Characterizing the left ventricular ultrasound dynamics in the frequency domain to estimate the cardiac function

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Abstract. Assessment of cardiac function typically relies on the Left Ventricular Ejection Fraction (LVEF), i.e., the ratio between diastolic and systolic volumes. However, inconsistent LVEF values have been reported in many clinic situations. This study introduces a novel approach to quantify the cardiac function by analyzing the frequency patterns of the segmented Left Ventricle (LV) along the entire cardiac cycle in the four-chamber-image of echocardiography videos. After automatic segmentation of the left ventricle, the area is computed during a complete cycle and the obtained signal is transformed to the frequency space. A soft clustering of the spectrum magnitude was performed with 7.835 cases from the EchoNet-dynamic open database by applying spectral clustering with Euclidean distance and eigengap heuristics to obtain four dense groups. Once groups were set, the medoid of each was used as representant, and for a set of 99 test cases from a local collection with different underlying pathology, the magnitude distance to the medoid was replaced by the norm of the sum of vectors representing both the medoid and a particular case making an angle estimated from the dot product between the temporal signals obtained from the inverse Fourier transform of the spectrum phase of each and a constant magnitude. Results show the four clusters characterize different types of patterns, and while LVEF was usually spread within clusters and mixed up the clinic condition, the new indicator showed a narrow progression consistent with the particular pathology degree.

Keywords: Echocardiographic videos· Left Ventricular Dynamics· Ejection Fraction· Segmentation· Fast Fourier Transform· Clustering

1 Introduction

Evaluation of the Cardiac Function (CF) is usually performed by estimation of the LVEF [13,8,2], which is computed as the volume fraction between the End-of-Systole and End-of-Diastole. This index is normal when greater than 50%, it is mildly reduced (MR-LVEF) between 40% and 50%, and reduced (R-LVEF) when lower than 40% [1,4]. Cardiologists calculate the LVEF using Simpson's method, i.e., the expert manually segments the LVEF in echocardiography videos [6] at the end-of-diastole and end-of-systole and approximate the LV volumes[1,3]. Despite being the most used cardiac function indicator, the LVEF has been reported to show low sensibility to changes in the cardiac function while it also underestimates such function variations [2,14].

The LVEF estimation usually requires an accurate segmentation of the LV chamber in several cardiac frames, which is hardly reproducible by both the multiplicative noise and the high inter-observer variability [3,7]. In this scenario, different approaches have attempted to automatize the segmentation, particularly sophisticated models such as Convolutional Neural Networks (CNN) [9], residual autoencoding networks and BERT model [10], and Graph Neural Networks (GNNs) [7]. Nevertheless, none of these approaches have coped with the real problem, i.e., the LVEF, computed from two times of the cardiac cycle, can hardly approximate the function of an organ designed to adapt to very different and complex conditions. In practice, a systematic incoherence has been observed between the degree of the pathology and the computed LVEF value [2,4,13]. The LVEF in particular depends on pre and post-load conditions which are highly variable within the cardiac cycle while it captures no information at all about the contractility or the condition of the cardiac muscle.[2,5,8,11].

Although currently used, the Left Ventricular Ejection Fraction (LVEF) is still limited in clinic practice [2,3,5,8,14]. A main contribution of this paper is an indicator of the cardiac function which establishes the notion of distance by quantifying the fundamental parts of a periodic signal: the phase and the magnitude. Spectral decomposition of echocardiography signals is not novel, a main example being tissue Doppler imaging. However, these frequential analysis methods use exclusively the magnitude information of the Fourier transform. What is new in the present proposal is how phase information is integrated into the analysis and the importance of considering this at categorizing different pathologies. In this case, phase information helps us to establish when a particular frequency component occurs during the cardiac cycle and use this to compare the severity of different cardiac stages. The combination of magnitude and phase allow us to refine the notion of distance between cases pushing similar cases closer and different cases farther away.

Using a large number of cases, four different magnitude patterns are set by a non supervised soft clustering method. Once these frequential representants, the medoid of each group, are available, the distance of each case with respect to the medoid is corrected. For doing so, temporal series of the medoid and each of the cases are reconstructed from the spectral phase of each and a unitary magnitude. The dot product between the medoid and each of the cases establishes an angle (the temporal phase) which is then used to correct the original cluster distance. The underlying idea behind this proposal is to summarize the entire cardiac cycle into features that can be comparable and describe complex states and patterns of heart dynamics.

The rest of the article is organized as follows: section 2 presents the methods used, section 3 introduces the principal results, and finally, section 4 discusses the main conclusions.

2 Methods

The approach involves three steps as shown in Fig. 1. Initially, the quality of echocardiographic videos is improved and standardized in the preprocessing. Afterward, a simplified U-Net architecture segments the left ventricle chamber along the entire cardiac cycle. Then, the Fourier transform is applied to the temporal series obtained from the area of the segmented LV chamber along the whole cycle. Afterward, the magnitude and phase are used to construct a similarity metric that drives the severity quantification. The details of each step are elaborated below.

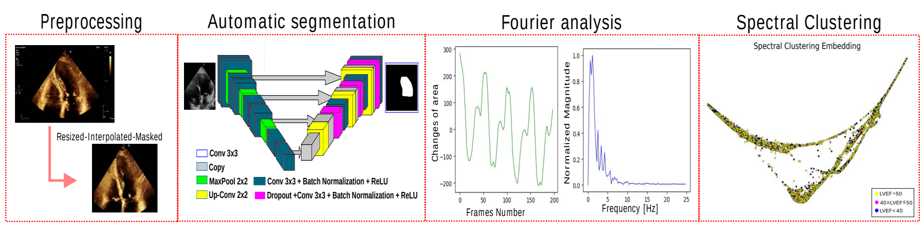

Fig. 1. Pipeline of the characterization of left ventricular dynamics in the frequency domain to estimate the cardiac function.

2.1 Preprocessing step

To ensure compatibility between datasets, specifically between the EchoNet-dynamic database [9] and a proprietary collection used in the evaluation, a series of preprocessing steps were performed as follows: firstly, the specific region of interest of the echocardiogram cone was identified, followed by cropping and removing any metadata information from the video. Afterward, a cubic interpolation was applied to each frame resized to 112×112 pixels, and finally, all the videos were re-sampled at 50 FPS.

2.2 Automatic segmentation

A customized U-Net segmented the left chamber in echocardiographic videos. In a previous work, this network demonstrated outstanding segmentation results

(Dice of 0.93), a considerable reduction of the number of parameters, and a similar performance, when compared with the original U-Net architecture [12].

2.3 Analysis in the Frequency Domain

After segmenting the left ventricular chamber during several cardiac cycles, the temporal series of the ventricular area showed a periodic pattern: Peaks and valleys correspond to the End-of-Diastole and End-of-Systole, respectively. After removing the DC component, only one cardiac cycle from each case was taken.

Fourier analysis transforms the temporal series into magnitude and phase spectra, being the magnitude the strength of the frequency components, and the phase their temporal locations. Specifically, the construction of the cardiac function descriptor is a modified version of the Euclidean distance among actual cases as follows in the algorithm 1.

Algorithm 1 Spectral Analysis to describe the cardiac function

Input: Temporal series of cardiac cases
Output: Assigned clusters with updated magnitude using phase information
Step 1: Mapping to the Fourier space
for each case in the dataset **do**
    Apply Fast Fourier Transform (FFT) to obtain magnitude and phase spectrum
end for
Step 2: Finding out the frequential representant of the cardiac cycle
Perform spectral clustering of the magnitude with 7,835 cases from the Echonet database and 99 cases from a local collection and registered clinic state
Step 3: Re-estimating intra-cluster distances using phase information for those cases with known clinical history
for each of the 99 cases **do**
    Set case_i to a particular group
    Apply inverse Fourier Transform using the phase spectrum and a **unitary magnitude** for both case_i and the medoid
    Compute dot product of the reconstructed temporal series between case_i and the group medoid
    Recover angle $\hat{\theta} = \arccos\left(\frac{\langle \text{medoid}, \text{case}_i \rangle}{|\text{medoid}||\text{case}_i|}\right)$
    Set a new case_i distance as the norm of the sum of two vectors, one with norm 1 and the other $1 +$ stored distance, and making angle $\hat{\theta}$
    Store this new distance for case_i
end for

2.4 Dataset

The EchoNet-dynamic database[9], a publicly available project, published 10,030 apical-4-chamber echocardiography videos from individuals who underwent imaging between 2016 and 2018 as part of routine clinical care at Stanford University

Hospital [9]. Only 7,886 were selected for the present investigation since they have the same sampling frequency (50 FPS), they did not present variable image orientation during acquisition (Figure 2-B), or breathing interference during the first or second cardiac cycle (Figure 2-C) and echo-Doppler mode cases were excluded (Figure 2-A). These videos were acquired with resolutions of 600×600 and 768×768 pixels from iE33, Sonos AcusonsC2000, Epiq 5G, or Epiq 7C ultrasound machines. Finally, each video was downsampled and resized to a dimension of 112×112 pixels. Additionally, the database provided the LV at the End-of-Systole and End-of-Diastole segmentation while also the LVEF and LV volume were informed [9].

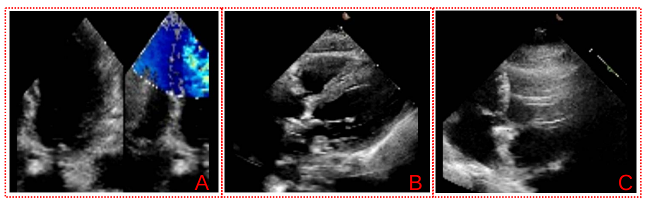

Fig. 2. Data exclusion criteria. A. Doppler mode. B. Abnormal orientation. C. Breathing interference during the first or second cardiac cycle.

Likewise, project 82335 from Minciencias provided an anonymized repository with 99 cases containing apical-4-chamber echocardiographic videos at a resolution of 1280×720 pixels, several sampling rates, and their respective clinical records. These videos were captured from three different ultrasound machines. A General Electric's echocardiography, Vivid I, and Vivid IQ, with a sampling frequency of 45 to 60 FPS. The other ultrasound equipment was a PHILLIPS healthcare echocardiography, AFFINITI 70C with a sampling frequency of 60 FPS.

This local repository consists of actual hospitalized cases from two local hospital centers with a large variety of clinical conditions along with their respective ejection fraction. These cases represent a large variability of real clinical scenarios, some cases presenting a severe cardiac condition, with or without concomitant pathology, and others with underlying cardiac pathology, but showing a stable clinical condition. A summary of the database is presented in the Tab. 1. More information related to the local repository can be found in this link [1]

2.5 Evaluation

To prove the presented indicator is more coherent with the degree of cardiac function deterioration than the ejection fraction two tests were conducted. The first consisted in constructing a feature space that summarizes the cardiac function.

[1] `https://gitlab.com/acarrera4/cardiac_functoin_analysis/`

Table 1. Distribution of actual hospitalized cases, divided into severe cardiac pathology associated or not with other underlying entity, and cardiac diseases with stable condition. This database illustrates how inconsistent the LVEF may be in many clinical conditions, being normal in frank cardiac deterioration and abnormal in stable states.

Severe Cardiac Pathology					
Unstable condition	**Cases**	**LVEF [%]**	**Stable condition**	**Cases**	**LVEF [%]**
Heart failure - Atrial fibrilation	8	21 - 65	Heart failure	2	13 - 46
Myocardial Infarction - Miocardial I.	14	34 - 67	Coronary Artery D.	7	37 - 65
Heart failure - Stroke	2	52 - 70	Stroke	4	36 - 52
Heart failure - Chagas	2	15 - 27	Mix cardiopathy	2	30 - 51
Heart failure - Lupus	2	55 - 60			
Total cases	28		Total cases	15	

No Cardiac compromise					
Unstable condition	**Cases**	**LVEF [%]**	**Stable condition**	**Cases**	**LVEF [%]**
Venous thrombosis - Angina	4	54 - 65	Hypertensive C.	16	15 - 62
Myocardiopathy - Tachycardia	5	33 - 71	Valvular heart disease	9	30 - 63
Valvular cardiopathy - Lupus	1	36 - 78	Right pontic Stroke	2	60 - 65
Hypertensive C. - Pulmonary cor	10	29 - 78	Endocarditis	4	46 - 67
Valvular C. - Bacteria	3	21 - 59	Myocarditis	2	56 - 59
Total cases	25		Total cases	31	

For doing so, a spectral clustering algorithm was applied to a distance matrix constructed from the magnitude differences of the estimated left chamber dynamics from 7,835 cases selected from the EchoNet-dynamic database [9] as well as the database collected locally. An optimal number of groups that describe the space feature was obtained by applying the Eigengap heuristic method.

A second test consisted in determining how the 99 collected clinical cases were distributed with respect to the cluster medoid and compared with the reported LVEF. For doing so, these cases were divided into three categories after the Stenveson Classification Score (A, B, C defines the levels of severity) of the stage of a cardiac failure, when this information was available, and a previous Z-score normalization was applied to both the Euclidean distance of the magnitude and the LVEF and the resultant quantities are plotted.

3 Results

The spectral clustering captures non-linear relations of the magnitude space. After applying the Eigengap heuristic method, four clusters were obtained. The results are observed in Fig 3, the left panel showing the spectral embedding where clusters are differently located within the obtained features space, while the right panel shows the temporal series of the four cluster medoids. Basically, the four clusters show similar curves, with a different height for the two diastole moments, likely due to the motion of the capturing plane which affects the ventricular area estimation. From this figure one infers that main differences should be observed at the phase components since some oscillation or peaks, yet they are present in the entire set, their main difference is expressed in terms of delays or abrupt changes in some of them, for instance in cluster 3 whose dynamics is completely different from the blue curve, cluster 2.

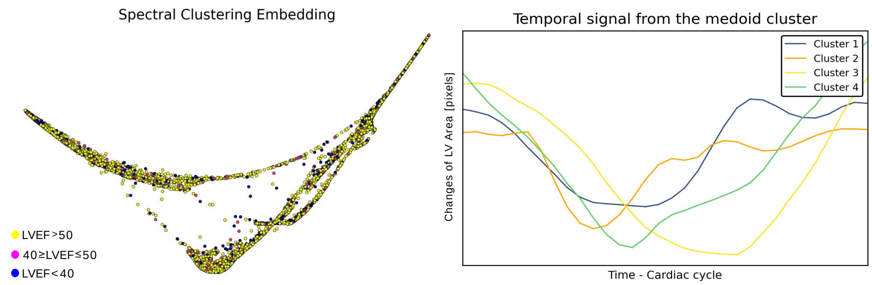

Fig. 3. Spectral embedding of the frequency space at the left and the original temporal series of the four medoids at the left.

Figure 4 shows the normalized value of the ejection fraction (LVEF) in the y axis and the presented indicator in the x axis for the four clusters of those cases for which clinic information was available (99 cases collected from two local hospitals). Just for analysis purposes, these cases were divided into three categories after the Stenveson Classification [1] of the stage of cardiac failure when this information was available. Otherwise, based on the number of associated pathologies and their degree of severity, cases were assigned to any of the three categories by the cardiologists coauthoring this publication. Overall, a pattern is repeated for the four groups, meaning the LVEF is much more spread than the presented indicator in the x axis. The more populated group is cluster 2, where the transition between the three categories looks more visible, from left to right, unlike LVEF where the three groups are quite mixed. Interestingly, when data are observed from left to right in the more populated cluster, the transition in cluster 2 starts with cases with pericardial effusion and heart failure of pulmonary origin (class 2), to cases reported as control (class 1) and ends with cases of heart failure of ischemic origin. The second more populated cluster was 1, which from left to right showed cases of infectious bacteria, control cases, and then some arrhythmias like tachycardia-bradycardia and atrial fibrillation. The number of cases in cluster 3and4 was to low as to observe any pattern.

4 Conclusions

This paper has introduced a new descriptor of the cardiac function which summarizes the frequential phase and magnitude components of the ventricular temporal series of the estimated area in the four-chamber image. The method is intuitive and fully integrable with the clinic workflow. In a series of cases with different degrees of pathology and complicated clinical conditions, the method

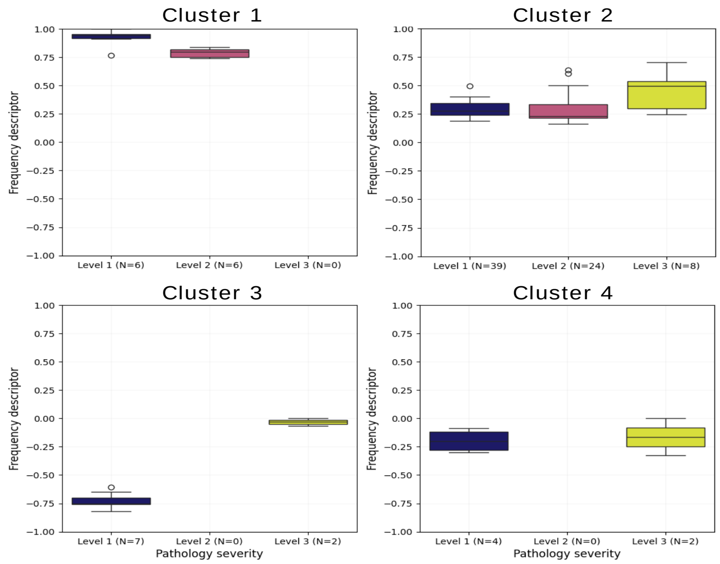

Fig. 4. Box plot of the normalized frequency descriptor by Z-score. The cases from the local repository were labeled in each cluster based on Tab. 1. Blue represents a low cardiac compromise, pink is moderate, and yellow is several compromises.

demonstrates to capture complex dynamics, improving what is observed with the ejection fraction for these very same cases.

Additionally, various challenges and limitations can be described as follows:

– A main issue is the variability of the capturing plane: entirely operator-dependent and highly variable after the particular pathology. Unlike classic indicators like the ejection fraction, the descriptor herein introduced is much more robust to this sort of variability by the redundancy of the temporal series.
– The local database contains a limited number of cases which hardly illustrate the large variability of the cardiac disease and the consequent series of adaptive mechanisms of the cardiac dynamics. However, the descriptor was able to separate groups with clinic meaning as shown by the small series of hundred patients.
– The present study compares individual cardiac cycles since cardiologists only register single cycles rather than longer periods. The resultant characterized dynamics ignores therefore the intrinsic cardiac variability which is more important in pathological stages.

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Disclosure of Interests. The authors do not have any competing interests.

References

1. Bozkurt, B., Coats, A.J., Tsutsui, H., Abdelhamid, C.M., Adamopoulos, S., Albert, N., Anker, S.D., Atherton, J., BÃűhm, M., Butler, J., et al.: Universal definition and classification of heart failure: A report of the heart failure society of america, heart failure association of the european society of cardiology, japanese heart failure society and writing committee of the universal definition of heart failure. European Journal of Heart Failure **23**(3), 352âĂŞ380 (2021). https://doi.org/10.1002/ejhf.2115
2. Carabello, B.A., Spann, J.F.: The uses and limitations of end-systolic indexes of left ventricular function. Circulation **69**, 1058–1064 (5 1984). https://doi.org/10.1161/01.CIR.69.5.1058, https://www.ahajournals.org/doi/10.1161/01.CIR.69.5.1058
3. Fernández-Caballero, A., Vega-Riesco, J.M.: Determining heart parameters through left ventricular automatic segmentation for heart disease diagnosis. Expert Systems with Applications **36**(2, Part 1), 2234–2249 (2009). https://doi.org/https://doi.org/10.1016/j.eswa.2007.12.045, https://www.sciencedirect.com/science/article/pii/S0957417407006409
4. Huang, Z., Jiang, Y., Zhou, Y.: Heart failure with supra-normal left ventricular ejection fraction: State of the art. Arquivos Brasileiros de Cardiologia **116**, 1019–1022 (5 2021). https://doi.org/10.36660/abc.20190835
5. Ilardi, F., Andrea, A.D., Ascenzi, F.D., Bandera, F., Benfari, G., Esposito, R., Malagoli, A., Mandoli, G.E., Santoro, C., Russo, V., Crisci, M., Esposito, G., Cameli, M.: Myocardial work by echocardiography: Principles and applications in clinical practice. Journal of Clinical Medicine **10**, 4521 (9 2021). https://doi.org/10.3390/jcm10194521, https://www.mdpi.com/2077-0383/10/19/4521
6. Kosaraju, A., Goyal, A., Grigorova, Y., Makaryus, A.: Left ventricular ejection fraction (Apr 2023), https://www.ncbi.nlm.nih.gov/books/NBK459131/
7. Mokhtari, M., Tsang, T., Abolmaesumi, P., Liao, R.: Echognn: Explainable ejection fraction estimation with nbsp graph neural networks. Lecture Notes in Computer Science p. 360 369 (2022). https://doi.org/10.1007/978-3-031-16440-8_35
8. Moya, A., Buytaert, D., Penicka, M., Bartunek, J., Vanderheyden, M.: State-of-the-art: Noninvasive assessment of left ventricular function through myocardial work. Journal of the American Society of Echocardiography **36** (10 2023). https://doi.org/10.1016/j.echo.2023.07.002
9. Ouyang, D., He, B., Ghorbani, A., Yuan, N., Ebinger, J., Langlotz, C.P., Heidenreich, P.A., Harrington, R.A., Liang, D.H., Ashley, E.A., Zou, J.Y.: Video-based ai for beat-to-beat assessment of cardiac function. Nature **580**(7802), 252–256 (2020). https://doi.org/10.1038/s41586-020-2145-8
10. Reynaud, H., Vlontzos, A., Hou, B., Beqiri, A., Leeson, P., Kainz, B.: Ultrasound video transformers for cardiac ejection fraction estimation. In: Medical Image Computing and Computer Assisted Intervention–MICCAI 2021: 24th International Conference, Strasbourg, France, September 27–October 1, 2021, Proceedings, Part VI 24. pp. 495–505. Springer (2021)
11. Russell, K., Eriksen, M., Aaberge, L., Wilhelmsen, N., Skulstad, H., Remme, E.W., Haugaa, K.H., Opdahl, A., Fjeld, J.G., Gjesdal, O., Edvardsen, T., Smiseth,

O.A.: A novel clinical method for quantification of regional left ventricular pressureâĂŞstrain loop area: a non-invasive index of myocardial work. European Heart Journal **33**(6), 724–733 (02 2012). https://doi.org/10.1093/eurheartj/ehs016, https://doi.org/10.1093/eurheartj/ehs016

12. Toro-Quitian, L., Torres, J.C., Carrera-Pinzón, A.F., Gutiérrez-Carvajal, R., Guerrero, M.I., Cruz-Roa, A., Davila, C.O., Romero, E.: Automatic estimation of the ejection fraction from diastole and systole ultrasound images by a simplified end-to-end u-net neural network. In: 2023 19th International Symposium on Medical Information Processing and Analysis (SIPAIM). pp. 1–5 (2023). https://doi.org/10.1109/SIPAIM56729.2023.10373544
13. Trainini, J.C., Elencwajg, B., López-Cabanillas, N., Herreros, J., Lago, N.E., Trainini, J.A.L., Trianini, A.: Fundamentos de la Nueva MecÃąnica Cardiaca - Bomba de succiÃşn. LUMEN (2015). https://doi.org/10.16309/j.cnki.issn.1007-1776.2003.03.004
14. Wisneski, J.A., Pfeil, C.N., Wyse, D.G., Mitchell, R., Rahimtoola, S.H., Gertz, E.W.: Left ventricular ejection fraction calculated from volumes and areas: underestimation by area method. Circulation **63**, 149–151 (1 1981). https://doi.org/10.1161/01.CIR.63.1.149, https://www.ahajournals.org/doi/10.1161/01.CIR.63.1.149