ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com

International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)
Vol. 10, Issue 5, May 2024

ENHANCING ECHOCARDIOGRAPHY SEGMENTATION INTEGRATING ENFORCED TEMPORAL CONSISTENCY

Chithra [1]
[1] PG –Department of Computer Science and Applications
Periyar Maniammai Institute of Science & Technology(Deemed to be University),Vallam,Thanjavur-613403, Tamilnadu,India
[1] mchithra577@gmail.com

Jeyachidra [2]
[2] Dean(Academic) / Teaching,Learning & Evaluation
Periyar Maniammai Institute of Science & Technology(Deemed to be University),Vallam,Thanjavur-613403, Tamilnadu,India
[2] chithu_raj@pmu.edu

Abstract:

The field of echocardiogram segmentation is explored in this study, which presents a new method that adopts ETC. When it comes to detecting cardiovascular diseases, echocardiography is crucial, and for correct clinical evaluations, proper segmentation is key. An improvement in the accuracy and consistency of delineating cardiac structures across time can be achieved with the incorporation of ETC, which seeks to increase the temporal coherence of segmented structures over successive frames. This work aims to optimize echocardiography segmentation algorithms using ETC, test the approach's efficacy across different datasets, and determine its influence on segmentation accuracy. By tackling these goals, the study hopes to increase diagnostic reliability and clinical decision-making by overcoming the present limits in echocardiography segmentation's temporal consistency.

Keywords: ETC, Machine Learning, Cardio, Temporal consistency

I. Introduction

When assessing heart function in a clinical setting, ultrasonography (US) imaging is usually preferred. The fact that it is noninvasive, inexpensive, and available in real-time is a major factor in its appeal [1].

These benefits, however, are at the expense of worse picture quality when compared to other modalities, such as computed tomography (CT) scans and magnetic resonance imaging (MRI) [2]. This is why automated systems have always failed miserably when it comes to analyzing data from the United States. However, other recent studies have shown the accuracy of well-trained CNNs in segmenting the ventricles, atria, and myocardium, the three primary components of the heart [3–4]. Even intra-observer variability can be reached by the most effective neural networks. But until recently, the best US segmentation approaches relied on 2D convolutional neural networks (CNNs) trained to handle critical points in the cardiac cycle, namely the end-diastolic (ED) and end-systolic (ES) instants [5-7]. One of the selling features of US for day-to-day clinical usage is its temporal richness, which is neglected in this concentration on static 2D pictures [8-9].

2D segmentation at ED and ES instants is where the temporal component is most often confirmed, as it offers context to the segmentation process [10]. A common way to evaluate the clinical performance of a segmentation method is by looking at the ejection fraction (EF), which is measured between the endocardial and extra ocular segmentations. This EF has been reported as a valuable indicator of various cardiovascular diseases [11–13], which explains why 2D segmentation is so popular. The EF ignores the frames that fall somewhere in the middle of the ED and ES sequences, which is a shame since these frames might help define additional diseases [14–17]. We were only able to find qualitative assessments based on global indices in the machine learning articles that have looked at the temporal consistency of 2D+time segmentation algorithms in the US up to now [18]. Consequently, we begin by providing a thorough evaluation of the limitations of SOTA approaches in creating segmentations that are constant over time, and then we provide measurable and clinically relevant measures to assess this consistency [19–20].

1.1 Motivation of the paper

Accurate and coherent temporal segmentation of cardiac structures over consecutive frames in echocardiogram recordings is a major difficulty, which is why Enforced Temporal Consistency (ETC) is being included into algorithms for echocardiography segmentation. When it comes to diagnosing and monitoring a wide range of cardiovascular disorders, echocardiography is essential. Precise segmentation of the heart's components is key to evaluating cardiac function and making informed clinical choices. On the other hand, current segmentation techniques have a hard time being consistent between frames, which might lead to inaccurate clinical evaluations and treatment choices.

II. Background study

A.Amer, X. Ye and F. Janan, [1] here, the author present ResDUnet, a straightforward deep learning network the author developed and refined for the express purpose of LV segmentation in echocardiogram pictures. The author have shown that cutting-edge U-net can be enhanced with new ideas including dilated convolution, squeeze and excitation units, and residual blocks, leading to improved performance. Despite the fact that echocardiography pictures might be difficult due to ventricular wall ambiguity and LV size and shape fluctuation.

Chernyshov, A., et al. [5] the author studied multiple deep learning architectures for automated right heart segmentation in two-dimensional ultrasound data, with a particular emphasis on right ventricle assessment. All of the evaluated topologies produced accuracy values that were on par with the findings from related studies on the left ventricle as well as the inter-observer variability amongst knowledgeable readers. It seemed that the suggested modified U-Net design for key point detection (U-Net KP) offered the greatest advantages when weighing the requirements for accuracy, robustness, and speed.

Heena, A., et al. [7] the pixels of a region that produced neural net entries were employed by the algorithm described in the research. This process produced satisfactory results, demonstrating that training a neural network to recognize picture representations was feasible. Ultimately, a neural network was used to demonstrate the algorithm for classifying images, and a comparison of Mean Square Error, PSNR, SSIM, and variance from the experimental results and analysis shows that the algorithm performs better than the various methods currently in use for standard medical image databases and other image databases.

Li, H., et al. [9] when it comes to the diagnosis and evaluation of cardiovascular disorders, LVEF has clinical significance. In this work, the author suggests using EchoEFNet to reliably compute LVEF automatically. Using the CMU Echo and CAMUS datasets, the author evaluated EchoEFNet's segmentation and landmark detection capabilities. EchoEFNet operates well on the A4C and A2C perspectives of echocardiogram, according to the testing data. The clinical application requirements were met because of the 0.916 and 0.854 consistencies between the estimated LVEF and clinical ground truth, respectively.

Paul, A. K., & Bhuiyan, Y. S. [13] because MobileNetV2 sacrifices some precision in favor of increased efficiency, it was ideal for low-power devices. Exception and InceptionV3 were better at acquiring high-quality visual data, but requiring more computer power. With its cutting-edge output, ResNet50 was a great option for a variety of computer vision applications. Although VGG16 was easy to use and performs exceptionally well, more computing complexity was required to produce the same results. EfficientNetB7 takes into account model size, accuracy, and efficiency while still meeting a range of processing needs.

Ragnarsdottir, H., et al. [15] the author experimented with spatial-only and spatio-temporal techniques from single or multiple views to determine the severity of Parkinson's disease. A spatio-temporal convolutional model on several views was used to get the best performance, with the validation set's final prediction coming from the majority vote of those views. More data will help the models become more accurate for the held-out test group. These authors approach could greatly reduce the frequency of missed or postponed diagnoses of severe PH in neonates by improving the accuracy, consistency, and reliability of PH estimation.

T. Iqbal, et al. [17] In order to identify and categories cardiovascular neurocristopathy disorders, the majority of evaluations currently in publication concentrate on the course and remission of conditions connected to aberrant migration or formation of cardiac neural crest cells.

2.1 Problem definition

The difficulty of attaining accurate segmentation in echocardiography—a vital imaging modality for the diagnosis of cardiovascular conditions—is the issue this study attempts to solve. The primary definition of the challenge centers on the requirement for improved temporal consistency in segmented structures between consecutive frames of echocardiogram images. The existing limits in the temporal coherence of echocardiogram segmentation make it difficult to reliably diagnose patients and provide correct clinical judgments. By putting forth a novel strategy that integrates Enforced Temporal Consistency (ETC) with echocardiogram segmentation methods, the research seeks to get over these restrictions. The main goals are to implement and optimize ETC, evaluate its effect on segmentation accuracy, and confirm its efficacy on a variety of datasets.

III. Materials and methods

The materials and methodology utilized to apply and assess the Enforced Temporal Consistency (ETC) strategy in echocardiogram segmentation are described in this section.

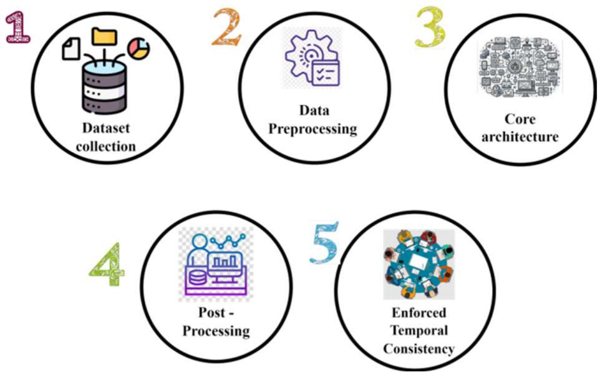

Figure 1: Overall architecture

3.1 Dataset collection

The dataset was collected from Kaggle website https://www.kaggle.com/datasets/toygarr/camus-dataset/data

3.2 Echocardiography Segmentation using Enforced Temporal Consistency

The goal of the Enforced Temporal Consistency approach for echocardiography segmentation is to improve the accuracy of the delineation of the heart anatomy in ultrasound images. By utilizing the temporal coherence of cardiac components in successive frames during a cardiac cycle, ETC refines segmentation findings by analyzing and integrating data from various time points. ETC allows more accurate identification of anatomical structures such ventricles, atria, and myocardium by identifying and correcting segmentation mask errors caused by noise and motion artifacts. This method enhances patient care and treatment outcomes by improving the quality of echocardiography image analysis and making it easier to diagnose and monitor cardiac problems.

Whether these variables be retrieved from latent space or pictures, it is feasible to identify temporal discrepancies by tracking their evolution across time. To make the values similar across domains, normalization is a must. When we have an attribute a, which is the set of all possible values for that attribute in a domain d, we can normalize all of its temporal sequences s_a using the following equation.

$$s_a \leftarrow \frac{s_a - min(A_d)}{max(A_d) - min(A_d)} \text{ ----------- } (1)$$

Referring to the attribute plots in figure 4, for instance, indicates that temporal inconsistencies or inconsistent inter-frame segmentations can exist if any of the attributes show significant, erratic fluctuations over time following normalization. The temporal smoothness of an attribute can be measured by computing its second-order derivative, or$d^2 s_a(t)/dt^2$. Thus, a small derivative indicates local smoothness, whereas a high derivative indicates intense variance. It is feasible to use this statistic as a discriminative indicator:

$$1(s_a, t) = \left|\frac{d^2 s_a(t)}{dt^2}\right| > \tau_a \text{ ------ (2)}$$

Being equal to 0 in all other circumstances and equal to 1 when the second-order derivative exceeds a predetermined threshold, τ_a. in this instance, the maximum permitted deviation is represented byτ_a, which is exclusive to the attribute.

The second-order derivative can be theoretically estimated in the following manner because cardiac time frames are discrete:

$$\frac{d^2 s_a(t)}{dt^2} \approx s_{a,t+1} + s_{a,t-1} - 2s_{a,t} \text{ ------ (3)}$$

During the heart cycle, it assesses the synchronization of three consecutive numbers, much like a Palladian filter. Strong recall for temporal differences can be achieved by experimentally establishing seven thresholdsτ_a, one for each attribute, using the maximum value discovered in the training data. In order to guarantee flawless precision for temporal discrepancies, these thresholds are then manually raised depending on the examination of evaluations on segmentation techniques. These graphs display the locations of the left ventricle, myocardium, and pericardium centers, in addition to local spikes along the temporal curve. These undesirable spikes can be lessened by temporal regularization, as will be covered in the next part.

Algorithm 1: Enforced Temporal Consistency
Input: • Echocardiography images obtained over multiple cardiac cycles. **Steps:** □ **Normalization**: • For each attribute a, normalize the temporal sequence s_a using: $s_a \leftarrow \frac{s_a - min(A_d)}{max(A_d) - min(A_d)}$ □ **Temporal Smoothness Calculation**: • Compute the second-order derivative $\frac{d^2 s_a(t)}{dt^2}$ for each normalized sequencess_a. Define the discriminative indicator $\frac{d^2 s_a(t)}{dt^2} \approx s_{a,t+1} + s_{a,t-1} - 2s_{a,t}$ □ **Approximation of Laplacian Filter**:

- Approximate the Laplacian filter as: $\frac{d^2 s_a(t)}{dt^2} \approx s_{a,t+1} + s_{a,t-1} - 2s_{a,t}$

 Threshold Determination:

- Empirically determine thresholds $s_a(t)$ from training data.
- Manually adjust $s_a(t)$ based on segmentation method evaluations.

 Identification of Temporal Inconsistencies:

- Apply the discriminative indicator $1s_a(t)$ to detect temporal inconsistencies.
- Identify patterns such as spikes in ventricle and myocardium positions.

Output:

- Identification of temporally inconsistent patterns.

IV. Results and discussion

The findings from the study or experiment are critically analyzed and interpreted in the results and discussion sections. These sections seek to address any limitations or uncertainties, examine the consequences of the results, and contextualize them within the body of existing knowledge.

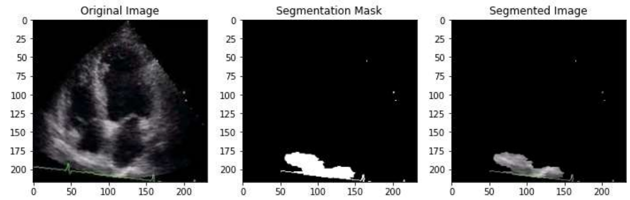

Figure 2: Segmented image

4.1 Performance evaluation

1. Accuracy: The fraction of samples with the right classification out of all samples. Mathematically:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \text{ ----------- (4)}$$

2. Precision: Ratio of samples with accurate identification to total samples with accurate identification. Mathematically:

$$Precision = \frac{TP}{TP + FP} \text{ ------------ (5)}$$

3. Recall (also known as sensitivity or true positive rate): The proportion of correctly classified samples out of the total number of actual samples. Mathematically:

$$Recall = \frac{TP}{TP + FN} \text{ -------------- (6)}$$

4. F1 score: A middle ground between accuracy and memory that strikes a harmonic mean. Mathematically:

$$F1\, score = 2 * Precision * Recall / (Precision + Recall) \text{ --------- (7)}$$

Table 1: Performance metrics comparison table

	Algorithm	Accuracy	Precision	Recall	F-measure
Existing methods	RNN	0.88	0.84	0.85	0.88
	ACM	0.89	0.81	0.83	0.84
	TCI	0.90	0.91	0.92	0.92
Proposed methods	ETC	0.91	0.93	0.94	0.95

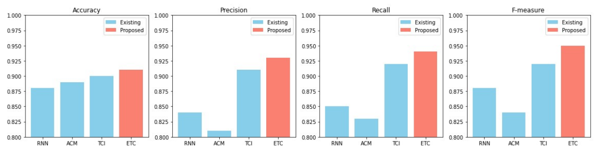

Figure 3: Performance metrics comparison chart

The table 1 and figure 3 shows performance of the current techniques, such as the Temporal Consistency Indicator (TCI), Active Contour Models (ACM), and Recurrent Neural Network (RNN), in echocardiogram segmentation showed differing degrees. RNN showed 0.88 accuracy, 0.84 precision, 0.85 recalls, and 0.88 F-measure. ACM obtained an F-measure of 0.84, recall of 0.83, precision of 0.81, and accuracy of 0.89. With an accuracy of 0.90, precision of 0.91, recall of 0.92, and F-measure of 0.92, TCI demonstrated exceptional performance. On the other hand, with an accuracy of 0.91, precision of 0.93, recall of 0.94, and F-measure of 0.95, the suggested approach, ETC, surpassed all other methods that were in use. These results imply that ETC provides improved segmentation precision and accuracy in comparison to existing methods, suggesting its potential as a useful supplement to echocardiography image processing algorithms.

V. Conclusion

Conclusively, this study represents a noteworthy progression in the domain of echocardiogram segmentation by presenting an innovative method that incorporates Enforced Temporal Consistency (ETC). The study tackles a significant difficulty in achieving temporal coherence across successive frames, acknowledging the important function of echocardiography in identifying cardiovascular diseases and the critical importance of precise segmentation for accurate clinical assessments. The impact on segmentation accuracy is seen from the successful deployment and optimization of ETC in echocardiography segmentation algorithms. The suggested method helps to more consistently and reliably demarcate cardiac structures by improving the temporal consistency of segmented structures throughout time. With the potential to overcome current constraints on temporal consistency in echocardiogram segmentation, this innovation presents a viable path towards increased clinical decision-making and greater diagnostic reliability. On the other hand, with an accuracy of 0.91, precision of 0.93, recall of 0.94, and F-measure of 0.95, the suggested approach, ETC, surpassed all other methods that were in use. The research ensures the generalizability and efficacy of the ETC-integrated segmentation algorithm in a variety of clinical contexts by emphasizing the evaluation of its proposed approach across distinct datasets. The results of this study support advances that directly improve patient care by adding to the expanding body of knowledge in medical imaging and computer-aided diagnosis.

VI. Reference

1. A.Amer, X. Ye and F. Janan, "ResDUnet: A Deep Learning-Based Left Ventricle Segmentation Method for Echocardiography," in *IEEE Access*, vol. 9, pp. 159755-159763, 2021, doi: 10.1109/ACCESS.2021.3122256.
2. A.Østvik *et al.*, "Myocardial Function Imaging in Echocardiography Using Deep Learning," in *IEEE Transactions on Medical Imaging*, vol. 40, no. 5, pp. 1340-1351, Can 2021, doi: 10.1109/TMI.2021.3054566.
3. Alvén, J., Hagberg, E., Hagerman, D., Petersen, R., & Hjelmgren, O. (2024). A deep multi-stream model for robust prediction of left ventricular ejection fraction in 2D echocardiography. Scientific Reports, 14(1), 2104.
4. Cheng, C. Y., Wu, C. C., Chen, H. C., Hung, C. H., Chen, T. Y., Lin, C. H. R., & Chiu, I. M. (2023). Development and validation of a deep learning pipeline to measure pericardial effusion in echocardiography. Frontiers in Cardiovascular Medicine, 10.
5. Chernyshov, A., Grue, J. F., Nyberg, J., Grenne, B., Dalen, H., Aase, S. A., ... & Lovstakken, L. (2024). Automated Segmentation and Quantification of the Right Ventricle in 2-D Echocardiography. Ultrasound in Medicine & Biology.
6. H. J. Ling, O. Bernard, N. Ducros and D. Garcia, "Phase Unwrapping of Color Doppler Echocardiography Using Deep Learning," in *IEEE Transactions on Ultrasonics,*

Ferroelectrics, and Frequency Control, vol. 70, no. 8, pp. 810-820, Aug. 2023, doi: 10.1109/TUFFC.2023.3289621.

7. Heena, A., Biradar, N., Maroof, N. M., Bhatia, S., Agarwal, R., & Prasad, K. (2023). Machine learning based biomedical image processing for echocardiographic images. Multimedia Tools and Applications, 82(25), 39601-39616.
8. Kampaktsis, P. N., Bohoran, T. A., Lebehn, M., McLaughlin, L., Leb, J., Liu, Z., ... & Giannakidis, A. (2024). An attention-based deep learning method for right ventricular quantification using 2D echocardiography: Feasibility and accuracy. Echocardiography, 41(1), e15719.
9. Li, H., Wang, Y., Qu, M., Cao, P., Feng, C., & Yang, J. (2023). EchoEFNet: Multi-task deep learning network for automatic calculation of left ventricular ejection fraction in 2D echocardiography. Computers in Biology and Medicine, 156, 106705.
10. Mortada, M. J., Tomassini, S., Anbar, H., Morettini, M., Burattini, L., & Sbrollini, A. (2023). Segmentation of Anatomical Structures of the Left Heart from Echocardiographic Images Using Deep Learning. Diagnostics, 13(10), 1683.
11. Munafò, R., Saitta, S., Ingallina, G., Denti, P., Maisano, F., Agricola, E., ... & Votta, E. (2024). A Deep Learning-Based Fully Automated Pipeline for Regurgitant Mitral Valve Anatomy Analysis From 3D Echocardiography. IEEE Access.
12. N. Painchaud, N. Duchateau, O. Bernard and P. -M. Jodoin, "Echocardiography Segmentation With Enforced Temporal Consistency," in *IEEE Transactions on Medical Imaging*, vol. 41, no. 10, pp. 2867-2878, Oct. 2022, doi: 10.1109/TMI.2022.3173669.
13. Paul, A. K., & Bhuiyan, Y. S. (2024). EchoTrace: A 2D Echocardiography Deep Learning Approach for Left Ventricular Ejection Fraction Prediction. Journal of Electronics and Electrical Engineering, 1-20.
14. R. Munafò *et al.*, "A Deep Learning-Based Fully Automated Pipeline for Regurgitant Mitral Valve Anatomy Analysis From 3D Echocardiography," in *IEEE Access*, vol. 12, pp. 5295-5308, 2024, doi: 10.1109/ACCESS.2024.3349698.

ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com

International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)
Vol. 10, Issue 5, May 2024

15. Ragnarsdottir, H., Ozkan, E., Michel, H., Chin-Cheong, K., Manduchi, L., Wellmann, S., & Vogt, J. E. (2024). Deep Learning Based Prediction of Pulmonary Hypertension in Newborns Using Echocardiograms. International Journal of Computer Vision, 1-18.
16. S. Sengan *et al.*, "Echocardiographic Image Segmentation for Diagnosing Fetal Cardiac Rhabdomyoma During Pregnancy Using Deep Learning," in *IEEE Access*, vol. 10, pp. 114077-114091, 2022, doi: 10.1109/ACCESS.2022.3215973.
17. T. Iqbal, O. Soliman, S. Sultan and I. Ullah, "Machine Learning Approaches for Segmentation of Cardiovascular Neurocristopathy Related Images," in *IEEE Access*, vol. 11, pp. 118301-118317, 2023, doi: 10.1109/ACCESS.2023.3325960.
18. Wifstad, S. V., Kildahl, H. A., Grenne, B., Holte, E., Hauge, S. W., Sæbø, S., ... & Lovstakken, L. (2024). Mitral Valve Segmentation and Tracking from Transthoracic Echocardiography Using Deep Learning. Ultrasound in Medicine & Biology.
19. Wu, H., Lin, J., Xie, W., & Qin, J. (2023, June). Super-efficient echocardiography video segmentation via proxy-and kernel-based semi-supervised learning. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 37, No. 3, pp. 2803-2811).
20. Zhang, J., Xiao, S., Zhu, Y., Zhang, Z., Cao, H., Xie, M., & Zhang, L. (2024). Advances in the Application of Artificial Intelligence in Fetal Echocardiography. Journal of the American Society of Echocardiography.