Effect of left ventricular longitudinal axis variation in pathological hearts using Deep learning

Yashbir Singh, Deepa S, Shi Yi Wu, João Manuel R. S. Tavares, Michael Friebe and Weichih Hu

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Yashbir Singh[1]
yashbir143@gmail.com
Chung Yuan Christian University, Zhongli, Taiwan
Deepa[1]
justdeepahbti@gmail.com
Shi-Yi Wu[1]
nora541520@gmail.com
João Manuel R. S. Tavares[2]
tavares@fe.up.pt
Instituto de Ciência e Inovação em Engenharia Mecânicae Engenharia Industrial, Departamento de Engenharia Mecânica, Faculdade de Engenharia, Universidade do Porto, Porto, PORTUGAL
Michael Friebe[3]
michael.friebe@ovgu.de
Otto-von-Guericke-Universität, Magdeburg, Germany
Weichih Hu[1*]
weichihhu@gmail.com; Chung Yuan Christian University, Zhongli, Taiwan

Abstract Cardiac disease is a primary cause of death worldwide. Prior studies have indicated that the dynamics of the cardiac left ventricular (LV) during diastolic filling is a major indicator of cardiac viability. Hence, studies have aimed to evaluate cardiac health based on quantitative parameters unfolding LV function. In this research, it is demonstrated that major aspects of the cardiac function, mainly ejection fraction, are due to abnormalities of the left ventricular on longitudinal axis variation. We used Bayesian deep learning algorithms to measure the wall motion of the LV that correlates well with the LV ejection fraction. Our results reveal relations among the wall regions of the LV. This research can potentially be used as determination value to identify patients with future cardiac disease problems leading to heart failure.
Keywords: Pathological heart, Ejection Fraction, Deep learning, longitudinal axis.

I. INTRODUCTION

Death caused by Heart Failure (HF) has remarkably increased in the past few years mainly due to the general aging of the human population. While modern developments in the biomedical field are surely helping in diagnosing and subsequently treating patients whether it is the cost related to the interventional device.
Research, production, distribution and subsequent clinical training is a huge concern that society has to deal with in form of ever-increasing healthcare expenses. Screening of the population that is susceptible to HF, can be helpful to reduce the deaths due to HF [1] and simultaneously reduce healthcare expenses through preventative treatments. By the guidelines of The American College of Cardiology Foundation and American Heart Association (ACCF/AHA), there are two classes of HF that has been categorized in these patients: class A and class B of HF [2]. In class A, patients are more susceptible to HF, but lacking any structural heart disease or symptoms. In class B, patients are seen with the structural disease, but lacking signs and symptoms of HF. Additional contributors to developing HF are other diseases like hypertension, diabetes mellitus, metabolic syndrome and atherosclerotic [2, 3]. Now, the question is that what else can be done in preventing HF at major scale. We see Bayesian deep learning (DL) research and recent algorithms as possible future tools for screening and diagnosis in order to facilitate the detection of patients prone to HF. DL is a technique that utilizes machine learning algorithms (supervised or unsupervised) that are perfectly dependent on the choice of the data representation used for training the algorithm on various layered models of non-linear operational input [4]. The applications may be multifunctional and involve pattern recognition, statistical classification, convolutional deep neural networks and deep belief networks [5]. In this research, we present our work on building a computer aided diagnosis system with the goal to detect wall motion of LV based on DL.

II.METHOD

In this study, our focus was on the classification portion of the LV; as to the image processing part, the reader can find the details in the referenced papers that address the automatically detection of the interior (endocardial) and exterior (epicardial) borders of the LV [6, 7]. The images were acquired using a computerized tomography scanner SIEMENS_LEOVB30B at the National Institute of Hospital of Yang Ming, National Yang Ming University, Taiwan. This study and the informed consent procedure were approved by the Institutional Review Board of National Yang Ming University Hospital. A number of features were studied to identify the cardiac motion in order to discover cardiac wall motion abnormalities, mainly: velocity, radial strain and circumferential strain, local and global Simpson volume and segmental volume, which are based on the inner (endocardial) contour.

We used Bayesian Networks (BNs) to detect both the interior (endocardial) and exterior (epicardial) borders of the LV [8, 9]. Motion interferences were compensated by using global motion estimation based on robust statistics outside the LV; this is done so that the heart's motion is only analyzed on the longitudinal axis (Fig. 1). Then, numerical feature vectors, which were calculated using the contours extracted from two consecutive time frames, were tracked through time. In general, velocity, radial strain and circumferential strain can be calculated in terms of standard deviation or/and mean of five segment's respective feature values from any one view.

The features used to help in the detection of local and global dysfunction of heart were:

(i) Velocity features used to determine how fast any pair of control point's change in the *x* and *y* coordinates per image frame;

(ii) Circumferential strain features to assess how much the contour between any two control points shrinks in the systolic phase;

(iii) Radial strain features also called Thickening of cardiac wall;

(iv) Local and global Simpson Volume to determine the volume as computed by the Simpson rule for each frame of the heart as a whole;

(v) Segmental Volume in order to obtain the volume per segment per frame and the segmental EF values.

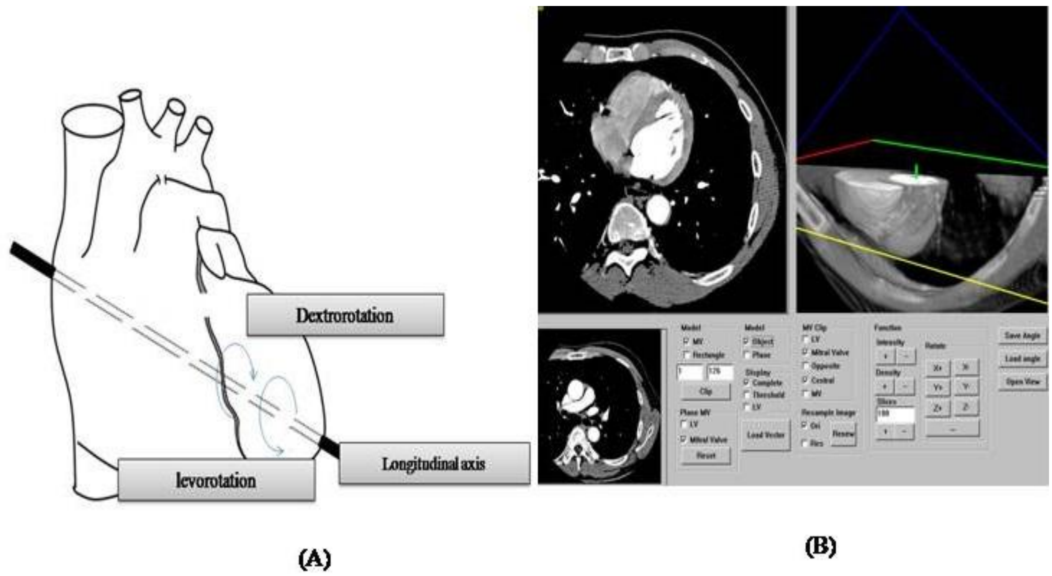

Fig. 1. (A) Longitudinal axis representation of LV; (B) Computer Tomography transverse section on the short axis of LV

III.RESULTS

Most of the research reported the longitudinal strain as a very sensitive parameter of sub endocardial dysfunction. In addition, evaluation of circumferential, radial strain and local and global Simpson Volume are also significant when assessing compensation patterns of LV function. Though, lack of a normal range of values and associated variation hinder their use for everyday clinical evaluation. We implemented Bayesian Network to detect wall motion abnormalities of LV and did parameter training using 220 training cases with CT images of size 512 × 512 pixels. Our feature selection resulted in every segment dependent on five features such as Velocity features, Circumferential strain features, Radial strain features, Local and global Simpson Volume, Segmental Volume. Table 1 is showing the Area under the ROC curve for the testing set. The classifier did well every heart segment, and entirely achieved high sensitivity and specificity between 84%, 98%.

Segment of LV	Bayesian Network of testing set	Segment of LV	Bayesian Network of testing set
1	0.90873	9	0.9648
2	0.8617	10	0.9176
3	0.9779	11	0.8450
4	0.91673	12	0.9837

5	0.84506	13	0.9715
6	0.9874	14	0.9155
7	0.8643	15	0.9471
8	0.8200	16	0.945

Table 1: Area under the ROC curve for the test set

This study defines the effect of ejection fraction due to LV variation on the longitudinal axis. We have also seen some variation about volume change and performed the simulation study with the actual volume of LV (Fig. 2), which has been done by Weichihhu lab [10]. We got the variation on the longitudinal axis performing a comparative study of actual and simulated LV heart. Variations of 1%, 4%, 7% and 10% were found on various points of LV (Fig. 2, Panel C). This can be seen as an initial step to recognize local and global dysfunction in the heart.

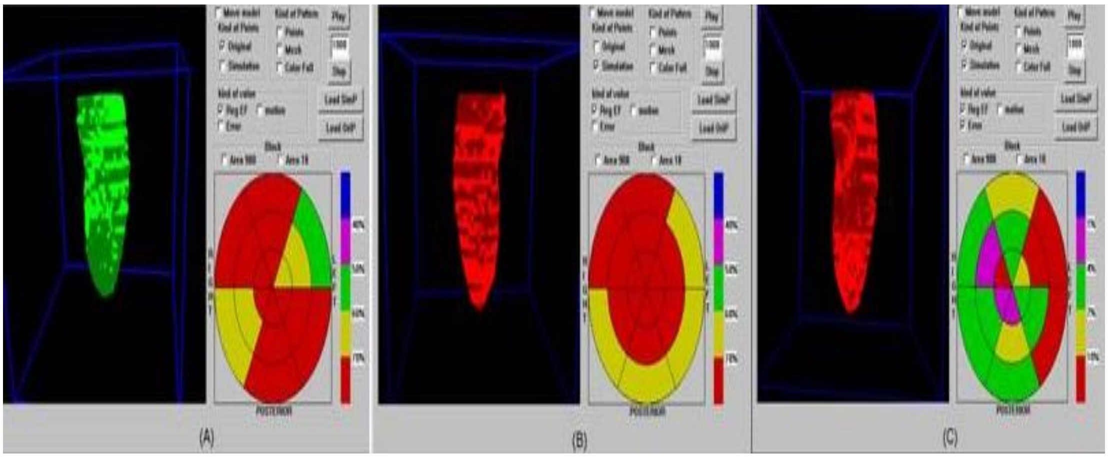

Fig.2 (A) Actual volume of heart model; (B) Simulated heart model; (C) Difference between the two models (A, B).

IV. CONCLUSION

In this research, we addressed the task of building an objective classification application for ejection fraction analysis and LV wall motion on the longitudinal axis based on extracted features. The simple, but effective feature selection technique used, resulted in a classifier that depends on only a small subset of the calculated features, and their limited number makes it easier to explain the final classifier result to physicians in order to get their feedback. Further research will integrate ejection fraction and LV motion of pathological heart.

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References

1. Nagueh, S. F., Smiseth, O. A., Dokainish, H., Andersen, O. S., Abudiab, M. M., Schutt, R. C., ... & Klein, A. L. (2018). Mean Right Atrial Pressure for Estimation of Left Ventricular Filling Pressure in Patients with Normal Left Ventricular Ejection Fraction: Invasive and Noninvasive Validation. Journal of the American Society of Echocardiography.

2. Yancy, C. W., Jessup, M., Bozkurt, B., Butler, J., Casey, D. E., Drazner, M. H., ... & Johnson, M. R. (2013). 2013 ACCF/AHA guideline for the management of heart failure. Circulation, CIR-0b013e31829e8776.

3. Chen, I. L., Singh, Y., & Hu, W. C. (2017). Comparative Study of Arterial Compliance Using Invasive and Noninvasive Blood Pressure Waveform. Journal of Biomedical Engineering, 5(1), 25-29.

4. Singh, Y., Wu, S. Y., Friebe, M., Tavares, J. M. R., & Hu, W. (2018). Cardiac Electrophysiology Studies Based on Image and Machine Learning.

5. Angermueller, C., Pärnamaa, T., Parts, L., & Stegle, O. (2016). Deep learning for computational biology. Molecular systems biology, 12(7), 878.
6. Georgescu, B., Zhou, X. S., Comaniciu, D., & Krishnan, S. (2008). U.S. Patent No. 7,421,101. Washington, DC: U.S. Patent and Trademark Office.
7. Zheng, Y., Georgescu, B., Scheuering, M., & Comaniciu, D. (2012). U.S. Patent No. 8,150,119. Washington, DC: U.S. Patent and Trademark Office
8. Fung, G., Qazi, M., Krishnan, S., Bi, J., Rao, B., & Katz, A. (2005, December). Sparse classifiers for automated heartwall motion abnormality detection. In Machine Learning and Applications, 2005. Proceedings. Fourth International Conference on (pp. 194-200). IEEE.
9. Murphy, K. P., & Russell, S. (2002). Dynamic bayesian networks: representation, inference and learning.
10. Deepa, D. , Singh, Y. , Wu, S. Y. , Friebe, M. , Tavares, J. M. , Wei-Chih, H. (2018). 'Development of 4D Dynamic Simulation Tool for the Evaluation of Left Ventricular Myocardial Functions'. World Academy of Science, Engineering and Technology, International Science Index, Computer and Information Engineering, 12(5), 2814.