Machine learning based automated dynamic quantification of left heart chamber volumes

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Aims

Studies have demonstrated the ability of a new automated algorithm for volumetric analysis of 3D echocardiographic (3DE) datasets to provide accurate and reproducible measurements of left ventricular and left atrial (LV, LA) volumes at end-systole and end-diastole. Recently, this methodology was expanded using a machine learning (ML) approach to automatically measure chamber volumes throughout the cardiac cycle, resulting in LV and LA volume–time curves. We aimed to validate ejection and filling parameters obtained from these curves by comparing them to independent well-validated reference techniques.

Methods and results

We studied 20 patients referred for cardiac magnetic resonance (CMR) examinations, who underwent 3DE imaging the same day. Volume–time curves were obtained for both LV and LA chambers using the ML algorithm (Philips HeartModel), and independently conventional 3DE volumetric analysis (TomTec), and CMR images (slice-by-slice, frame-by-frame manual tracing). Automatically derived LV and LA volumes and ejection/filling parameters were compared against both reference techniques. Minor manual correction of the automatically detected LV and LA borders was needed in 4/20 and 5/20 cases, respectively. Time required to generate volume–time curves was 35 ± 17 s using ML algorithm, 3.6 ± 0.9 min using conventional 3DE analysis, and 96 ± 14 min using CMR. Volume–time curves obtained by all three techniques were similar in shape and magnitude. In both comparisons, ejection/filling parameters showed no significant inter-technique differences. Bland–Altman analysis confirmed small biases, despite wide limits of agreement.

Conclusion

The automated ML algorithm can quickly measure dynamic LV and LA volumes and accurately analyse ejection/filling parameters. Incorporation of this algorithm into the clinical workflow may increase the utilization of 3DE imaging.

Keywords

3D echocardiography • cardiac chamber quantification • automation • machine learning

Introduction

The ability to automatically identify cardiac structures and accurately measure standard cardiac parameters would revolutionize the clinical practice of echocardiography. This is especially true with respect to 3D echocardiography (3DE), an evolving new standard for chamber quantification, which has been shown to be more accurate and reproducible compared with 2D echocardiography (2DE). The most recent American Society of Echocardiography (ASE)/European Association of Cardiovascular Imaging (EACVI) guidelines

recommend the use of 3DE,¹ however, this methodology has not been fully adopted into routine clinical practice, as it requires specialized training and experience and is time consuming. Over the years, multiple techniques aimed at automation of echocardiographic analysis have been tested with mixed levels of success. Recent development of artificial intelligence approaches, such as machine learning (ML) algorithms, have resulted in a 3DE analysis technique that automatically detects left heart chamber boundaries and allows accurate near-automated measurements of minimum and maximum volumes and basic functional parameters derived from these volumes, such as

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ejection/filling fractions. This adaptive analytics approach has been developed using a training set of thousands of 3DE studies and validated by several investigators^{2–6} in patients with good quality images, and most recently was found to provide robust assessment of left ventricular (LV) and left atrial (LA) size and function in an unselected patient population.⁷

To date, software implementation of this methodology has been limited to end-systolic and end-diastolic frames only, while ignoring dynamic volume changes that occur during the cardiac cycle. Previous studies have demonstrated that assessment of these dynamic volume changes can be used to derive potentially clinically important information reflecting pathophysiology of disease, especially with regards to impairments in diastolic function and remodelling.^{8–13} However, the use of dynamic indices, such as ejection and filling rates or percent ejection or filling at certain phases of the cardiac cycle, has been limited to the research arena, mostly because their derivation relies on specialized, time-consuming, off-line analysis that adversely affects clinical workflow, and impedes the implementation in busy laboratories.

Most recently, the combination of these ML techniques with speckle-tracking echocardiography (STE) led to the development of the first dynamic 3DE ML analysis software, which provides frame-by-frame measurements of left heart chamber volumes. This analysis allows a more comprehensive evaluation of the LV and LA function, including a number of additional indices of ejection/filling/emptying, which are otherwise not assessable. The aim of this study was to test this new automated ML algorithm and compare LV and LA volume–time curves and derived indices to those obtained using independent well-validated reference techniques, including conventional 3DE volumetric analysis and cardiac magnetic resonance (CMR) imaging.

Methods

Population

We prospectively studied 20 patients (age 54 ± 19 , 12 females, body surface area $1.9 \pm 0.2 \text{ m}^2$) referred for clinically indicated CMR for a variety of suspected cardiovascular conditions, who underwent, in addition, transthoracic 3DE imaging for the purposes of this research protocol. Exclusion criteria were: history of mechanical valve replacement, pacemaker or defibrillator leads, arrhythmias during imaging, LV aneurysm and poor quality images, defined as poor endocardial visualization on 2DE or 3DE in >2 contiguous segments using a 17-segment model. The protocol was approved by the Institutional Review Board and informed consent was obtained from each patient.

Study design

Figure 1 depicts a schematic representation of the study design. Volume–time curves were obtained simultaneously for both LV and LA chambers from 3DE images using the novel ML algorithm (Philips HeartModel), and independently using the conventional volumetric 3DE analysis (TomTec, 4D LV analysis and LA function), and also from CMR images by using frame-by-frame manual tracing of multiple short-axis slices. All analyses were performed by three independent experienced readers with extensive training in 3DE and CMR (level III training), respectively, who were blinded to the results of all prior measurements. Time curves obtained using the three techniques were analysed to obtain LV and LA volumes and ejection/filling parameters. Then, those obtained with the ML algorithm were compared against the latter two reference techniques.

3DE imaging

Imaging was performed using the EPIQ system (version 7C, Philips Medical Systems, Andover, MA, USA) and an X5-1 phased-array transducer with the patient in the left lateral decubitus position. Before each

Figure 1 A schematic representation of the study design (see text for details).

acquisition, images were optimized for endocardial visualization by modifying the gain, compress, and time-gain compensation controls. Image acquisition included wide-angled, single-beat, high frame rate 3DE datasets (HM ACQ key on the EPIQ system) from the apical position during a single breath-hold (frame rate of 19 ± 3 Hz). Care was taken to include the entire LV and LA cavity within the scan volume. Imaging depth and sector width were optimized to obtain the highest possible frame rate.

ML image analysis

Automated analysis was performed using HeartModel software (HM, Philips) described in detail in our recent publications,^{2,3,7} which uses knowledge-based identification to orient and locate cardiac chambers and patient-specific adaptation of endocardial borders. This software was modified to use ML techniques and thus provide chamber volumes frame-by-frame throughout the cardiac cycle. The initial segmentation process identifies anatomical features, including LV and LA chambers, and creates contours, which are then combined with an ML approach to fit actual ultrasound image information to these anatomical structures. This ML algorithm utilizes training information from experts over a large number of clinical images spanning a wide range of image quality. With this training information, the computer effectively learns where an expert user would position boundaries between structures in actual clinical images, resulting in robust contour identification even on images of marginal quality, where less sophisticated approaches would produce unsatisfactory results.

Using this ML approach, 3D casts of the LV and LA cavities (Figure 1, centre) were created for each frame throughout the cardiac cycle, from which LV and LA volume–time curves were derived without geometrical assumptions. Manual corrections of the automatically detected LV and LA endocardial surfaces were performed, when the operator felt that the automatically detected surface were incorrect. This was achieved by displaying the LA and LV contours on four-, three-, and two-chamber cut-planes extracted from the 3DE datasets and allowing the user to edit the contours to optimize the match between the detected and the perceived endocardial boundaries.

Conventional volumetric image analysis

The same 3DE datasets were analysed using the conventional volumetric approach on the same cardiac cycle used for the ML analysis. This analysis is based on manual initialization of the endocardial boundaries in non-foreshortened views extracted from the 3DE datasets and tracking the boundary throughout the cardiac cycle using speckle tracking techniques (4D LV Analysis software, a module of Research Arena 2.0, TomTec Imaging Systems, Unterschleissheim, Germany). These anatomically correct LV- and LA-focused apical two- and four-chamber views were identified as those in which the long-axis dimension of the relevant chamber was maximized. This methodology has been extensively used previously, including publications from our laboratory.^{14–17} Briefly, after the long axis of the relevant chamber is identified and endocardial boundaries initialize in a single frame, the software creates a 3D cast of the chamber, which is automatically tracked throughout the cardiac cycle using speckle tracking. Fine-tuning of the endocardial surface was performed interactively to optimize boundary position as necessary. Finally, the actual chamber volume inside each cast was calculated throughout the cardiac cycle, resulting in volume–time curves.

CMR imaging

CMR images were obtained using a 1.5-T scanner (Achieva, Philips Healthcare) with a 5-channel cardiac coil. Steady-state free precession dynamic gradient-echo cine loops were obtained using retrospective electrocardiographic gating and parallel imaging sensitivity encoding

during approximately 5 s breath-holds (TR 2.9 ms, TE 1.5 ms, flip-angle 60° , and temporal resolution approximately 30–40 ms). Cine loops of 6-mm thick short-axis slices with 2-mm gaps and 2.0×2.0 -mm in-plane spatial resolution were obtained from above the left atrium to below the LV apex at a rate of 30 frames per cardiac cycle.

CMR image analysis

Images were analysed using commercial software (Medis, Best, Netherlands). LV analysis included careful tracing of the circumference of the LV cavity surrounded by myocardial tissue from the basal slice to the last apical slice depicting the LV cavity. The basal and apical slices were confirmed on long-axis views. The LV endocardial boundary was manually traced frame-by-frame throughout the cardiac cycle with the papillary muscles and trabeculae included in the LV cavity. For each frame, LV volume was calculated using the disk-area summation method, resulting in a LV volume–time curve. On average, there were approximately 10 LV slices with 25–30 frames per slice, totalling 250–300 manual tracings. Similarly, LA borders were manually traced frame-by-frame throughout the cardiac cycle in each of the 5–7 slices with 25–30 frames per slice, totalling 125–210 tracings. The LA appendage and pulmonary veins were not included in the LA volume (LAV). LAV calculated by adding up the volumes from each slice, resulting in a LA volume–time curve.

Analysis of volume–time curves

The LV and LA volume–time curves obtained using all three techniques (ML, conventional volumetric analysis, and CMR) were analysed using Microsoft Excel worksheet designed to calculate a number of LV and LA volume and timing indices. The different phases of the cardiac cycle were identified using maxima and minima of the volume curves and their first time-derivative curves. The resultant LV ejection and filling indices included: end-diastolic and end-systolic volumes (EDV, ESV) and ejection fraction (EF), volume at 50% ejection time (ET), volumes at 25%, 50%, and 75% filling time (FT), volume at diastasis, rapid filling volume (RFV), and atrial filling volume (AFV) (Figure 2). LA filling and emptying indices included: maximum and minimum volumes ($V_{\max}$, $V_{\min}$) and filling fraction, volume at 50% FT, volumes at 25%, 50%, and 75% emptying time, volume at diastasis, passive emptying volume (PEV), and active emptying volume (AEV) (Figure 3).

Statistical analysis

For each parameter, the inter-technique comparisons included paired two-tailed student's *t*-tests, linear regression with Pearson correlation coefficients and Bland–Altman analyses to assess the bias and limits of agreement (defined as 2 SD around the mean). Values of $P < 0.05$ by *t*-tests were considered significant.

Results

The study group of 20 patients was formed by initially screening 24 patients, and excluding four with image quality that was deemed inadequate. Minor manual correction of the automatically detected LV and LA borders was performed in 4/20 and 5/20 cases, respectively. Time required for generation of time–volume curves from 3DE (including manual correction) was significantly shorter (0.6 ± 0.3 min per patient), compared with both the conventional 3DE volumetric analysis (3.4 ± 1.1 min, $P < 0.05$) and CMR manual frame-by-frame tracing of every slice from base to apex (96 ± 14 min, $P < 0.0001$).

Figures 4 and 5 show examples of LV and LA volume–time curves and their time-derivatives, obtained in one study subject using the

Figure 2 Analysis of left ventricular volume–time curves, resulting in dynamic ejection and filling parameters: end-diastolic and end-systolic volumes (EDV, ESV) and stroke volume (SV), volume at 50% ejection time (ET), volumes at 25%, 50%, and 75% filling time (FT), volume at diastasis (DIA), rapid filling volume (RFV), and atrial filling volume (AFV).

Figure 3 Analysis of left atrial volume–time curves, resulting in dynamic filling and emptying parameters: maximum and minimum volumes ($V_{\max}$, $V_{\min}$) and filling volume (FV), volume at 50% filling time (FT), volumes at 25%, 50%, and 75% emptying time (ET), volume at diastasis (DIA), passive emptying volume (PEV), and active emptying volume (AEV).

three analysis techniques: CMR, ML, and the conventional volumetric 3DE analysis based on speckle tracking. Both LV and LA curves derived by the automated ML algorithm are similar in their shape and magnitude to those obtained from CMR images and from the same 3DE datasets using the conventional volumetric analysis. LV volume–time curves depicted systolic contraction followed by biphasic filling with a period of diastasis separating the active, rapid LV filling phase from the passive LV filling phase as a result of atrial contraction (Figure 4). Similarly, LA volume–time curves depicted atrial filling followed by biphasic emptying with a quiescent period of diastasis (Figure 5). Importantly, the time-derivative of both LV and LA volumes showed detectable peaks and troughs despite the signal noise. The LV volume time-derivative showed an early peak reflecting

maximum rate of systolic contraction, followed by zero crossing, indicating end of systole, and then followed by two troughs: first one reflecting peak rate of rapid filling and the second reflecting peak rate of LV filling due to atrial contraction (Figure 4). The LA volume time-derivative showed an early trough reflecting the peak rate of atrial filling during ventricular systole, followed by two peaks: the first reflecting the maximum rate of emptying during the conduit phase and the second one reflecting the maximum emptying rate of the atrial contractile phase (Figure 5).

These peaks and troughs allowed the determination of the timing of events during the cardiac cycle and thus resulted in the aforementioned dynamic indices of LV and LA ejection and filling. Table 1 shows the summary of LV ejection and filling parameters measured

Figure 4 Example of left ventricular volume–time curves (dark blue, thick lines) and their time-derivatives (lighter blue, thinner lines), obtained in one study subject using the three analysis techniques: CMR (top), machine learning (centre), and the conventional volumetric analysis (bottom) (see text for details).

by the automated ML algorithm, as well as by the two reference techniques: CMR and the conventional volumetric 3DE analysis. No significant inter-technique differences were detected in any of the measured parameters. Similarly, Table 2 shows in the same format the summary of the inter-technique comparisons for the measured LA ejection and filling parameters, which were also not significantly different with the exception of one comparison (passive emptying volume, which was smaller for CMR than for the ML analysis).

Figure 5 Example of left atrial volume–time curves (dark blue, thick lines) and their time-derivatives (lighter blue, thinner lines), obtained in one study subject using the three analysis techniques: CMR (top), machine learning (centre), and the conventional volumetric analysis (bottom) (see text for details).

Tables 3 and 4 show the results of the detailed analysis of inter-technique agreement for the LV and LA parameters, respectively, including correlation coefficients and Bland–Altman biases and limits of agreement for all measured parameters. Generally, ML derived indices were in good agreement with both reference techniques, CMR and the conventional volumetric 3DE, as reflected by high correlations and small biases ($\leq 10\%$ of the measured values in the majority of cases), although the limits of agreement were rather wide,

Table 1 Left ventricular ejection and filling parameters derived from volume–time curves obtained using the automated machine learning algorithm (HeartModel software) in 20 study subjects, as well as by using conventional CMR and volumetric 3DE analyses

Left ventricle		CMR	Heart Model	TomTec
Ejection indices	End-systolic volume	76 ± 25	69 ± 21	66 ± 22
	Ejection fraction	58 ± 9	59 ± 7	62 ± 8
	Volume (50% ejection time)	123 ± 32	108 ± 29	105 ± 29
Filling indices	End-diastolic volume	175 ± 36	167 ± 36	170 ± 41
	Volume (25% filling time)	101 ± 35	91 ± 26	93 ± 27
	Volume (50% filling time)	136 ± 40	123 ± 26	121 ± 31
	Volume (75% filling time)	148 ± 40	141 ± 39	136 ± 34
	Volume at diastasis	145 ± 41	133 ± 32	139 ± 53
	Rapid filling volume	69 ± 27	64 ± 18	73 ± 44
	Atrial filling volume	31 ± 15	34 ± 13	31 ± 38

All volumes are expressed in units of mL; fractions are in percentage.

indicating considerable inter-technique differences in individual subjects. Of note, for the left ventricle, the agreement between the ML measurements and the conventional volumetric analysis was better than that with CMR, as reflected by higher correlations and smaller biases for the majority of indices (Table 3). This trend was less clear for the LA indices (Table 4).

Discussion

The emerging applications of artificial intelligence and ML to cardiac imaging have great potential to revolutionize the way in which we diagnose and manage patients with cardiovascular disease. Specifically, in echocardiography, ML-based algorithms offer the promise of providing automated measurements of chamber quantification that are accurate, improve efficiency, and may in the future provide valuable information to aid in patient diagnosis and prognosis. This is the first study using an automated ML algorithm that demonstrated that: (i) ML is capable of accurately measuring dynamic LV and LA volumes and analysing ejection/filling parameters when compared with conventional 3DE volumetric analysis and CMR reference standards, (ii) ML greatly shortens the time to analyse 3DE datasets necessary to generate clinically important volume–time curves when compared with CMR, and (iii) incorporating ML into daily practice is a promising way to overcome challenges associated with the routine incorporation and analysis of 3DE in the clinical workflow.

The concept of ‘computer aided diagnosis’ has existed for decades, particularly in radiology, to assist with chest imaging.¹⁸ This ultimately paved the path for the development of artificial intelligence, ML, and deep learning. ML is an application of artificial intelligence that enables a computer programme to learn complex relationships or patterns from empirical data and generate accurate decisions.¹⁹ By definition, ML programmes improve their performance (or analysis quality) by increasing exposure to datasets without the need for explicit

Table 2 Left atrial filling and emptying parameters derived from volume–time curves obtained using the automated machine learning algorithm (HeartModel software) in 20 study subjects, as well as by using conventional CMR and volumetric 3DE analyses

Left atrium		CMR	Heart Model	TomTec
Filling indices	Maximum volume	86 ± 24	81 ± 25	75 ± 33
	Filling fraction	49 ± 11	56 ± 12	58 ± 13
	Volume (50% filling time)	68 ± 24	59 ± 22	59 ± 21
Emptying indices	Minimum volume	45 ± 24	36 ± 18	42 ± 24
	Volume (25% emptying time)	74 ± 26	67 ± 18	63 ± 29
	Volume (50% emptying time)	68 ± 22	56 ± 18	55 ± 28
	Volume (75% emptying time)	65 ± 22	52 ± 18	50 ± 28
	Volume at diastasis	66 ± 22	55 ± 21	57 ± 24
	Passive emptying volume	20 ± 9*	26 ± 10	33 ± 19
	Active emptying volume	21 ± 11	19 ± 8	15 ± 14

All volumes are expressed in units of mL; fractions are in percentage.
*P < 0.05 vs. HeartModel.

programming. Unlike chest radiography or even computed tomography, which have static images to interpret, echocardiography, requires interpretation of dynamic images. As a result, the incorporation of artificial intelligence and ML into echocardiography has been slower. Nonetheless, the recent decade has seen significant work to realize the potential of ML algorithms in this context.

The current chamber quantification guidelines emphasize that 3DE measurements are preferred over 2DE because of their superior accuracy and reproducibility.¹ However, 3DE has been incorporated into routine clinical practice only in a small number of laboratories as it requires specialized training, expertise in image interpretation and is time consuming. Applying artificial intelligence or ML techniques to 3DE is a novel solution to this problem. Several recent studies have focused on testing an automated technique developed to circumvent this hurdle using an artificial intelligence based adaptive analytics approach, which was initially validated in patients with good image quality and was found to be fast, highly reproducible due to its automated nature and accurate when compared with conventional 3DE volumetric analysis⁴ and CMR reference values.^{2,5} Importantly, it was found to provide almost the same values across laboratories, independently of the user’s experience.³ More recently, this methodology was found to be feasible in approximately 90% of non-selected patients and was able to provide accurate measurements of LV and LA volumes in the majority of them.⁷ Although this new methodology was viewed as an important technological breakthrough, its inherent limitation was that it only provided chamber volumes at two phases of the cardiac cycle, while not allowing dynamic measurements.

Recent developments in artificial intelligence technology, and specifically ML algorithms, have paved the way for the development of a new, fully-automated algorithm for dynamic quantification of cardiac chamber size and function, which only a few years ago seemed to be not even remotely possible. Dynamic left heart chamber quantification based on invasive haemodynamics techniques is widely used to

Table 3 Inter-technique agreement (linear regression and Bland–Altman analysis) between left ventricular ejection and filling parameters derived from volume–time curves obtained using the automated machine learning algorithm (HeartModel software) and two different reference techniques: conventional CMR and volumetric 3DE analyses

Left ventricle		HeartModel vs. CMR		HeartModel vs. TomTec	
		<i>r</i>	Bias ± LOA (%)	<i>r</i>	Bias ± LOA (%)
Ejection indices	End-systolic volume	0.86	-9 ± 35	0.97	4 ± 18
	Ejection fraction	0.79	2 ± 22	0.91	-4 ± 11
	Volume (50% ejection time)	0.78	-13 ± 35	0.90	3 ± 24
Filling indices	End-diastolic volume	0.97	-5 ± 10	0.95	-2 ± 16
	Volume (25% filling time)	0.80	-10 ± 44	0.89	-3 ± 27
	Volume (50% filling time)	0.81	-10 ± 37	0.90	1 ± 22
	Volume (75% filling time)	0.88	-5 ± 27	0.93	4 ± 20
	Volume at diastasis	0.86	-8 ± 30	0.76	-9 ± 40
	Rapid filling volume	0.78	-7 ± 52	0.65	-12 ± 27
	Atrial filling volume	0.64	10 ± 73	0.71	12 ± 50

Bias and limits of agreement (LOA) are expressed in percentage of the corresponding measured value.

Table 4 Inter-technique agreement (linear regression and Bland–Altman analysis) between left atrial filling and emptying parameters derived from volume–time curves obtained using the automated machine learning algorithm (HeartModel software) and two different reference techniques: conventional CMR and volumetric 3DE analyses

Left atrium		HeartModel vs. CMR		HeartModel vs. TomTec	
		<i>r</i>	Bias ± LOA (%)	<i>r</i>	Bias ± LOA (%)
Filling indices	Maximum volume	0.95	-7 ± 18	0.90	7 ± 60
	Filling fraction	0.72	14 ± 34	0.87	-4 ± 23
	Volume (50% filling time)	0.91	-14 ± 31	0.88	0 ± 37
Emptying indices	Minimum volume	0.90	-19 ± 39	0.84	1 ± 25
	Volume (25% emptying time)	0.93	-8 ± 22	0.84	6 ± 69
	Volume (50% emptying time)	0.91	-16 ± 23	0.92	1 ± 74
	Volume (75% emptying time)	0.86	-17 ± 28	0.79	5 ± 88
	Volume at diastasis	0.86	-17 ± 26	0.80	-4 ± 53
	Passive emptying volume	0.80	12 ± 49	0.68	-6 ± 76
	Active emptying volume	0.66	-10 ± 50	0.73	-1 ± 68

Bias and limits of agreement (LOA) are expressed in percentage of the corresponding measured value.

obtain pressure–volume loops for diagnosis of a valvular heart disease and systolic/diastolic heart failure. These techniques provide critically important information for clinical management, and the ability to non-invasively assess how chamber volumes change over the cardiac cycle would likely prove clinically useful. Our current study focused on the recently expanded technique for dynamic left heart chamber quantification based on a ML algorithm that allows automated frame-by-frame measurement of chamber volumes. This technique provides volume–time curves suitable for analysis of potentially useful indices of LV and LA ejection/filling parameters that cannot be assessed from static volume measurements traditionally performed at end-systole and end-diastole. These parameters may become part of future more comprehensive analysis of LV and LA function, which may be particularly useful when simultaneous analysis of LA and LV functional indices may provide incremental information, such as in

the evaluation of patients with diastolic dysfunction. Our study was designed to test the accuracy of this methodology, by comparing the automatically derived indices to those derived from curves obtained using conventional 3DE volumetric analysis based on speckle tracking, as well as CMR reference.

We found that the automatically derived dynamic LV and LA ejection/filling indices were largely in agreement with those obtained using the above two reference techniques. Importantly, this finding has the potential to obviate the need for 3DE training that is essential to obtain accurate measurements using the conventional methodology, which relies on computer–user interaction at multiple phases of analysis. We also found that the automated technique was considerably faster than the conventional analysis indicating that it may contribute to further integration of 3DE chamber quantification into routine clinical practice. In fact, because of the automated nature of

this analysis, it is conceivable that it could provide reasonably accurate measurements when performed by a computer, before a physician starts reading and interpreting the patient's images.

An important advantage of this novel methodology is that in addition to the LV quantification, it simultaneously measures LA volume from the same 3DE dataset and can provide a more comprehensive assessment of LA function than conventional measures of maximal LA volume. As recommended by the ASE-EACVI guidelines,¹ LA volume measurements should be performed in LA focused views to avoid foreshortening and thus underestimation of volumes. The new software automatically detects the LA boundaries in 3D space, measures the true, non-foreshortened LA volume without any geometrical assumptions and is thus more accurate than the conventional 2DE methodology, which requires dedicated LA focused views for accurate bi-plane measurements.²⁰ Similar to LV endocardial contour editing, the new software allows correction of LA borders. These corrections are also performed on three anatomically correct non-foreshortened LA-focused views, which are also automatically extracted from the 3DE dataset, and displayed similar to that used for LV border editing.

Another important feature of the new algorithm is that it was designed to analyse 3DE datasets acquired in the fast single-beat mode. This acquisition mode has the advantage of avoiding one of the most frequent limitations of multi-beat 3DE imaging, commonly referred to as 'stitch' artefacts. The consequence of this incremental improvement is that it allows clinical use of 3DE imaging in a considerably higher number of patients in whom 3D analysis has been challenging, such as patients with frequent arrhythmias (21% in our cohort) and/or those unable to hold their breath.

Future directions

The ability to generate dynamic curves of the left heart chamber volumes throughout the cardiac cycle has important future implications, some of which are being actively investigated. A potentially important direction could be the use of the dynamic HeartModel software to study changes in ventricular or atrial shape throughout the cardiac cycle. This is because the automatically identified dynamic endocardial surface carries more information than just the volume, and the shape of the 3D endocardial surface can be analysed frame-by-frame. Several recent studies have demonstrated the potential use of 3D shape analysis to obtain not only new global indices, such as sphericity and conicity,²¹ but also regional shape indices, such as 3D curvature.^{22–24} Having access to these parameters on a frame-by-frame basis from 3DE images without extensive user interaction and time commitment is likely to prove clinically useful from both diagnostic and prognostic points of view.^{25,26} Harnessing this information for potential clinical use may prove beneficial in future studies designed to investigate this aspect of cardiac chamber shape in different disease states. Our recent study showed that regional LV shape indices (specifically the septal and inferior wall curvatures) were independently associated with increased risk of CV mortality.²⁶ Dynamic LV and LA shape analysis may provide a reliable automated means to monitor changes over time, especially as there is momentum to better understand cardiac remodelling in response to medical therapy.

Lastly, as this ML technique continues to improve, the dynamic evaluation of right heart chambers will become a reality and may

allow advanced dynamic RV shape analysis²⁷ that will provide diagnostic information in a variety of disease states.

Limitations

First, one of the inclusion criteria was the need for sufficiently good image quality to allow automated measurements. Therefore, our results cannot be extrapolated to consecutive patients, and future studies are needed to determine the feasibility of this automated approach in the general patient population. However, no technique, either automated or manual can be expected to accurately measure cardiac chambers on images of substandard quality.

Secondly, our sample was small, raising the question whether our measurements were not significantly different between techniques because of insufficient statistical power. However, our detailed analysis of inter-technique agreement, which included linear regression and Bland–Altman analyses, demonstrated good correlation and small biases for the majority of indices, even if limits of agreement were rather wide for some of the indices, indicating less than perfect agreement in some individual patients. These findings indicate that additional studies in larger homogeneous groups of unselected patients are needed to further validate the new methodology.

Thirdly, low frame rates are a known limitation of 3DE imaging, especially of the single-beat acquisition, because low frame-rate datasets may miss the true peaks or troughs of volume–time curves. However, in this study, comparisons with conventional volumetric 3DE analysis were performed on the same cardiac cycle and thus, low frame rates could not have confounded these comparisons.

Lastly, in this study, ejection and filling indices were calculated using custom Excel worksheet from volume–time curves and their time-derivative curves, which had varying degrees of signal noise. Specifically, small changes in volumes are magnified in the derivative curves, and their random nature may have affected the biases in the calculated indices. Future refinements in the algorithms used to extract functional indices from these curves, such as the use of smoothing, may further reduce the noise and result in more reliable indices.

Conclusions

In summary, this is the first study to test a new automated ML-based analysis of 3DE datasets. We demonstrated that this approach allows dynamic measurement of LV and LA volumes throughout the cardiac cycle, including an accurate calculation of useful ejection and filling indices, reflecting the function of these chambers in a more comprehensive manner than the conventional single-phase volumes or ejection/filling fraction. Importantly, the automated nature of this analysis promises to contribute to overcoming the workflow limitations of 3D echocardiography and may thus facilitate the integration of 3DE quantification in routine clinical practice. We anticipate that in the near future, physicians will start their interpretation of echocardiography exams with multiple automatically measured numerical functional indices, which will be presented to them alongside the images as a basis for diagnostic interpretation.

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Conflict of interest: none declared.

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