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Left Ventricular Entropy as a Measure of Wall Motion Abnormalities in Echocardiography Images

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Abstract: Cardiovascular diseases (CVD) are today a major cause of death globally that is diagnosed by measurement and quantification of left ventricle (LV) wall motion (WM) abnormality of heart. The aim of this study was to assess the utility of left ventricular (LV) entropy, a novel measure of disease derived from two-dimensional (2D) echocardiography images that assesses the probability distribution of pixel intensities in the LV. The proposed of this research is to develop the method of LV entropy to predict heart diseases. In this algorithm, a frame is usually chosen as the reference frame to extract region of interest (ROI) around LV and then it is mapped to all images in a cardiac cycle. Then Shannon Entropy transform was applied to calculate the distribution of pixel intensities across the LV so we obtained entropy curves and compared them. The main idea is to find a motion estimation accuracy. The results obtained by our method are quantitatively evaluated to those obtained by an experienced echocardiographer visually on 22 normal cases and 19 myocardial infarction (MI) cases in apical four-chamber (A4C) view. The entropy of diastole in MI cases was 0.50 (0.29-0.58) while in normal cases was 0.75 (0.64-1.13). The entropy of systole in MI cases was 0.64 (0.26-1.04) while in normal cases was 0.81 (0.63-1.26). The percent change of entropy for diastole and systole between normal and MI cases are 33.3% and 20.2%. The results indicate that the LV entropy curves of MI cases have less changes than normal cases.

Keywords: Echocardiography, Cardiac cycle, Entropy, Left ventricle, Wall motion.

1 Introduction

CARDIOVASCULAR diseases (CVD) is the leading cause of death globally according to World Health Organization (WHO). About 19.91 million people died from CVD in 2021, mainly from heart diseases and stroke the number is still increasing annually. In recent decades, major advances have been made in cardiovascular research and practice aiming to improve diagnosis and treatment of cardiac diseases as well as reducing the mortality of CVD Deaths attributable to diseases of the heart and CVD in the United States increased steadily during the 1900s to the 1980s and declined into the 2010s but increased again in the later 2010s to 2020. It is estimated that roughly 127.9 million Americans (48.6%) ≥20 years of age have CVD, including coronary heart disease, heart failure, stroke, or hypertension [1, 2].

Different modalities for cardiac imaging including magnetic resonance, computed tomography, and echocardiography are used. Ultrasound (US) imaging has gained much popularity; and some of the main reasons of its prominence are due to high speed of imaging, small instruments, low cost, high degree of time resolution, being non-invasive, harmless for human body, and portable in all places. That's why physicians use this kind of imaging as the first step to recognize the disease [3].

One of the main drawbacks of this US imaging is its

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high noise, especially speckle noise. Speckle noise is different in imaging of different organs, but always appears as small grains depending on structure and composition of the tissues [4]. Echocardiography video is used to analyze cardiac performance of patients. Echocardiography uses techniques by emitting US waves to determine the size, shape, function of the heart, and the condition of the heart wall, valves, and beginning of main arteries visualized into the video image [5]. In the usual method, the echocardiographer analyzes the echocardiographic images and follows features that indicate the presence or absence of heart disease. Due to the length of time for a training course needed for interpretation of the images, longevity, and error in manual methods, an automatic analysis is needed. These methods are scientific, accurate, rapid, and independent of subjective opinions [5, 6].

Many researches used several methods to determine the cardiac performance from echocardiographic videos. These methods are based on deep learning, machine learning, and image processing. Several methods have been proposed for the analysis of 2-D echocardiographic sequences [4].

The most famous method is segmenting the heart borders using mechanical and deformable models. In these methods, with geometric and mechanical models, using active boundaries or surfaces, a displacement field is extracted and cardiac motion is analyzed. These methods try to overcome complexities of echocardiographic data using a statistical model of motion and the shape of the heart muscles. However, these methods estimate the motion of the heart considering the myocardial borders only. As a result, when the motion is parallel to the boundary, it estimates a wrong movement. Another problem with these methods is that boundaries are not always clear in echocardiographic images [6]. Another automatic technique to characterize cardiac motion abnormalities, is based on nonrigid image registration for classifying the regional wall motion of left ventricle (LV). In this algorithm, all frames of one cycle of heart are registered to a reference image (end diastolic image) [7]. This model is based on an affine transformation for modeling the global LV motion and a B-spline free-form deformation transformation for modeling the local LV deformation. The automatic detection of the end-diastole and end-systole frames will lead to automatic calculation of end-systolic and end-diastolic volumes, stroke volume, ejection fraction ratio, cardiac output and wall thickening which are fundamental parameters for heart function assessment [8].

More recently, deep neural networks have been used in medical research due to their ability to automatically learn features from data Specifically, in medical image analysis, convolutional neural networks have proven to be a powerful tool. The convolutional layer reduces the dimensionality of the images without losing information. These features make convolutional neural networks suitable for image analysis. Researchers proposed a three-phase approach for early myocardial infarction (MI) detection. This consists of three stages: LV wall segmentation, feature extraction as preprocessing steps, and MI detection. Supervised machine learning techniques were used for motion classification. The Support Vector Machine gave the best results [9].

Researchers proposed a fully automated analysis of echocardiographic images by deep learning models via convolutional neural networks that included view classification of the mitral valve leaflet diseases [10]. Researchers proposed an intelligent identification system for left ventricular hypertrophy etiology classification based on routine Transthoracic echocardiography video images with good diagnostic performance. This deep learning method is feasible in automatic transthoracic echocardiography images interpretation and expected to assist clinicians in detecting the primary cause of left ventricular hypertrophy [11]. To classify US images, another method proposed a novel deep learning based on approach to breast mass segmentation in US imaging. In comparison to commonly applied segmentation methods, which use US images, their approach is based on quantitative entropy parametric maps. To segment the breast masses they utilized an attention gated U-Net convolutional neural network [12, 13]. However, deep learning systems learn gradually, massive volumes of data are necessary to train them. Another issue with deep learning is that it demands a lot of computational power. We are looking for a simple and efficient method.

Entropy is a classical measure of uncertainty in information theory. Recently, several methods based on entropy have been proposed to measure the heterogeneity. First method is an additional cardiac magnetic resonance imaging based method for refining arrhythmic risk prediction in ischemic cardiomyopathy. This method accurately predicted the risk of ventricular arrhythmia events in patients with ischemic cardiomyopathy and LV systolic dysfunction. They utilize the concept of Shannon entropy, which was initially described in 1948 by Claude Shannon as a method of quantifying information in communication systems. Shannon established a mathematical theory of communication and defined entropy as a measure of uncertainty in a random variable [14-17]. Second, there have been few reports on the prognostic value of the entropy for cardiac diseases to evaluate the prognostic value of LV end-systolic contractile entropy in patients with complete left bundle branch block, including various conditions ranging from normal LV function and

no symptoms, to impaired LV function and severe cardiac symptoms based on electrocardiogram ECG signal [18].

LV entropy is a novel measure of heterogeneity, rapidly measured, and highly reproducible. It demonstrates promising ability to predict heart diseases. The aim of this study was to assess the utility of LV entropy, a novel measure of LV disease derived from echocardiography that assesses the probability distribution of pixel intensities in the LV. The proposed of this research is to develop the method of LV entropy to predict heart diseases. We applied the proposed approach to the 41 echocardiography videos. To study the wall motion abnormality we compared the resulted entropy. This parameter is suggested as a criterion to evaluate heart health.

2 Method

The 2-D image sequences of 22 normal and 19 anterior MI heart disease are used. It is known that a heart attack is caused by decreased or complete cessation of blood flow to a portion of the myocardium. Echocardiography images were acquired during standard clinical examinations. All data were collected using a Philips Affinity 70c Ultrasound with a frame rate of 42–87 frame per second and the cases had heart rate of 45-108 beats per minute (bpm). Including the electrocardiogram display, each data contains 1 to 6 cardiac cycles and 25 to 250 frames which were provided as retrospective data by Tehran Heart Center hospital, Tehran, Iran. In this research, all calculations were done using Matlab software (The Math Works, Inc., MATLAB, version 2020a).

2.1 Shannon Entropy

In this paper, a new method for quantification of left ventricle wall motion abnormality of echocardiography image using the Shannon entropy has been proposed. We propose LV entropy, a novel method of examining the cardiac disease in which the distribution of pixel intensities across the LV is assessed and compared. This method is based on a property used in photo editing, referred to as image entropy. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. At a conceptual level, Shannon's Entropy is simply the "amount of information" in a variable. In other words, that translates to the amount of storage (e.g. number of bits) required to store the variable, which can intuitively be understood to correspond to the amount of information in that variable.

Entropy in this context describes the complexity of an image; an image with completely homogenous pixels (e.g., a black square) would have entropy of zero. As the image becomes more complex, with many different pixel values, it has a higher entropy. Thus, by applying this principle to the cardiac image, the “complexity” of the total LV can be quantified. Information entropy Sen of a random variable X that takes the values x1, x2, ..., xn is defined as Eq. (1):

$$s_{en} = \sum_{i=1}^{n} p(x_i) \log_a \frac{1}{p(x_i)} = -\sum_{i=1}^{n} p(x_i) \log_a p(x_i), a > 1 \quad (1)$$

where p(xi) are probabilities of acceptance of xi by the random variable X.

Shannon entropy is characterized by a degree of uncertainty associated with the occurrence of the result. A higher value of the entropy gives a more uncertain outcome and is more difficult to predict. Generally, the entropy of X is a measure of expected uncertainty obtained during the measurement of that variable [19].

2.2 Proposed Method

We convert echocardiographic videos to a sequence of frames. Therefore, a cardiac cycle is shown as a number of consecutive frames that are proper for our work. We usually consider the end-diastolic frame corresponding to the peak R (R waves of ECG are the excitation process of ventricular free wall and represent ventricular depolarization in clinic) on the electrocardiography signal. As a result, a cardiac cycle is the distance from R to R, and the number of frames in this cycle will vary according to the echocardiography frame rate and the heart rate.

First, the approximate region of LV was extracted from echocardiography images in each data. This was done by manually defining a rectangular region of interest (ROI) around LV. Then, the coordinates of the extracted rectangular ROI were automatically applied on all images of one cardiac cycle. These images are used for the following analysis Fig.1. Next, Shannon entropy calculation was applied to calculate the distribution of pixel intensities across the LV. Finally, for each data, we obtained the entropy curve and each curve is separately considering the left ventricular volume that is analyzed, Fig.2. The entropy values presented as median and inter-percentile range (10^{th}-90^{th}).

Measuring end-diastolic and end-systolic volume is important in cardiovascular diseases because these values help doctors to evaluate heart function. The end points of diastole and systole are critically important in measuring heart diseases for several reasons: The end of diastole marks the point when the heart's ventricles are filled with blood and are about to contract. This is known as end-diastolic volume, which is a determinant of stroke volume and cardiac output. The end of systole indicates the completion of the heart's contraction phase, where the blood has been ejected from the ventricles. This is measured as end-systolic volume. Abnormalities

at this stage, such as reduced ejection fraction, can signal systolic dysfunction, which can be due to ischemic heart disease or cardiomyopathies.

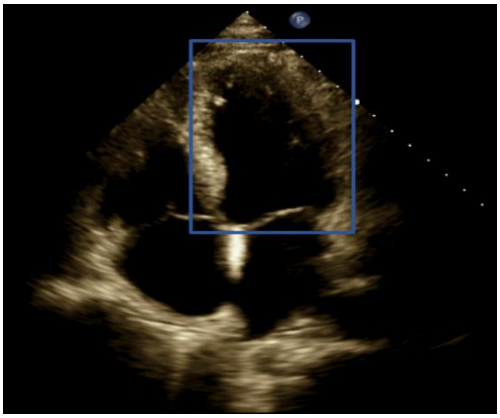


Fig .1 One image from the sequence with the rectangular box shows the localized LV in A4C view

The entropies of the beginning and end of diastole and systole are used in the detection of cardiac abnormalities because these phases of the heart cycle reflect significant physiological information. During a cardiac cycle, the heart undergoes periods of contraction (systole) and relaxation (diastole), which are associated with the opening and closing of heart valves and the flow of blood.

Entropy, in this context, is a measure of the randomness or disorder within a signal. In the case of heart sound signals, entropy can provide insights into the complexity of the signal during different phases of the heart cycle. By analyzing the entropy at the beginning and end of diastole and systole, it's possible to capture changes in the heart's behavior that may indicate abnormalities. The entropies of diastole and systole are used because they can reveal subtle changes in the heart's function that are not easily detectable through other means, thus providing a non-invasive and effective way to monitor heart health and detect abnormalities.

In the clinical setting it is especially important to determine the state of the left ventricle. This requires the measurement of its volume in the end-diastolic and end-systolic frames within the sequence trough segmentation methods.

Understanding the dynamics of end-diastolic volume and end-systolic volume is essential for diagnosing and managing various cardiac conditions, as they provide insights into the heart's pumping efficiency and blood flow regulation throughout the body. In the clinical setting, several parameters are used to characterize LV, specifically its volume in end-diastole, which corresponds to the state of maximum relaxation, and in end-systole which corresponds to the state of maximum contraction. Using these two values the ejection fraction can then be derived.

To compare entropy curves, we estimated the following parameters Fig.2:

Diastolic entropy = End diastole entropy - Beginning diastole entropy.

Systolic entropy = End systole entropy - Beginning systole entropy.

It should be noted that this algorithm takes longer than one cycle to have a systole phase and diastole phase in it, and the number of cycles has no effect on improving the result.

A cardiac cycle is the distance from a R wave (The largest wave in QRS complex is R wave. R waves of ECG are the excitation process of ventricular free wall and represent ventricular depolarization in clinic) to the next R wave in electrocardiogram.

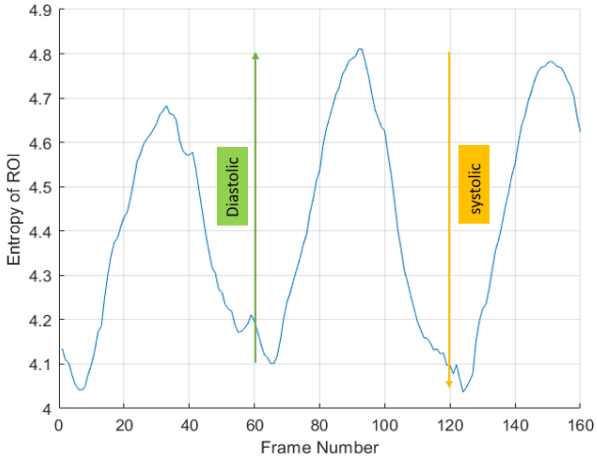
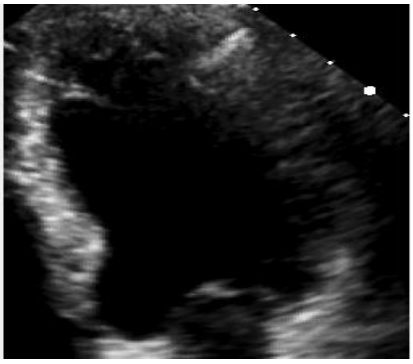


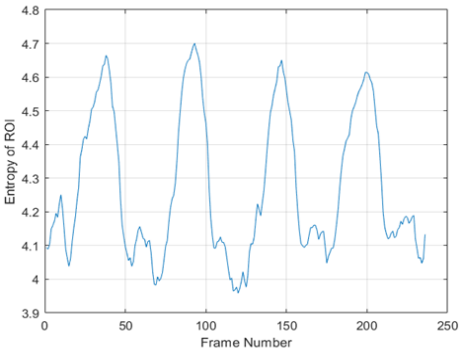
Fig .2 The image shows the diastolic and systolic entropy on a normal case.

3 Results

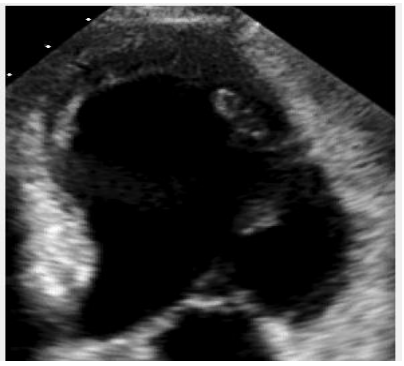
To evaluate the proposed method and to compare it, we applied the proposed method on the MI and normal datasets. First, the reconstructed US images were used by an experienced radiologist to outline ROI indicating LV areas. Next, Shannon entropy transform was applied to calculate the distribution of pixel intensities across the LV. Finally, for each data, we obtained the entropy curve. Fig .3 shows the image process between two images in A4C view for normal and MI cases. The left parts show the ROI around LV as a reference image. The right parts show the entropy of ROI for all frames. The approximate of diastolic entropy and systolic entropy for the normal case are 0.70 and 0.75 respectively, but the approximate of diastolic entropy and systolic entropy for the MI case are 0.20 and 0.15, respectively.



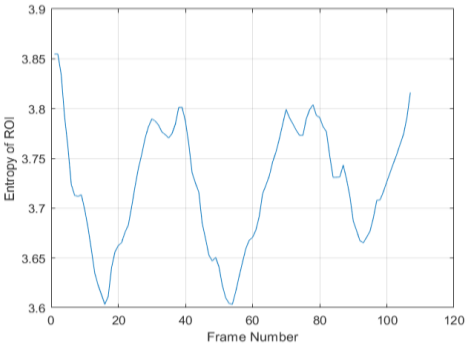
(a) Normal case (The image witch we extract ROI)



(b) Entropy curve (Normal case)



(c) MI case (The image witch we extract ROI)

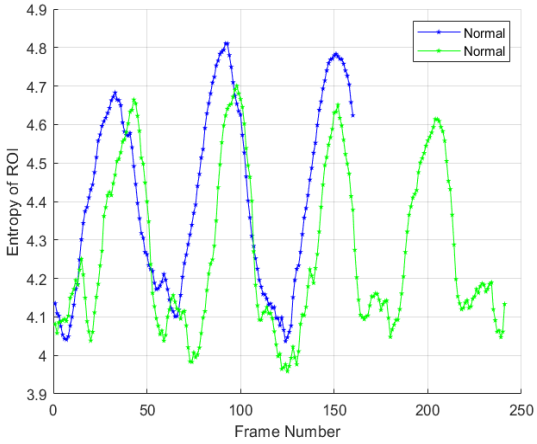


(d) Entropy curve (MI case)

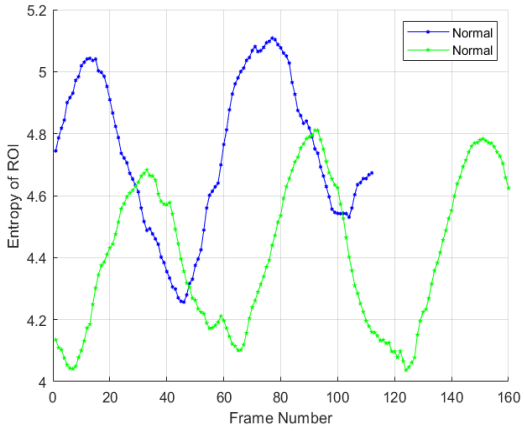
Fig .3 The process between two images in A4C view for two cases. The left parts (a, c) show ROI and the right part (b, d) shows the entropy curve for each case.

3.1 Wall motion (WM) abnormality quantification of LV

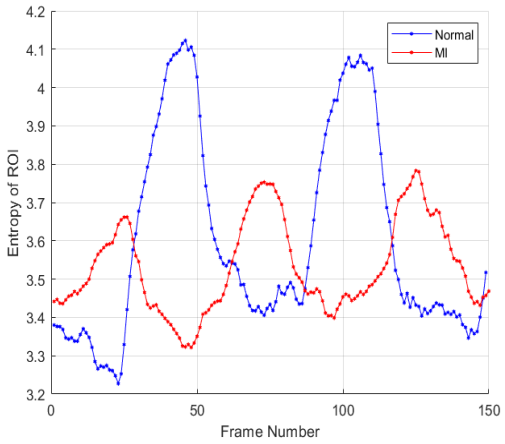
After extracting rectangular ROI Shannon entropy transformation Eq. (1) is applied to all frames in one cycle of heart in A4C view. As it shows in Fig. 4 to compare the normal cases results, we put the entropy curves of four normal cases with green and blue color (above plots), to compare the normal and MI results, we put the curve of a normal case as a reference and displayed it with blue color, and then compare it with the curves of four MI cases with red color (middle and bellow plots). It shows that the LV entropy curves of MI cases have less changes than normal cases.



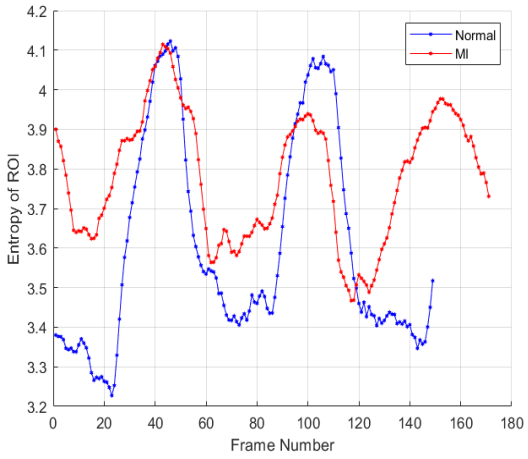
(a)The LV entropy curves of two normal cases



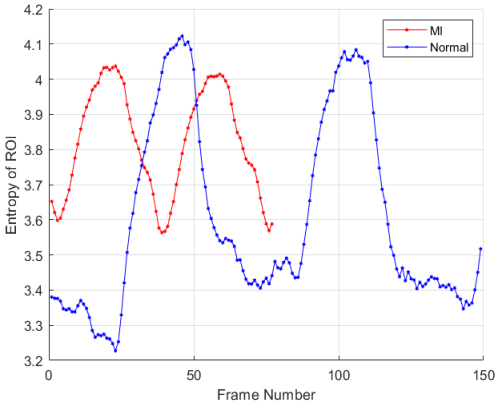
(b)The LV entropy curves of two normal cases



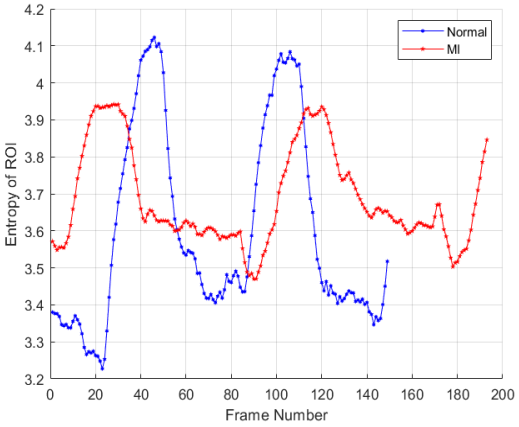
(c)The LV entropy curves of normal and MI cases.



(d)The LV entropy curves of normal and MI cases.



(e)The LV entropy curves of normal and MI cases



(f)The LV entropy curves of normal and MI cases

Fig .4 The above plots (a, b) obtained from normal cases, the middle (c, d) and the bellow (e, f) obtained from MI and normal cases.

The entropy curve of a normal case (blue) and two MI cases (red and pink) are compared in Fig. 5. It shows that the LV entropy curves of MI cases have less changes than normal case.

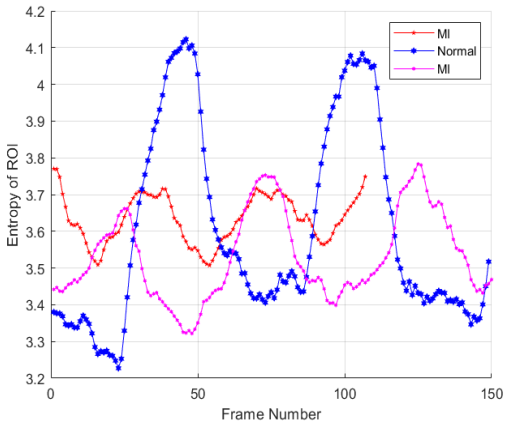


Fig .5 Comparing the curves of a normal case (blue) and MI cases (red and pink).

We applied the proposed approach to the 41 echocardiography dataset that include 22 normal data and 19 MI data. The LV entropy for normal cases is demonstrated in Table 1 and the MI cases is demonstrated in Table 2. The entropy of diastole in MI cases was 0.50 (0.29-0.58) ($0.29< \text{Entropy}_{\text{diastole}} <0.58$) while in normal cases was 0.75 (0.64-1.13) ($0.64< \text{Entropy}_{\text{diastole}} <1.13$ in addition, 0.50 and 0.75 report median. The entropy of systole in MI cases was 0.64 (0.26-1.04) $0.26<$ ($\text{Entropy}_{\text{diastole}}$) <1.04) while in normal cases was 0.81 (0.63-1.26) ($0.63< \text{Entropy}_{\text{diastole}}<1.26$) in addition, 0.50 and 0.75 report median. The results show that MI cases have less changes than normal cases. The percent change of entropy for diastole and systole between normal and MI cases are 33.3% and

20.2%. The vertical axis of the figures shows the calculated entropy value, and in the tables, the entropy difference between the maximum and minimum points in two phases of systole and diastole is reported, which is similar to what is read between the maximum and minimum in figures.

Table. 1 In this table diastolic entropy, systolic entropy, median and inter-percentile range (10th-90th) for 22 normal cases were calculated.

Number	Diastolic	Systolic
1	0.75	0.86
2	0.77	0.71
3	0.65	0.88
4	1.40	1.46
5	0.85	0.89
6	0.68	0.78
7	0.74	0.78
8	0.81	1.23
9	0.67	0.76
10	0.68	0.92
11	0.79	0.93
12	0.75	0.81
13	0.80	0.64
14	0.66	0.85
15	1.05	0.94
16	1.16	1.27
17	0.68	0.80
18	0.86	0.63
19	0.90	0.72
20	0.65	0.63
21	0.63	0.67
22	0.64	0.61
Median and inter-percentile range	0.75 (0.64-1.13)	0.81 (0.63-1.26)

Table. 2 In this table diastolic entropy, systolic entropy, median and inter-percentile range (10^{th}-90^{th}) for 19 MI cases were calculated

Number	Diastolic	Systolic
1	0.45	0.60
2	0.54	0.64
3	0.53	0.61
4	0.51	0.60
5	0.71	1.07
6	0.50	0.68
7	0.37	1.04
8	0.53	0.66
9	0.58	0.76
10	0.45	0.78
11	0.56	0.26
12	0.51	0.66
13	0.31	0.38
14	0.50	0.36
15	0.29	0.45
16	0.35	0.75
17	0.39	0.73
18	0.20	0.21
19	0.49	0.55
Median and inter-percentile range	0.50 (0.29-0.58)	0.64 (0.26-1.04)

In addition, after extracting rectangular ROI and applying Shannon entropy transformation Eq. (1) we compared the systolic and diastolic entropy results of normal and MI cases with blue and red stars in Fig. 6. As it shows the entropy of MI cases are less than normal cases.

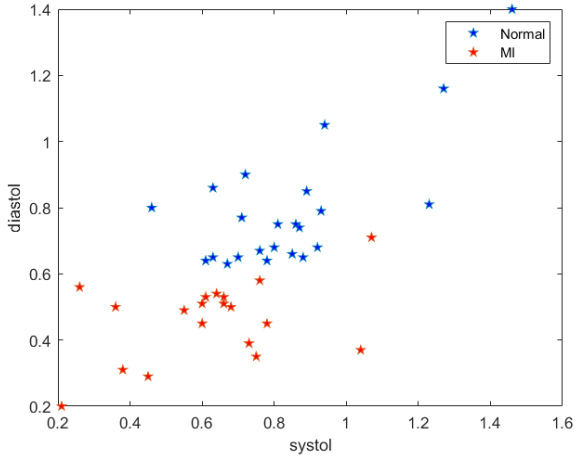


Fig .6 The systolic and diastolic entropy for normal (blue stars) and MI (red stars) cases.

4 Discussion

In this paper, a new suitable method, based on Shannon entropy is presented for 2-D echocardiography images. The proposed algorithm is able to accurately estimate the LV changes over a cardiac cycle. To do this, a frame is usually chosen as the reference frame to extract ROI around LV and then it is mapped to all images in a cardiac cycle. Then Shannon entropy transform was applied to calculate the distribution of pixel intensities across the LV to compare WM changes between cases. Providing an automatic image processing method based on entropy algorithm to identify and quantify, accurately and quickly evaluate these anomalies was the main focus of this research. We applied the proposed approach to the 41echocardiography dataset. The LV entropy for normal cases is demonstrated in Table 1 and of the MI cases is demonstrated in Table 2. We compared the results of the entropy curves in Fig. 4. Obviously, there is a difference between the entropy of abnormal and normal cases. In the case of entropy of diastole, the distribution of data was almost separated because there was no overlap of the inter-percentile range. However, in the case of entropy of systole, there was a significant overlap between values of normal cases and MI cases. This tip points out that the entropy of diastole is very more effective than the entropy of systole for the separation of normal from MI cases. Our findings can be clinically implicated in a remote area, rural region, or overcrowded area where special services are unavailable or mass

population screening that requires a rapid and relatively effective method for separation of abnormal from normal. In addition, it can be applied in the education of medical novice trainees.

Our proposed methods have some advantages over the other conventional approaches of cardiac cycle evaluation. First, our algorithm does not need to detect ED and ES frames. Second, any LV myocardial segmentation and tracking that are particularly difficult in the echocardiography images are not required. Third, our method does not require a large amount of data and computational complexity like deep learning.

The current study has several limitations. ROI extraction was done manually which can include errors and the number of frames and cardiac cycles were different in cases. The performance of this method can be affected by the severity of this disease. As a future work, we will investigate this relationship by collecting more data.

In this research, the standard video of echocardiography used was taken by the operator at the hospital in a A4C view of the heart. However, as noted above, due to the length of time needed and tiresome manual methods, we use the automatic method proposed in the paper to make the diagnosis quantitative, scientific, accurate, and fast. This parameter is a criterion to evaluate heart health. Results showed significant differences between normal and abnormal hearts.

The results showed that this technique could be a way to compare the cardiac WM in echocardiographic data. As future research activities, we can also test other views, such as two-chamber, long-axis, and short-axis views, and achieve more accurate information of the heart disease. As it was said, in this study, the sections in which there isn't LV were removed manually. In order to estimate the volume automatically, first a classification can be used to detect a presence or absence of the LV in images, then it will be extracted automatically in the images that have the exact region of LV [20]. As future research is recommended to use classifiers like SVM to present the accuracy of recognizing abnormalities. The proposed method can be used to investigate other cardiovascular diseases by determining the area of interest on atrium. Implementing this method on a large database and investigating the behavior of this method for different heart diseases and comparing the results can be suggested as future works.

5 Conclusion

Left ventricular entropy has been used as a measure of wall motion abnormalities in echocardiography images. The goal of this research was to investigate the abnormalities of the LV using Shannon entropy. The solution based on detection of LV function is presented. Quantitative measurement of the function of the LV, which is the largest and strongest chamber of heart, is an essential step in the evaluation and investigation of most cardiovascular diseases. From the echocardiography sequence, the first frame is determined as a reference to manually determine ROI on it, then it is applied to all frames and the entropy function is obtained and the result is displayed as a curve.

Obviously, there is a difference between the entropy of abnormal and normal cases. In the case of entropy of diastole, the distribution of data was almost separated because there was no overlap of the inter-percentile range. However, in the case of entropy of systole, there was a significant overlap between values of normal cases and MI cases. This tip points out that the entropy of diastole is very more effective than the entropy of systole for the separation of normal from MI cases. The results showed that this technique could be a way to compare the cardiac WM in echocardiographic data. Our findings can be clinically implicated in a remote area, rural region, or overcrowded area where special services are unavailable or mass population screening that requires a rapid and relatively effective method for separation of abnormal from normal. In addition, it can be applied in the education of medical novice trainees.

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