Automated Measurments of Echocardiographic Global Longitudenal Strain

Hisham Safawi, Mohamad Hajj-Hassan, Hussein Hajj-Hassan
Department of Biomedical Engineering
International University of Beirut
Beirut, Lebanon
Email: mohamad.hajjhassan@b-iu.edu.lb,

Hassan M. Khachfe
Lebanese Institute for Biomedical Research and Application (LIBRA)
Lebanese International University
Beirut, Lebanon
Email: hassan.khachfe@liu.edu.lb

***Abstract*— Echocardiographic determination of Global Longitudinal Strain (GLS) by manual tracing of endocardial borders is time consuming and operator dependent, whereas visual assessment is inherently subjective. In this paper, the development of a fully automated software using machine learning-enabled image analysis is presented. For a total of 30 patients, apical 4, 2 and 3-chamber views were collected from a center that assessed GLS using manual tracing. Manual tracing was done by the same user to calculate user inimitability. In addition, datasets were saved in a centralized database, and machine learning-enabled software (AutoStrain, TomTec-Arena 1.2, TomTec Imaging Systems, Unterschleissheim, Germany) was applied for fully automated GLS measurements. AutoStrain measurements were feasible in 95% of studies and the average analysis time was less than 3 sec/ patient. Interclass correlation coefficients and Bland-Altman analysis revealed good ratios compared to manual tracing and user to user ratios. Fully automated analysis of echocardiography images provides rapid and reproducible assessment of left ventricular GLS compared to manual tracing.**

Keywords-Global longitudinal strain; Echocardiography; Machine learning.

I. INTRODUCTION

As medical technology in healthcare continues to get more advanced, medical companies invent new algorithms claiming to facilitate everyday workflow. Technology involves lots of research and development, which results in selling those algorithms in the form of software. The purpose of those pieces of software is to facilitate the everyday workflow of end-users making the workflow more atomized. Atomization, artificial intelligence, augmented intelligence and machine learning are all dependent on algorithms targeting time management and consistent reading.

Cardiology is one of the major fields in healthcare where automated measurements have been widely spread. According to the results seen, critical decisions are taken by cardiologists towards their patients. Measurements like Left Ventricular Ejection Fraction (LVEF) were, for a long time, one of the main values cardiologists look into to evaluate the heart function. Lately, Two-dimensional STE-derived Global longitudinal Strain (GLS) appears to be reproducible and feasible for clinical use and offers incremental prognostic data over LVEF in a variety of cardiac conditions, although measurements vary among vendors and software versions [1].

The quantification of left ventricular (LV) size, geometry, and function represents the most frequent indication for an echocardiographic study and is pivotal for patient evaluation [2]. LV volumes, Ejection Fractions (EFs) and GLS can be measured using different imaging modalities. 2-dimensional echocardiography continues to be the most commonly utilized technique in clinical practice due to low radiation doses, feasibility and availability of this modality. Although the recommendations are to use 3D echocardiography to evaluate volumes and strains [3], 2D echocardiography is still by far the most common used technique.

Visual assessment is still popular within cardiologists while manual tracing lacks reproducibility in a very sensitive marker in cardiac function [4][5]. In this study, we used a novel, fully automated software to generate GLS from biplane views of the LV and compare them with manual tracing.

In Section 2, we will explain the methodology we used to prepare the data sample and extract numbers. In Sections 3, we will discuss the results. Section 4 will present the conclusion and future works.

II. METHODOLOGY

A total of 30 cases were collected from a Lebanese cardiology lab randomly. The collected studies were anonymized to ensure data privacy. Afterwards, Apical 4 Chamber (4-C), Apical 2 Chamber (2-C) and Apical 3 Chamber (3-C) views where selected with a minimum 1 heart cycle; see Figure 1.

All studies were imported to TOMTEC-Arena 1.2 (TOMTEC Imaging Systems, Unterschleissheim, Germany), a computer vision vendor-independent software package that applies a machine-learning algorithm for DICOM images [6]. AutoStrain, a fully automated software algorithm to calculate GLS in a very simple way was applied. A standard workflow requesting to allocate 4-C, 2-C and 3-C views was followed. The same workflow was followed all over the studies in Auto-Strain and manual tracing to ensure consistency and minimize any user workflow errors.

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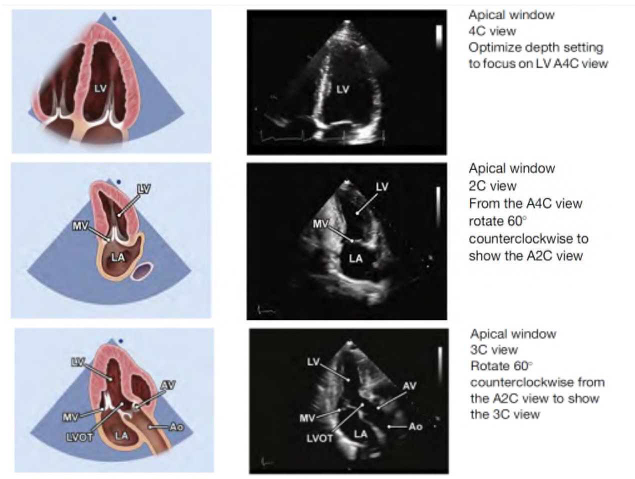

Figure 1. Apical 4C, 2C and 3C views.

The algorithm would then run the automated boarder detection and identify the end systole and end diastole; see Figure 2.

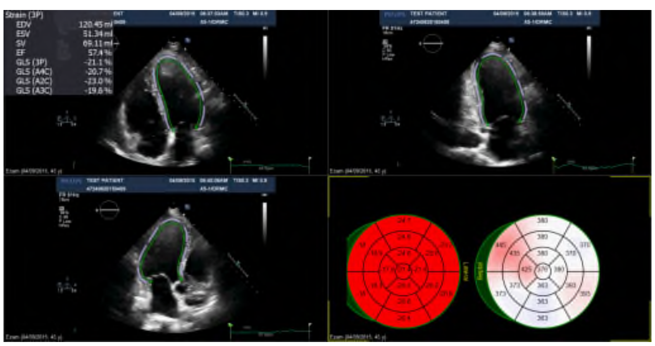

Figure 2. AutoStrain software, tracing of 4-C, 2-C and 3-C views; GLS (3P) automatically calculated.

GLS triplane, GLS (3P), will be saved and same frames will then be given to an expert investigator to manually change boarder detection in case the auto-tracing was not correct. As the boarders are being edited, software is automatically applying corrections all over the targeted heart cycle. New GLS (3P) is generated and saved offline to be compared with AutoStrain results.

To measure imitability ratio, the same studies are manually traced again by the same investigator following the same workflow and using the same frames. New GLS (3P) measurements were collected.

Due to poor image quality and missing Echo Cardiogram (ECG) data, for studies were eliminated (study 1, 20, 22 and 30). ECG data is essential for the software to detect End-Systole and End-Diastole.

III. Results

While Auto-strain has 100 % reproducibility, manual tracing has an obvious inimitability ratio; see Figure 3.

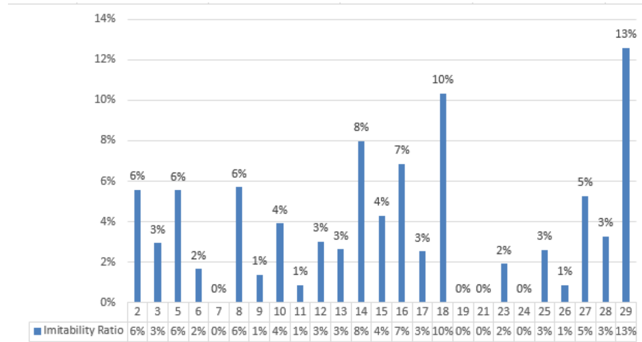

Figure 3. Manual tracing imitability ratio.

Figure 3 shows recordings for the GLS (3P) variance percentage between manual tracing 1 and manual tracing 2. Although same user was involved, same studies and frames, it is obvious that manual tracing lacks consistency. The average variance was 4% all over the data set in comparison with a 3% variance between manual tracing and automatic tracking; see Figure 4.

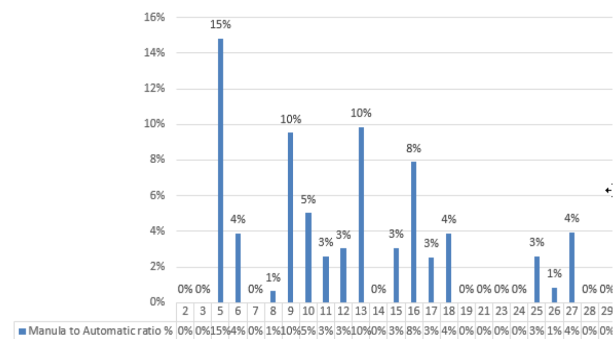

Figure 4. Manual tracing to Auto-Strain ratio.

Figure 4 shows recordings of the ratio between manual tracing results to Auto-Strain GLS values. Auto-strain has a huge advantage in terms of reproducibility and time saving in comparison to manual tracing. In the data sample we worked on, we had patients with poor GLS and others with normal GLS. Data accuracy does not depend on GLS value and patient condition, but on image quality and the right acquisition windows.

IV. Conclusion and Future work

The goal of the work reported here is to prove the functionality of machine learning automatic algorithms. Those algorithms can never replace cardiologists in the daily work they do, however, as they claim, their main purpose is to facilitate the workflow and increase reproducibility and accuracy. Physician will always have the superiority, especially when it comes to irregular anatomy, for example patients with congenital heart diseases, where no algorithm can detect the anatomy and explain the physiology of the heart.

As future work, increasing the number of analyzed studies will provide more accurate results. Moreover, comparing results from different user's manual tracing ratio is a result to monitor.

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