. There are a variety of membership functions, including triangular, Gaussian, exponential, and bell-shaped functions. This research uses triangular membership functions to perform and implement fuzzy logic. These functions are determined using their special features, i.e., the center of 'a' and the range of 's' in accordance with Fig. 4; clearly, the vertical axis also always has a value between 0 and 1. The task of these functions is to assign a value corresponding to between 0 and 1 for each value of the variable in the horizontal axis.

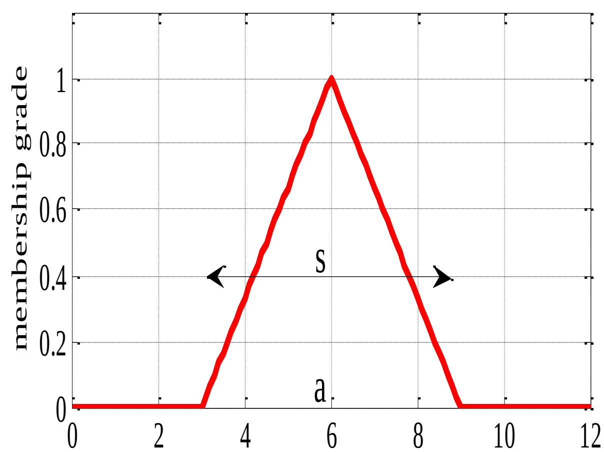


Figure 4. Triangular membership function used

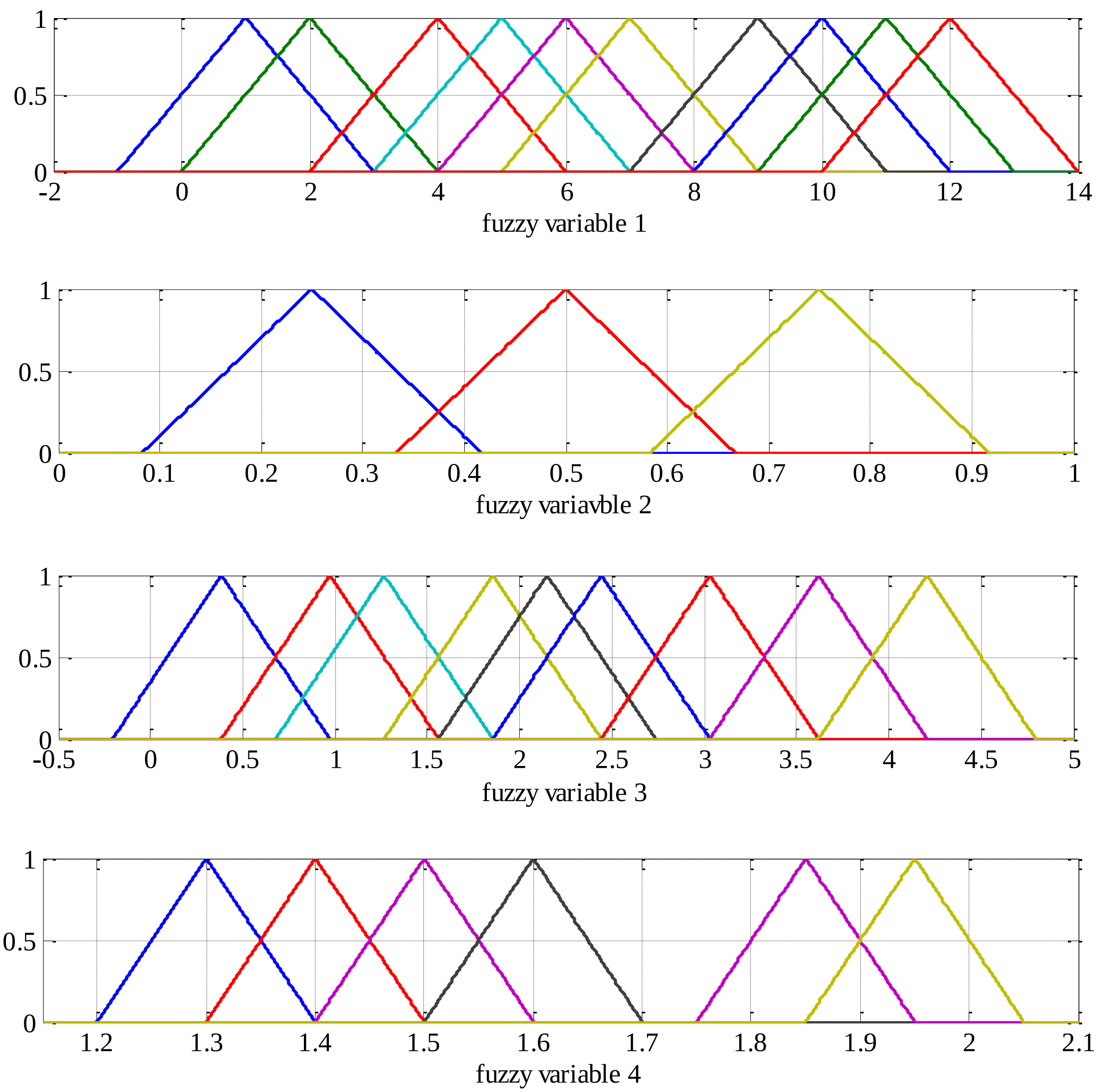
Each triangle represents the membership function of an input parameter in the first layer. To simplify and reduce the number of functions, positions, and values of variables that are 0 have been attempted not to draw the membership function.

- ### Using functions

The database, which contains fuzzy rules, contains 62 rules. However, for the sake of simplicity and a better understanding of the subject, only six rules following Table 2 are used to explain an example.

Table 2. How to use the six rules?

Rule	Variable 1 Fuzzy Set	Variable 2 Fuzzy Set	Variable 3 Fuzzy Set	Variable 4 Fuzzy Set	Variable 5 Fuzzy Set	Variable 6 Fuzzy Set
1	mf 1_1	mf 2_1	mf 3_1	mf 4_3	mf 5_1	**mf 6_1**
2	mf 1_2	mf 2_1	mf 3_3	mf 4_1	mf 5_1	**mf 6_1**
3	mf 1_3	mf 2_1	mf 3_3	mf 4_1	mf 5_1	**mf 6_1**
4	mf 1_3	mf 2_1	mf 3_5	mf 4_2	mf 5_1	**mf 6_2**
5	mf 1_4	mf 2_2	mf 3_7	mf 4_1	mf 5_2	**mf 6_2**
6	mf 1_5	mf 2_2	mf 3_4	mf 4_1	mf 5_2	**mf 6_2**



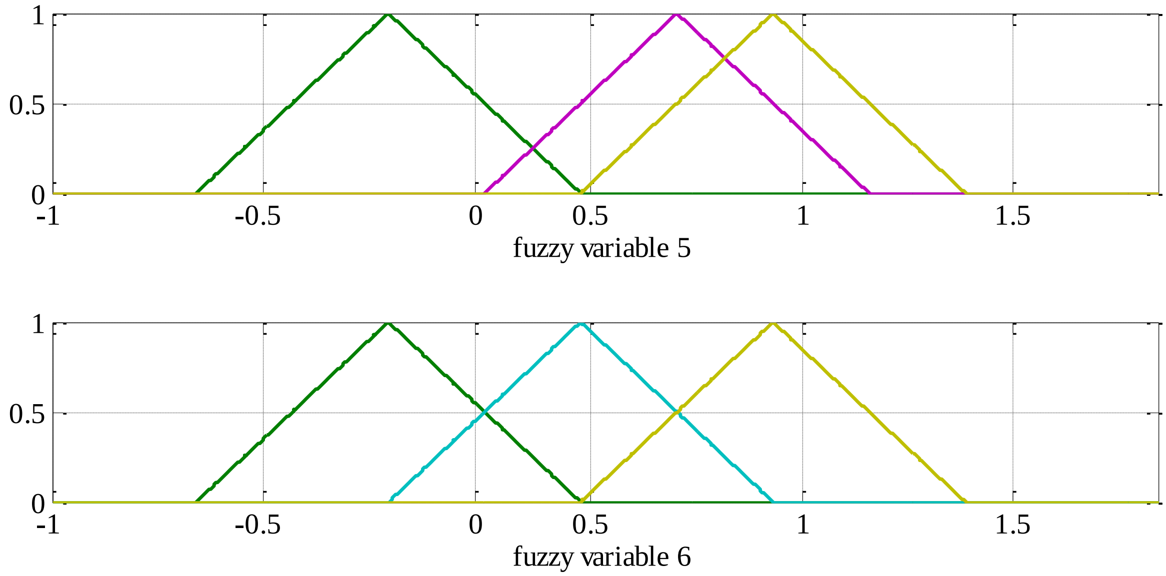


Figure 5. Membership functions for different input variables in Layer 1

An example of the results extracted

How to use Table 2 for Rule 1 is as follows:
If variable1 is mf 1_1
and variable2 is mf 2_1
and variable3 is mf 3_1
and variable4 is mf 4_1
and variable5 is mf 5_1
and variable6 is mf 6_1
THEN left_verticle is the fired strength of the rule.

The strengths of the rules used and their relevance to the relevant areas are obtained after evaluating and analyzing the image data using the system. By applying the Max operator to each of the processed images, the corresponding area is obtained according to the existing algorithm as well as the fuzzy rules used. Table 3 presents calculated points of interest along with the selected area representing the left ventricle (shadow area).

Table 3. Calculated and selected strengths for the left ventricle of Example 2

Slice	explode	fired	fired	fired	fired	fired	**fired**
5.00	1	0	0	0	0	0	**0**
5.00	2	0	0	0	0	0.2241	**0.3026**
5.00	3	0	0	0	0	0.7507	**0.1137**
5.00	4	0	0	0.0533	0.0524	0	**0**
5.00	5	0	0	0.0034	0	0	**0**

Figures 6 to 4-6 show the medical image segmentation and image matching rate according to the proposed algorithm, and the common selection area most consistent with a square has been presented.

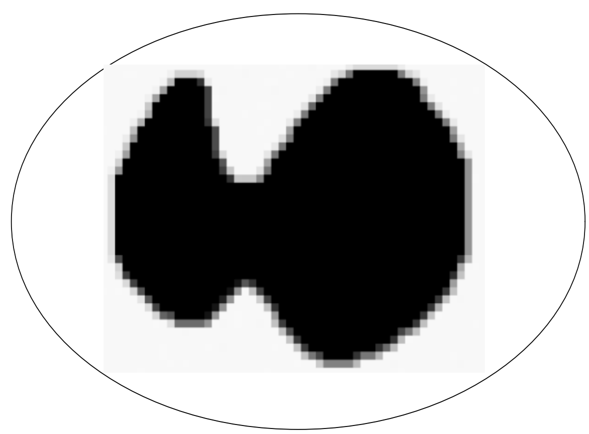


Figure 6. One area: left ventricular area with 0% compliance (matching)

In this image, due to the continuity of the two parts, the algorithm was unable to comply with the rules defined for the ventricle. Hence, the matching rate of the received image is 0.

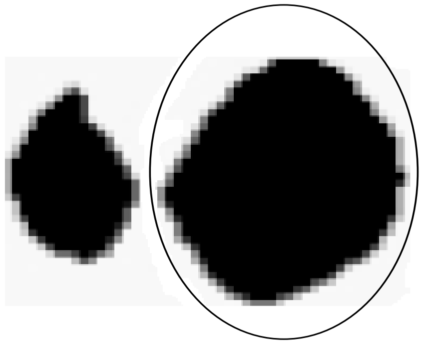


Figure 7. Segmented areas, left ventricular area with 30.26% compliance

Nuclear medicine imaging has been divided into two areas. According to the features defined for the area in question, the right part of the image corresponds somewhat to the features of the left ventricle.

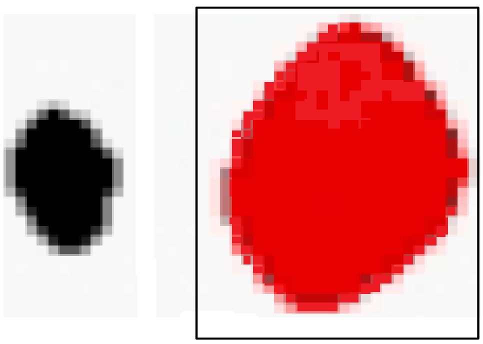


Figure 8. Segmented areas, left ventricular area with 75% compliance

Most correspondence between the right image and the left ventricular profile is observed and reported in this image. The right-hand match rate is reported at about 75%; this figure is reported as the highest match, and hence the image is of the left ventricle. Figure 9 shows other cases of image matching. These are the same images as in Figure 2 that were analyzed in the previous section.

A) Left ventricular area with 5.33% compliance. B) Left ventricular area 0.34% compliance

Figure 9. Medical images desired

The above results allow us to distinguish the right area first and then identify the contours of the area, which ultimately describes the left ventricle, which is obtained by knowing the gray level of the selected area and its location. Finally, a search algorithm called the Zigzag algorithm is considered to analyze the whole area and identify the points of the environment. This algorithm continues until all points around it are summed. Figure 10 presents the basics of the final operation and its results.

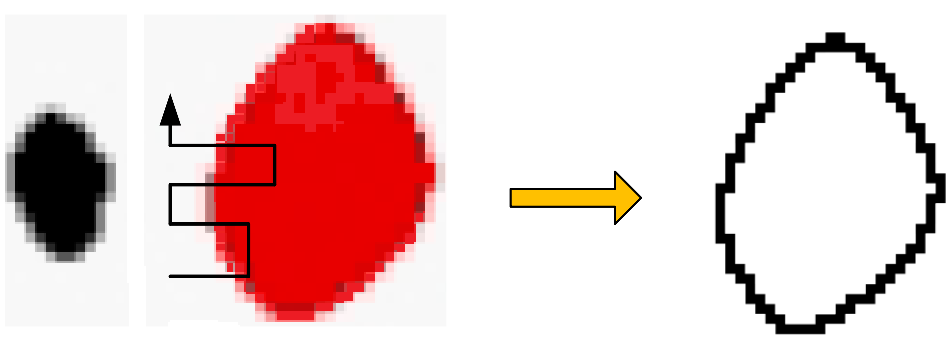


Figure 10. Basics of the final analysis step (zigzag search algorithm) and the result

Conclusion and Recommendations

Conclusion

This research has demonstrated a new method for the automated analysis of SPECT images, especially used to detect LVV, which is needed to perform Left Ventricular Ejection Fraction (LVEF). LVEF is an important and effective parameter in the diagnosis of cardiovascular diseases. The proposed method is based on three successive separate phases of the application. In the first step, image wavelet-based preprocessing is done. This will reduce both noise and distortion in the image and increase the resolution of the image, making it easier and more accurate to differentiate different areas of the segmented image.

At this stage of processing, it is very important to find a boundary point between the regions corresponding to the left ventricle and the right septum; respectively. The output of this step is the start of the second stage of the process, which is performed using the neural network algorithm image segmentation. At this stage, the classifications are presented according to Gaussian functions. As a starting point, the first class around the boundary point is investigated by the wavelet-based processing algorithm. The third step is to select a part of the image corresponding to the left ventricle, using a fuzzy logic decision that acts as a three-layer neural network. This method requires training to build a knowledge base, which is developed through new tools and is capable of automatically generating fuzzy rules and membership functions. This way, both the rule and the membership function can be produced and expanded. The proposed method has high reliability and can detect noise images optimally.

• Recommendations

Nowadays, the detection of different types of cardiovascular diseases using SPECT images is one of the important methods. The amount of information extracted from these images depends on the method used to analyze them. Hence, it is possible to improve the results by using existing smart methods such as advanced algorithms or combining several intelligent algorithms. Since the required operations are performed on the data extracted from the images, most of the existing intelligent methods and algorithms can be used in this work, and the results are compared to select the best and most appropriate method.

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