ORIGINAL ARTICLE

Mechanical Performance Separation of Cardiac by Nonlinear Processing of Ultrasound B-Mode Images

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Abstract

Purpose: Accurate measurement of Left Ventricular Ejection Fraction (LVEF) is critical for diagnosis of and predicting Left Ventricular (LV) arrhythmias. This study aims to estimate LVEF using nonlinear and statistical analysis in echocardiography images.

Materials and Methods: The Cardiac Acquisition for Multi-Structure Ultrasound Segmentation (CAMUS) dataset is used to estimate LVEF. This dataset includes ultrasound images of 60 patients in two different groups (LVEF > 55%, LVEF < 45%). Region growing technique and Anatomical markers were used for segmentation of LV in images to measure region changes. LV region changes were investigated using nonlinear and statistical analysis. To facilitate estimating LVEF, feature extraction and Artificial Neural Networks (ANN) have been used.

Results: The results show that the changes in the LV region in LVEF < 45% have a mean value of 3.254 while LVEF > 55% has a lower mean value of 3.071, but the mean of variance is 3.818 while for LVEF < 45% is 3.471 which can be concluded that the data scatter in LVEF > 55% was higher than the mean and indicates more significant changes in the LV region.

Conclusion: LVEF estimated using nonlinear and statistical analysis shows a Mean Square Error (MSE) of 5.15.

Keywords: Ultrasound; Left Ventricular Ejection Fraction; Nonlinear Analysis; Statistical Analysis; Image Segmentation; Feature Extraction.

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1. Introduction

Left ventricular ejection fraction is the most common and valid measurement of echocardiography in the study of systolic function with the aim of diagnosis and treatment, which is the basis of diagnosis and prognosis in heart disease [1]. Any symptoms that indicate low Left Ventricular Ejection Fraction (LVEF) are very risky and have many consequences, which is why measuring LVEF is so important [1]. Ejection Fraction (EF) expresses the amount of blood drawn after the diastolic volume phase of the heart. The LVEF is a fraction that is calculated as chamber magnitude ejected in Systole (SV) divided by the volume of the blood in the ventricle at the End of Diastole (EDV) multiplied by 100 [2].

After years of extensive research on the cardiovascular system, complex behaviors continue to emerge that are not easy to analyze. Analyzing these behaviors can be effective in obtaining useful information about cardiac structures and analyzing the functioning of the cardiovascular system. Taking advantage of nonlinear analysis and chaos theory can be useful in the field of diagnosis and treatment for physicians and specialists to understand cardiac behaviors [2]. Nonlinear and chaos analysis has applications in modeling such as understanding the behavior of the system, the study of arrhythmias behavior, time series analysis, the study of blood flow mechanics, and quantitative measurement of chaos such as the unpredictability of system, periodicity, and complexity [2, 3]. Because the heart is fractal structured and is considered a biological system, it can exhibit chaotic behavior, so nonlinear analysis of the cardiac system is of particular importance [4]; therefore, this study aims to create a new method in estimating the LVEF using nonlinear analysis.

To date, various methods have been used to estimate LVEF. [5] reviewed 2D and 3D echocardiography and contrast echocardiography. They examined these tools in assessing LVEF. They conclude that even though the two-dimensional echocardiography is the primary tool for evaluating LVEF, it does not have high accuracy in estimating LVEF and its volume, while contrast echocardiography has much higher accuracy, higher magnetic resonance, and lower cost. They also concluded that 3D echocardiography is more accurate than the other two instruments and has more magnetic resonance. It also requires less time but high-quality images. Due to the low spatial resolution, its accuracy may be affected [5]. [6] used two geographic models of Left Ventricular (LV) and a paraboloid model to model the left ventricle. They also used an LV reconstruction algorithm to generate ventricular blood pool volume. Their work showed that the use of these models causes the LV blood volume to be considered 13% to 14% less. It was mathematically and experimentally proved that this method causes the LV blood volume to be smaller. They developed a new way to show the position of 2D ultrasound images to reconstruct LV blood volume using the actual LV geometry illustrated by 2D ultrasound images and their relative position to reconstruct the true volume of LV blood [6]. In 2019, they reviewed volume-based necessity and developed a method for measuring LVEF based on 2D blood pools from 2D multi-plane ultrasound images and 3D volumes during cardiac cycles [7]. [1] examined the limitations of LVEF and the role of the Global Longitudinal Strain (GLS) from the Speckle Tracking Echocardiography (STE) method in overcoming existing limitations. They concluded that due to the limitations of measuring LVEF, the GLS is the best method for assessing and evaluating left ventricular systolic function [1]. The innovation of this research is the nonlinear analysis of ultrasound images to create an accurate, faster, and low-cost way to estimate LVEF and measure the basic parameters that express the cardiovascular system. Nonlinear measurements are thought to provide good information about the functioning of the cardiovascular system.

2. Materials and Methods

2.1. Data Set

The data used in this study was extracted from the Cardiac Acquisition for Multi-Structure Ultrasound Segmentation (CAMUS) data set, which is the only available data set to the public, and was created with the aim of 2D echocardiographic image assessment. This dataset includes clinical data from 500 patients registered at the University Hospital of St Etienne (France). 2D apical 2-chamber and 4-chamber views for each patient were exported from EchoPAC analysis software (Vivid Ultrasound, GE Healthcare). Each exported view is available as a sequence of B-mode ultrasound images. The acquired images of each patient have a different number of frames. At least one cardiac cycle was recorded from each patient. The data set was obtained using GE Vivid E95 ultrasound scanners (Vivid Ultrasound, GE

Healthcare) with a probe of GE M5Sc-D (GE Healthcare, US) [8].

In this paper, 60 patients (50 patients for training and ten patients for testing Artificial Neural Networks (ANN)) have been employed, divided into two groups of LVEF < 45% and LVEF > 55%. Table 1 shows the information about the data used in this work. This table shows that half of the training data have LVEF < 45%, and the other half have LVEF > 55%. In test data, six patients have LVEF > 55%, and four patients had LVEF < 45%. The sex of the selected patients is both male and female, and their age range is 18-87. Attempts have been made to use data from patients whose image sequence has more frames. The higher the number of frames, the more accurate chaos, and statistical measurements are performed.

Table 1. The main characteristics of the dataset in full, training and testing separately

Data	LV_{EF}	
	LV_{EF} > 55% (number of patients)	LV_{EF} < 45% (number of patients)
Full	60	
Training	25	25
Testing	6	4

2.2. LV Segmentation

Automatic image segmentation is one of the essential topics in image processing, which is widely used in various fields such as medicine. The main application of image segmentation in therapy is to observe the organs and tissues of the body for diagnosis and prediction [9]. Region Growing (RG) is one of the first automatic tools for image segmentation.

The region growing algorithm performs six steps as follows: seed point and threshold value selection, compare seed point pixel with neighboring pixels, measurement of pixel intensity and average region intensity (homogeneity criterion), assign neighboring pixels to the region with the least difference, check the difference between the average region intensity and the new pixel from the threshold (stop condition), and the output image of the extracted region.

The problem with the region growing technique is the allocation of neighbor pixels to the area, which can be seen in poor quality images where several pixels are incorrectly assigned to the left ventricular region. Figure 1 is an example of a segmented image where the left ventricular region is segmented, and the seed point is selected manually. As shown in Figure 1, some neighboring pixels are incorrectly assigned to the LV.

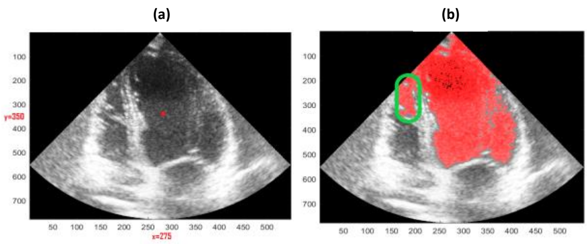

Figure 1. Segmented frame using region growing (a) selected seed point and (b) incorrectly assigned pixels

In this paper, a manual method has been used to eliminate the problem with the RG technique. This method creates a closed curve that causes the LV region to segment exactly from its border. This is done by creating points at the boundary of the region. The closed curve is completed when the last point reaches the first drawn point. Figure 2 shows a frame after segmentation using the RG technique resolves the existing

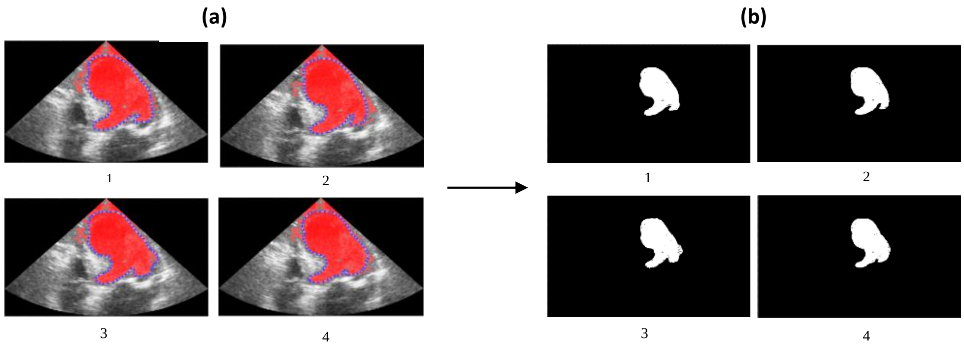

Figure 2. (a) The closed curve created after using the RG technique and (b) the threshold image of the segmented left ventricular

problem by creating a closed curve and completing the image of the left ventricular segmented threshold image.

It can be said that using the RG technique and creating a closed curve increases the accuracy of the LV segmentation. As mentioned, creating a closed curve eliminates the problem with the RG technique. If the LV is segmented only by creating a closed curve in low-quality images, part of the border, corners, and apex of the LV will probably not be recognizable, which reduces the accuracy of the segmentation. It can be said that using these two methods together eliminates all defects, and the LV segmentation will be performed with high precision.

The mentioned techniques are performed for 60 patients on each frame, and finally, for each patient, the region changes of the extracted LV region in 2D echocardiographic image sequences are calculated. Nonlinear and statistical analysis of LV region changes provides valuable information about LV diastolic function.

2.3. Nonlinear Analysis

As mentioned, as the cardiac system is a biological system, it can show chaotic and unpredictable behaviors, so nonlinear analysis is a suitable tool to analyze the performance of the cardiac system in the field of diagnosis and treatment. In this paper, basic statistical and chaos features have been used to analyze and study the changes in the LV region extracted in the images.

Mathematically, chaos can be defined as the unpredictable long-term behavior that occurs in definite systems when sensitivity to initial conditions is present [10]. This sensitivity to the initial conditions is known as the Butterfly Effect. In the cardiovascular system, an external factor such as cardiac arrhythmias disrupts the normal rhythm of the cardiac system and makes its behavior unpredictable. Because the initial recognition with very high accuracy is practically impossible, long-term estimation is impossible even when the governing physical laws are definitive and well known. It is believed that a decrease in LVEF alters the normal function of the LV and the behavior of the cardiovascular system. Therefore, nonlinear analysis of LV region changes in the image sequences will help to analyze ventricular behavior and quantitatively measure the amount of chaos. Hence, we have considered 4 important and main characteristics of chaos: correlation dimension, fractal dimension, approximate entropy, and Lyapunov exponent.

2.3.1. Correlation Dimension

In chaos theory, the correlation dimension (indicated by the symbol V) is the dimension measurement of the space occupied by a set of random points. These points can be a circle or sphere, or other shapes. It is also an indicator to measure the system's complexity [4]. The main application of the correlation dimension is in small-scale data. The next advantage is the direct calculation, and it has little noise when few points are available. The correlation dimension is one of the main tools to determine the chaos obtained in time series. The correlation dimension of a stochastic process has continuous (infinite) dimensions, but a chaotic process has more limited dimensions. The correlation dimension method, described by Embrechts in 1994, is to form a sphere around a point in the state space so that the radius of the sphere increases to the next m until all the points are enclosed in that space. The solid-state integral space for enclosed points is equal to (Equation 1):

$$C(r) = \lim_{N\to\infty} \frac{N}{N(N-1)} \sum\nolimits_{i,j} H(r - |Y_i - Y_j|) \qquad (1)$$

Where H is a Heaviside step function with $H(u) = 1$ for $u \geq 0$ and $H(u) = 0$ for u ≤ 0 and also u is equal to $r - |\,Yi - Yj\,|$, N number of points in this space created, r is the radius of the sphere and the center of Y_i or Y_j.

2.3.2. Approximate Entropy

Entropy is the degree of uncertainty that measurements show and determines the regularity of time series [11]. In other words, it indicates the amount of information obtained from the measurements. This characteristic also shows the number of signal fluctuations in the time domain and in the field of dynamic systems, random process, and time series analysis to estimate a signal's periodicity and repeatability. This method can detect intangible changes in biological time series. This is a characteristic for showing the scatter of nonlinear and Non-Gaussian signals. The entropy value is higher for data with high variability, so time-domain signals have higher entropy values, while regular and predictable time-series signals have lower entropy values (Equation 2).

$$ApEn\,(m, r, N) = \frac{1}{N-M+1} \sum_{i=1}^{N-M+1} \log C_i^m(r)\ \frac{1}{N-m} \sum_{i=1}^{N-m} log C_i^{m+1}(r) \qquad (2)$$

Where C_i^m is the correlation integral and is equal to (Equation 3):

$$C_i^m(r) = \frac{1}{N-M+1}\sum_{i=1}^{N-M+1} \Theta(r - \|x_i - x_j\| \qquad (3)$$

Where x_i and x_j are trajectory points in phase space, N is the number of phase space points, r is the radius of a disk to the center of the point (x_i, x_j), which is usually selected by 20% of the standard deviation and Θ is a function of a single step, and m is called the embedded dimension.

The vital point about entropy is that changing the entropy for a reaction can be negative. There are several possible reasons for this. One of the reasons can be the final entropy of the system, which is less than the initial entropy of the system, which causes a negative entropy in the system. Another reason is the short time series because in any system with chaotic behavior, the entropy is 0, negative, or very small, which increases over time, and the system becomes unpredictable. Negative entropy does not indicate the absence of entropy in the system, and it cannot be said with certainty that there is no entropy.

2.3.3. Fractal Dimension

Fractal or fractal behavior is a behavior that exists in nature and anything that tends to have a state of balance. In chaos theory, the fractal is an infinite model. Fractals are incredibly complex patterns that have similar properties at different scales. Fractals are formed by repeating a simple process repeatedly in a continuous loop of feedback. In simple terms, it is a picture of a dynamic and chaotic system. The importance of the fractal dimension is in measuring the repetitive patterns of the cardiovascular system, which can provide helpful information about the functioning of the cardiovascular system. The larger the value of this parameter, the more repetitive patterns we observe. Geometrically, fractals have three main properties: self-similarity, complexity, and non-integer dimension.

Time series are the accumulation of parameters that are visible over time. Some experimental data have fractal statistics. Analysis and modeling of these statistics can be done using fractal methods. Time series fractal analysis is of particular importance in investigating system behavior; for a fractal time series at an interval of a period t0 < t < T, the amplitude of the changes, R, depends on the power at time t.

$$R(t) = R(t_0)(\frac{t}{t_0})^{2-D} \qquad (4)$$

Where D is the time-series fractal dimension, the probability of the desired parameter can be predicted in subsequent rotations. By analyzing the changes of parts to different fractal dimensions and how the system is affected by internal and external factors, the behavior of the system can be predicted. A significant point is the ability to predict and detect unstable system conditions. When D = 1.7 ~ 1.6, the system is unstable, and its parameters are rapidly decreasing or ascending depending on the current trend. In the cardiac system, the presence of an arrhythmia disrupts the normal functioning of the physiological process, leading to pathological methods to affect the functioning of the system. A pathological procedure examines signals that are out of their typical properties.

2.3.4. Lyapunov Exponent

Lyapunov exponent is a characteristic of chaotic systems to measure the sensitivity of the system's response to minor stimuli through this quantity and is used to detect the nonlinear behavior of the system [12]. Lyapunov exponent actually shows the divergence or convergence diagram of the neighbor paths of the system responses in the phase diagram. For 1D mapping, this quantity measures the average rate of divergence of the response to related initial conditions. In the sense that if we have two related initial conditions such as x_0, $x_0 + dx_0$ by applying mapping M, we will have N consecutive times (Equation 5):

$$dx_n \approx exp(hn)dx_0 \qquad (5)$$

h is called Lyapunov's view for this mapping. Therefore:

$$h = \lim_{T\to\infty}\frac{1}{T}ln\left|\frac{dx_T}{dx_0}\right| \qquad (6)$$

$$\frac{dx_T}{dx_0} = \frac{dx_T}{dx_{T-1}}\frac{dx_{T-1}}{dx_{T-2}}\ldots\frac{dx_1}{dx_0} = M'(x_{T-1})M'(x_{T-2})\ldots M'(x_0) \qquad (7)$$

Therefore:

$$h = \lim_{T\to\infty}\frac{1}{T}\sum_{n=0}^{T-1} ln\,|M'(x_n)| \qquad (8)$$

For a set, h can also be represented as follows (Equation 9):

$$h = \int ln\,|M'(x)|d\mu(x) \qquad (9)$$

The Lyapunov most significant positive representation of a system is used as an indicator to describe the behavior of a distinct dynamic system [12]. It should be noted that the Lyapunov method is not valid for direct periodic or irregular detection of a system if it cannot define a dynamic system.

2.4. Statistical Analysis

In statistics, the maximum of a function is the coordinates in which the function reaches its maximum value relative to its surrounding points. The minimum function is the point at which the function has the lowest value close to its nearest points [13]. Mean is also a measure of the tendency to the center and is defined as the sum of the values in a data set divided by the number of data [13].

Median is another statistical indicator commonly used in descriptive statistics, along with mode and mean. A median is a number that divides a statistical population or a probabilistic distribution into two equal parts [13]. One of the significant advantages of median over average is that the median is not affected by very large and very small numbers in the set of dimensions.

The standard deviation (usually denoted by the σ symbol) is one of the scatter plots that shows how far the mean data is from the mean [13]. If the standard deviation of a set of data is close to 0, it indicates that the data is relative to the mean and has little scatter, while a large standard deviation indicates a significant spread of data. The standard deviation is equal to the second root of variance. Standard deviation is also used to determine reliability in statistical analyzes. In scientific studies, data with a difference of more than two standard deviations from the mean value is usually excluded from the analysis. A Variance is defined as the average of the squared value differences from the mean. Variance is a number that shows how a series of data is spread around the mean.

2.5. Feature Extraction

Feature selection is one of the dimension reduction methods used to remove irrelevant or redundant features. In addition, it improves classification accuracy and speeds up training and inference [14]. Feature extraction methods obtained newly created properties by performing combinations and converting the main feature set. Unlike the feature extraction method, the feature selection methods make a new generalized feature set from the original set. Due to the increase in the volume of processed data in the last five years, feature selection has become an essential step before classification. Feature extraction has four main aspects: creating features, creating a subset of features, determination of evaluation criteria, and estimation of evaluation criteria.

This paper uses a Genetic Algorithm (GA) to extract the appropriate features. GA was first developed about three decades ago and inspired by natural structures. GA is optimized for various problems in many disciplines of engineering, image processing, and economics (Hilali-Jaghdam *et al.*, 2020). The genetic algorithm has four main functions: Evaluation, selection, crossover, and mutation, which are shown in Figure 3 [15]. GA has many advantages, such as solving problems continuously or discretely or creating optimal solutions by random operators. One of the essential features of a genetic algorithm is the coding of the needed variables to describe the problem. The best performance of genetic algorithms usually occurs when binary representation is used to encode problem variables. In this research, binary mode is used.

In the first step of the genetic algorithm implementation, a set consisting of the P entity or chromosome is formed by pseudo-random generators. Each of the entities with the chromosomes in this population represents a

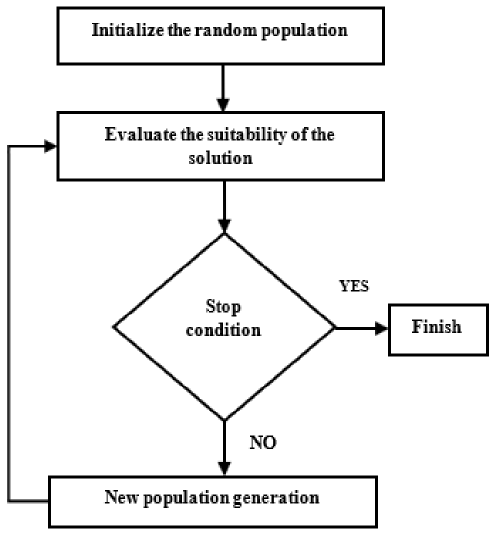

Figure 3. Genetic algorithm flowchart

candidate and possible answer to the problem. Each of these entities is a representation of the answer to a problem in an answer space, also called the initial answer. In the second step, an external penalty function is usually used to turn the constrained optimization problem into an unbound optimization problem. Such a conversion will vary depending on the different optimization problems (problems for which optimal solutions are to be generated). In the third step, the objective function of the problem is mapped to a fit function. Through the fit function, the fit value of each member of the initial population is determined. After determining the suitability of the candidate answers, the genetic algorithm operators are used to make changes to the candidate answers.

2.6. Artificial Neural Network

ANN are intelligent dynamic systems based on experimental data that do not require any reception and transfer the knowledge or law behind the data to the network structure by processing the experimental data. In this paper, the Multilayer Perceptron network (MLP) of the perceptron is used. This network can solve linearly separable problems. The number of layers in this network can be added, and it has one or more hidden layers, as shown in Figure 4. This network is of a feed-forward and supervised type [16, 17]. The main application of this type of network is in pattern recognition, classification, and prediction [17].

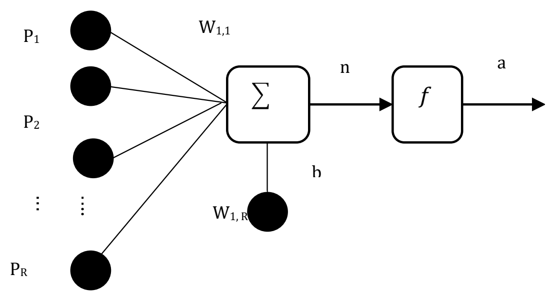

Figure 4. MLP neural network architecture

The position of the neural network in this study is the measurement of LV_{EF} based on the measured parameters. An attempt has been made to increase the detection speed of the proposed method by using the neural network. The MLP used in this paper has ten neurons in the input layer and one neuron in the hidden layer. The input of this network is the extracted features, and the output is the estimated LV_{EF}. In order to test the network, data from 10 patients have been applied to the network. 70% of the training data is for training, 15% for validation, and 15% for testing. In order to investigate the effect of features without feature extraction, the LV_{EF} estimation feature has been measured in 3 cases, a total of ten features, six statistical features, and four chaos features separately.

3. Results

The RG technique generally had good accuracy in detecting the LV region in images, but in images that do not have the desired quality, it is difficult to identify the border or apex. One solution to this problem is to capture high-quality images and change the structure of the region growing algorithm, so that neighbor pixels are allocated to the region more accurately. After segmentation of the LV region, the problem related to the RG technique was eliminated by creating a closed curve. In such a way, the LV is precisely segmented from the boundary and apex with an infinite number of points, as shown in Figure 2.

After LV segmentation, changes in the LV region are calculated frame by frame for each patient. Figure 5 shows the LV region changes for both LVEF > 55% and LVEF < 45%. As can be seen in Figure 5, there is a significant difference in both LVEF > 55% and LVEF < 45% in LV region changes. As Figure 5 shows, the region changes in LVEF > 55% and LVEF < 45% are very different. It seems that the rate of change in the region of the LV is less in LVEF < 45%, while in LVEF > 55%, these changes are much larger. Table 2 shows the mean of measured features. According to the measured statistical characteristics, the mean of changes in 45% is 3.254, and for LVEF > 55% is 3.071, and also the median in LVEF < 45% is 3.263, and for LVEF > 55% is equal to 3.107. Although the mean and median are higher in LVEF < 45%, the variance and standard deviation in LVEF > 55% are larger. In LVEF > 55%, the variance is 3.818, and the standard deviation is 3.934, and for LVEF < 45%, it is 3.471 and 3.222, respectively. The larger variance and standard deviation in the LVEF > 55% can be concluded that the data scatter was higher than the mean, indicating larger changes in the left ventricular region.

There are also differences in the measured chaos characteristics at 45% and 55% (Table 2). Entropy was negative for all patients. The main reason could be the shortness of the time series because entropy directly relates to time and increases over time. The ApEn mean

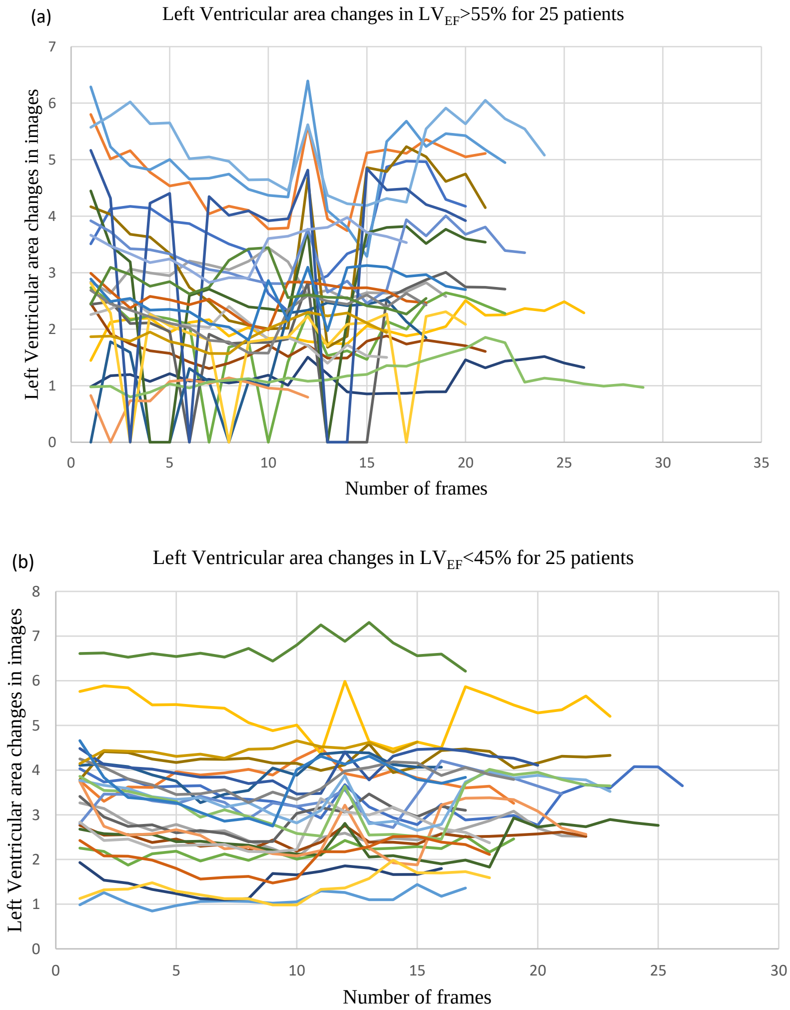

Figure 5. LV region changes for 50 patients (a) 25 patients with $LV_{EF} > 55\%$, (b) 25 patients with $LV_{EF} < 45\%$ which shows the differences in LV region changes

for LVEF > 55% was -0.549 for LVEF < 45% was 0.561. The absolute entropy is higher for data with high variability, so the ApEn is larger for LVEF > 55%. The correlation dimension also shows a significant difference. According to the obtained value, it can be said that the dependence is directly related to the number of normal rhythms of the cardiac system; the higher the normal rhythm, the higher the correlation dimension value. The mean correlation dimensions for LVEF > 55% and LVEF < 45% were 0.984 and 0.880, respectively. Regarding LE, the results showed that in LVEF < 45%, the system is more sensitive to stimulation. As expected, the Lyapunov Exponent (LE) level in LVEF < 45% is larger than LVEF > 55%. The mean LE values were 0.021 and 0.019 for LVEF < 45% and LVEF > 55%, respectively. The fractal dimension mean calculated in both LVEFs is also close, but at LVEF < 45%, the mean is slightly larger. Fractal dimension mean at LVEF < 45% and LVEF > 55% was obtained at 1.566 and 1.507, respectively. A larger fractal dimension indicates the presence of more fractured surfaces. According to the obtained results, it can be said that the differences between LVEF < 45% and LVEF > 55% are observable to a desirable extent.

Table 2. Mean value of chaos and statistical feature for LV region changes

	$LV_{EF} > 55\%$	$LV_{EF} < 45\%$
Mean	3.071	3.2549
Median	3.107	3.263
Variance	3.818	3.471
Standard deviation	3.934	3.222
Approximate Entropy	-0.549	-0.561
Correlation dimension	0.984	0.880
Lyapunov exponent	0.019	0.021
Fractal dimension	1.507	1.566

In the feature extraction, it is important to determine the value of the adding features cost (β). Determining the value of this parameter depends on the number of initial features, which directly affects the accuracy and number of extracted features. The larger the value of this parameter, the greater the number of features extracted. Conversely, the smaller the value of this parameter is selected, the number of features extracted decreases. In other words, if the number of initial features is higher, we get the desired result at lower β values, and the lower the number of initial features, we get the desired result at higher β values. Therefore, increasing or decreasing the value of this parameter is determined based on the number of features. If the appropriate β value is not selected, the appropriate performance algorithm will not have a feature in the extraction and will be out of balance. In this study, different values of β have been used, which are shown in Table 3, along with the number of extracted features. Regarding the repetition of network training, it should be said that it greatly affects reducing errors. The lower the number of repetitions, the higher the error, and the higher the number of repetitions, the lower the error. Repetition of network training helps to find the right features in a better way. The samples are provided as a suitable feature for each set of extracted features in which the network has the least (Mean Square Error) MSE in sampling. As a result, it can be concluded that as the value of β changed from 2 to a smaller value, the number of selected features decreased, and the network MSE decreased. Analyzing the results, it can be concluded that increasing or decreasing the value of β to the permissible level increases the accuracy of feature extraction, which can be realized according to the obtained MSE. Reducing the value of β to 0.8 reduces the MSE, but at values of 0.5 and 0.001, the genetic algorithm goes out of balance, and the network MSE increases. It should be noted that feature extraction and ANN have a random function. For this purpose, to better evaluate the results, measured data from 10 patients were applied to the ANN for testing. Table 4 shows the results of estimating ventricular output for the β values specified in Table 3. According to the results in Table 4, it can be concluded that the network with the extracted features at β = 1 and β = 2 had the best accuracy in estimating LV_{EF}. In the case of β = 0.001, it can be seen that in some cases, the accuracy is very low, and there is a big difference with the real values. The results prove the randomness of the feature extraction process of the neural network function. Generally, the best measurement accuracy and the least difference with the actual values in the extracted properties are obtained at β = 2 (Table 4).

Table 3. Extracted features based on different values of β along with MSE

β	Feature extracted	MSE
2	min, mean, med, var, Std, ApEn, CD, FD	5.54
1	max, mean, var, std, ApEn, LE, CD, FD	5.54
0.8	max, var, ApEn, CD, LE, FD	5.26
0.05	Min, mean, med, var, ApEn, FD	6.04
0.001	max, min, mean, med, var, ApEn, FD	6.28

LVEF estimation in three cases without feature extraction was performed, once with every ten features (statistical and chaotic), six statistical features, and four chaotic features to view the effect of chaos and statistical features independently and together. As mentioned, feature extraction is random, and the extracted features may not be appropriate for the intended purpose. For this reason, the mentioned features have been used to estimate LVEF without the benefit of feature extraction. The created ANN has a similar architecture to the ANN architecture used in the feature extraction. This network has ten neurons in the input layer. The network inputs are once ten statistical and chaotic features together, six statistical features, and four chaotic features separately. By examining the results of this section, it is possible to understand the effect of the mentioned features together or individually.

Table 4. Estimation of LV_{EF} by ANN with different β values for ten patients

β	True value of LV_{EF}	61.2	41.8	55.5	41.9	60.2	69.7	30.9	61	57.8	39.4
2	LV_{EF} estimated by ANN	57.4	38.6	35.2	47.5	81.5	74.1	94.1	54.4	55.3	33.4
1		50.4	50.4	57.3	64.7	34.4	62.1	9.2	22.4	60.8	41.9
0.8		37.4	64.4	45.6	43.3	41.4	60.1	46.1	50.1	38.9	50.9
0.05		68.1	35.5	59.5	55.4	48.4	57.7	57.6	22.6	22.1	23.4
0.001		17.9	46.2	54.4	44.9	-0.2	72.8	30	47	37.8	41.3

As shown in Table 5, according to MSE, it can be said that the effect of Chaos characteristics in estimating the LV_{EF} is more than statistical features, and less MSE is obtained, but the least MSE is obtained when all features are used to estimate LV_{EF}. The results of estimating LV_{EF} can be seen in Table 6. According to Table 6, in the case where all ten features are used together, the values are more accurate than the other two cases, have the least MSE of all, and have the best LV_{EF} estimation mode in this paper.

4. Discussion

This study aimed to estimate LVEF by examining the displacement and changes of the LV region in echocardiographic images using nonlinear and statistical analysis. Since there is a clear relationship between the mean characteristics of chaos and LVEF, measurements of parameters such as Poincare conjecture or Recurrence Quantification Analysis (RQA) should be considered. Despite the chaos in the behavior of the cardiac system, the mean fractal dimension showed that there are repetitive patterns in the behavior of the system, although proof of this requires more extensive research.

As expected, the presence of any LV dysfunction causes changes in its behavior. The results showed good accuracy and low MSE in the case that all features were used, of which MSE was 5.15. Due to the lack of a sufficient number of features, feature extraction caused it to have a poorer performance than the non-feature extraction mode. If higher quality echocardiographic images are acquired, LVEF will be performed as best as possible, resulting in increased measurement accuracy. According to the correlation dimension obtained values, a direct correlation was observed between this parameter and the health of the cardiovascular system. Despite the small differences between the correlation dimensions of the two groups of LVEF, it can be seen that the function of the system has an effect on increasing the value of the correlation dimension. Of course, the small difference in this parameter for these two groups of LVEF is due to the shortness of the time series, which is thought to be significant in longer time series. Also, more repetitive patterns were observed in the LVEF > 55% more than the LVEF < 45%, which is indicated by the higher value of the fractal dimension. Of course, the short time series still causes a small difference between this parameter in these two LVEF groups.

In comparison to previous studies, She *et al.* (2019) [4] studied the chaotic characteristics of heart sound by examining the correlation dimension and K entropy. They then obtained the correlation dimension of 0.3 to 4.5, which depends on the patient's age. In our method, the correlation dimension is 0.7 to 1.4, in which the shortness of the ultrasound image sequence, age, and the LVEF are effective. In addition to the correlation dimensions and entropy, Lyapunov exponent and fractal dimensions were used in this work, which led to more information about the

Table 5. Estimation of LV_{EF} by ANN in 3 different feature modes with ten patients

	Features	MSE
All Features	Max, min, mean, med, var, std, ApEn, CD, LE, FD	5.15
Chaos features	ApEn, CD, LE, FD	8.83
Statistical features	Max, min, mean, med, var, std	6.71

Table 6. Estimation of LV_{EF} by ANN using all features, chaos features, and statistical features separately for ten patients

Features	**The true value of LV_{EF}**	**61.2**	**41.8**	**55.5**	**41.9**	**60.2**	**69.7**	**30.9**	**61**	**57.8**	**39.4**
All Features		65	41.8	50.6	36.5	74	63.2	55.8	59.2	64.3	39.8
Chaos features	LV_{EF} estimated by ANN	62.4	48.7	46.8	47.4	57.2	53	58	43	45.1	51
Statistical features		46	49	56	36.8	49.6	54.3	47.9	50.1	49.7	54.5

function of the LV and cardiac system. Zheng and Guo (2017) identified Chronic Heart Failure (CHF) using linear and nonlinear analysis. They observed that CHF reduces the LVEF and thus increases the characteristics of chaos and complexity. They then calculated the correlation in patients at 6.019 ± 0.1986 and in healthy individuals at 7.180. 0.2153 that there is a significant difference. In our method, for LVEF < 45%, the average correlation dimension is 0.88, and in LVEF > 55%, it is 0.984. Due to the shortness of the image sequence, the difference between the two groups is small, but the difference is also noticeable. In this study, it was observed that the reduction of the LVEF also caused chaotic behavior and increased the mean of chaotic characteristics and system complexity. Oktay *et al.* (2018) measured the LVEF of 30 patients diagnosed with myocardial infarction or dilated cardiomyopathy from the CETUS (https://www.creatis.insa-lyon.fr/Challenge/CETUS/index.html) database using the neural network by segmentation of ultrasound images. The correlation dimension measured in their method was 0.91, which is 0.98 compared to the correlation obtained in our method.

To conduct more research activities by other researchers, predicting the behavior of biological systems in short time series with statistical analysis and nonlinear analysis and creating a new way to diagnose or predict cardiac arrhythmias in echocardiographic images by examining cardiac component movements in the image are suggested.

5. Conclusion

In this study, a method for estimating LVEF by nonlinear analysis was presented. It can be said that low LVEF will change the behavior of the cardiovascular system. Changing the behavior of the system has a unique effect on each chaotic parameter; for example, the correlation dimension decreases with the number of normal rhythms while the Lyapunov exponent increases. These findings indicate that nonlinear and statistical analysis of LVEF could be used to diagnose arrhythmias.

According to the results, it can be said that in short time series, correlation dimension measurement is a reliable parameter to investigate the behavior of the system, but the mean of ApEn, Lyapunov exponent, and fractal dimension are slightly different in these two groups of LVEF. Therefore, by increasing the number of chaos characteristics considered, the difference between these two groups of LVEF can be further determined.

However, this method has some limitations. First, the image quality of the data makes it difficult to extract the LV region in images. The second is the shortness of the time series, which significantly affects the measurement of features. The longer the time series, the more significant the difference between the LVEF > 55% and LVEF < 45%. To overcome these limitations, image acquisition needs to be improved. The advantage of this method is the speed in LV segmentation in the image, low cost, and desirable accuracy. This method allows physicians to extract sufficient and essential information from ultrasound images without long-term imaging. This eliminates the extra cost of imaging and shortens processing time.

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