White paper

# Next-generation AI-powered measurement features for cardiovascular ultrasound

ACUSON Origin Ultrasound System

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# Introduction

## Artificial intelligence at the core of modern echocardiography

Echocardiography is a primary diagnostic resource for assessing heart conditions. A complete echo exam provides comprehensive quantification of cardiac anatomy and function, leveraging a variety of measurement techniques and instrumentation according to best practices and clinical guidelines. The value of echocardiography is founded on high accuracy examinations, efficiency and throughput.

The role of the cardiac ultrasound system is to deliver value added benefits and features for each procedure. First and foremost, the system needs to perform the task that is appropriate to the given context, with a high level of accuracy. But, equally important, it needs to simplify and streamline the process through automation.

Artificial intelligence is the tool enabling the system to automatically recognize and label clips based on the image content, automatically create annotations for the extraction of measurements, automatically quantify heart function and motion patterns with global and segmental analysis. Through state-of-the-art artificial intelligence techniques, the system incorporates clinical experts' knowledge by learning how to perform each task from a large database of annotated examples. The AI-powered measurement features for cardiovascular ultrasound can become an ideal companion to enhance the value of echocardiography, as a trusted data and image reader, interpreter and reporter.

# AI unleashes the potential of Cardiac Ultrasound

High performance artificial intelligence creates value at multiple levels of the healthcare continuum

Artificial intelligence (AI) is a disruptive tool in cardiac ultrasound. It is boosting a wave of innovation in echocardiography, affecting the way images are acquired, how they are interpreted and their relevance in decision making.

While increased automation and reproducibility are arguably its most visible benefits, the transformative potential of AI is deeper. An AI-powered measurement features capable of creating value in clinical practice behaves as a trusted data processor and image reader, and can provide its users with relevant information without increasing their workload. Simple and powerful application interfaces are important features, and the combination of consistency, robustness and accuracy in the produced data enables efficient workflows, with the potential to impact not only user experience but also resource allocation in the healthcare system.

## AI creates value at multiple levels of the diagnostic process

The diagnostic process can be considered at multiple levels of analysis. The most foundational level deals with the instruments used to acquire signals from a subject leveraging physical phenomena and properties (e.g., echo from sound waves). At a higher level of complexity, measured signals are converted into interpretable images from which measurements of clinical significance can be extracted. At even higher levels, the focus of the diagnostic process is the integration of available data into a holistic representation of the patient, and the localization of the individual patient in the context of a population.

AI plays a visible and relevant role in improving performance and ease of use of software applications for the recognition of cardiac views and anatomy to automate measurements and clinical workflows. ACUSON Origin leverages AI to provide more than 5,600 automated measurements. AI Assist demonstrates a 99% accuracy rate for proper view classification and placement of the color box or PW/CW Spectral Doppler gate, across 12 echocardiographic views which encompass 23 anatomic features of interest, as assessed by multiple expert users [7]. AI Measure automatically produces standard measurements in B-mode, M-mode and spectral Doppler which are accepted without editing in 89% of the cases by multiple clinical experts [21].

### AI value in Echocardiography

- Better data
- Better interpretation
- Better diagnosis

Integration, access, complexity

| | |
|---|---|
| **Patient Cohort** | • Population health management, process optimization<br>• Outcome analysis, quality care, meaningful use |
| **Patient Centric** | • Digital twin<br>• Predict, plan, prescribe |
| **Reading/Reporting** | • Measure and quantify<br>• Detect, diagnose and guide |
| **Scanner/Instrument** | • Scan automation<br>• Reconstruction, advanced physics |

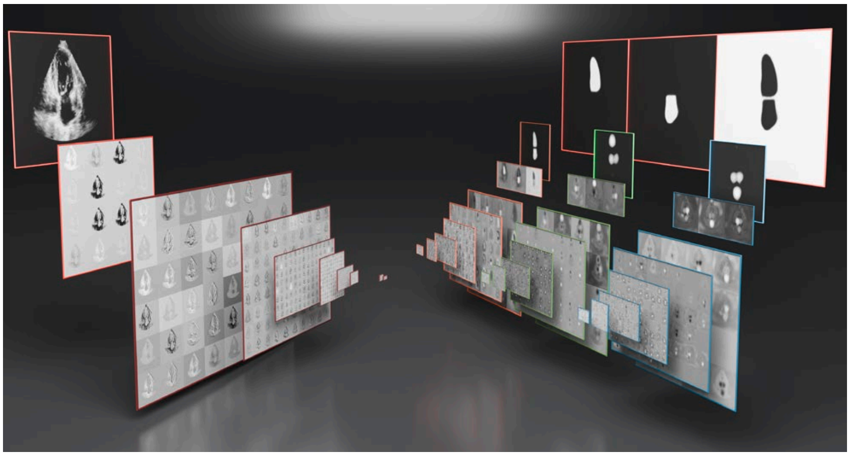
Multiple level of analysis of the diagnostic process, and the role of AI in supporting the process.

A natural extension of the acquisition step, the interpretation of the measurements also sees an important role of artificial intelligence, more specifically the capability of detecting patterns to support triaging, diagnosis and potentially guiding decision making. ACUSON Origin's 2D Heart$^{AI}$ and 4D Heart$^{AI}$ take significant steps in this direction by offering a comprehensive view on the heart anatomy and mechanics, including function quantification of all visible chambers. 2D Heart$^{AI}$ automatically produces estimates of left ventricular volumes and GLS, both for contrast enhanced and non contrast enhanced acquisitions, achieving 81% correlation coefficient with ejection fraction estimates provided by the consensus of three experienced readers for 45 clips with or without contrast opacification [18]. The left ventricular function estimates provided by 4D Heart$^{AI}$ achieve 84% correlation coefficient with GLS provided by the consensus of three experienced readers for 32 TTE and TEE volumes [19].

The contributions of artificial intelligence will increasingly expand to other aspects of the diagnostic process. At the level of the scanner or data acquisition instrument, AI will continue to enable improved quality of the imaging signal through denoising and sharpening. Siemens Healthineers has demonstrated the power of AI in dramatically improving image reconstruction speed and quality for MRI with the suite of applications, Deep Resolve, enabling 70% faster brain MRI scans without compromising image resolution or signal-to-noise ratio [20].

At the level of analysis, focusing on patients and patient cohorts, a feature of interest is the capability of predicting disease evolution and potentially estimating the effect of different intervention options. Even more broadly, an important asset is a model of the system in which the individual patient is observed – for instance the healthcare system or the cohort to which the patient belongs. AI can contribute at this level by supporting the management and analysis of complex health information through powerful pattern recognition as well as efficient data-driven simulations of human physiology. A specialized AI system can extract structures and patterns from heterogenous data going beyond comprehensive echocardiography exams and including multi-modality health data. By efficiently analyzing large patient cohorts, such a system can help uncover determining factors for disease progression, and identify the most beneficial course of action for the individual patient.

While applications at this level go beyond the scope of a cardiovascular ultrasound system, they provide the context in which we see our systems operating in the near future. Siemens Healthineers is the global leader when it comes to AI patent applications in medical imaging and has been a pioneer in AI development for more than 20 years. We own more than 1,100 patent families related to machine learning, of which more than 550 are rooted in deep learning. Siemens Healthineers is uniquely positioned to support the journey towards the future of healthcare.



A glance at the multiple layers of the neural network powering the chamber autocontouring feature in 2D Heart[AI]. When presented with an apical 4-chamber view, the neural network produces a hierarchy of features which are combined to produce a visualization of the blood pool and anatomical landmarks for the left atrium and ventricle.

## Inside a neural network for automatic contouring of the heart chambers

The task of contouring anatomical structures in a medical image is a form of image interpretation. When looking at a 2D echocardiography image, a trained observer recognizes image patterns that are usually associated to specific portions of the myocardial wall, or vascular structures, or blood pool. Similarly, a neural network trained for the task of image segmentation transforms the input image into a new image, representing the recognized objects.

The basic mechanism of a convolutional neural network performing segmentation is the combination of image intensity values into patterns (or features) which can be reliably associated with the presence or absence of the object of interest in specific positions in the input image. To create reliable features, the neural network leverages two assets: on the one hand, the availability of a large number of training samples, i.e., input images paired with an example of correct segmentation; on the other hand, the expressive power of the network architecture.

A convolutional neural network is typically structured in multiple layers. Each layer performs the task of combining intensity values from the input image into features which can be collected in an output image. Each output image can be provided as input to the next layer, obtaining yet another set of features. By virtue of this structure, each output image is connected to the input image through the features generated in each layer. In particular, the final layer of the convolutional neural network converts the features of its input into a human readable image, which highlights the position of the recognized objects in the pixel space of the original image. A visual representation of the multiple layers of a convolutional neural network trained to segment into clinically significant regions a 2D echocardiography image is depicted in the right figure at the top of this page.

The training process iteratively modifies the neural network mechanism producing output features from input data, until the generated features reliably associate each pixel of the input image with its correct label (i.e., its identification as part of one object) in the final output.


Deep convolutional neural networks, i.e., convolutional neural networks featuring a large number of layers, can be very sensitive to small changes in the image intensities of the input image. Such small changes can lead to larger differences in the corresponding cascade of generated features, therefore potentially producing different outputs. This offers an opportunity to obtain sophisticated segmentation behavior – for instance, reliably determining the boundary of the blood pool in presence of visible papillary muscles and trabeculae, based on subtle image cues.

On the other hand, the sensitivity of the neural network to variation in the input image intensities and its capability of sophisticated behavior can only be elicited by leveraging large databases of training samples. During the training process, the neural network evolves the definition of its layers so as to produce segmentation results consistent with the available examples. The more data examples provided increases the neural networks ability to produce features that are helpful to correctly segment the target structures, even for images not previously encountered.

To increase the performance of such an AI system, therefore, a crucial factor is the capability to scale the training process to leverage large databases. This includes the collection of a large amount of carefully curated and labeled data; but also the availability of a scalable, massive computational infrastructure to securely and efficiently manage a large amount of data, while at the same time reducing the system development time.

Siemens Healthineers has created an AI factory to efficiently develop state-of-the heart AI-powered systems and products. The AI factory is founded on curated data, supercomputing and advanced neural networks. The company's data lake hosts more than 2 billion medical images and data from more than 200 collaborations. Dedicated teams provide clinical reading and annotations while AI scientists design and train neural networks leveraging a 200 petaFLOPS supercomputing system running several hundreds experiments per day.

### AI value from scale

- Large collections of curated data
- Massive computational power
- Advanced neural network architectures

# 2D Heart$^{AI}$

TTE offers an ideal window to visualize the state of the heart. 2D Heart$^{AI}$ offers the tools to interpret it.

2D echocardiography is a staple modality for the assessment of heart disease. Evaluation of the size and function of all heart chambers is recommended by clinical guidelines as part of a comprehensive, standard echocardiography examination. This includes strain imaging, a crucial tool in early detection of subtle changes at the myocardial level needed for cardio oncology and degenerative cardiomyopathies.

Heart function assessment based on 2D TTE is an intrinsically complex task. It requires the acquisition and interpretation of multiple planar views of the heart to ensure proper segmental analysis; the selection of key frames in each temporal sequence, for proper assessment of end systolic and end diastolic heart configurations; the integration of information into a holistic representation of the heart dynamics.

2D Heart$^{AI}$ is a feature designed to understand and help manage the complexity of the task that is typically manual or semi-automated in an effort to provide a more efficient workflow. Once the heart is measured, the available data is utilized to highlight key clinical metrics. 2D Heart$^{AI}$ is an evolution of the technology at the core of the pioneering eSie Left Heart application (ACUSON SC2000), featuring AI-based left ventricular motion analysis. 2D Heart$^{AI}$ dramatically expands its functionality to the analysis of the function of all visible chambers, leveraging AI to perform and coordinate multiple tasks, and incorporating clinical experts' knowledge through a large database of annotations and state-of-the-art artificial intelligence techniques.

## Recognize and label 2D TTE clips

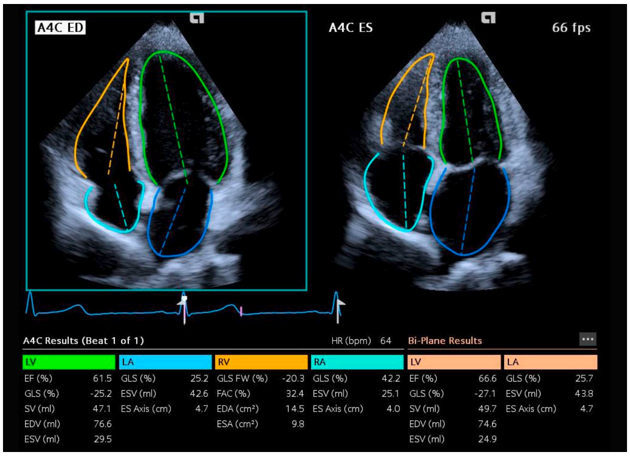
The necessary information to recognize a clip is extracted from the image intensity patterns of a single static frame part of the temporal sequence of a 2D TTE clip. In a cascaded approach, three fully convolutional neural networks are used to classify the clip.

The first neural network is trained to determine whether or not opacification (contrast) agent used during the acquisition is visible in the image content. Based on the output of the first neural network, the second or third is used next. The second neural network discriminates whether the clip represents an apical 4-chamber, apical 3-chamber, apical 2-chamber or parasternal short axis view of the heart, in non contrast enhanced acquisitions. The third neural network performs the same discrimination in contrasted acquisition.

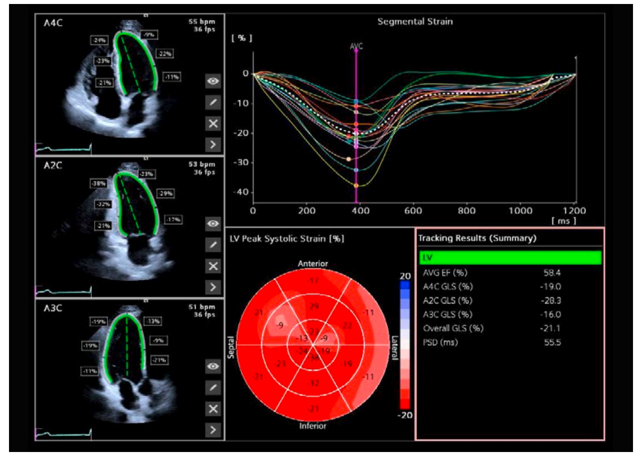
AI-enabled View classification of over 45 images (A4C, A3C, A2C) with and without contrast was 100% accurate according to sonographers [9].

## No ECG needed

Proper estimation of left ventricular ejection fraction relies on accurate identification of end-diastolic and end-systolic frames in the image sequence. Although ECG signal is commonly used to guide frame selection, for the purpose of LV volume and ejection fraction




AI powered view classification and contouring enable automated analysis of the function of all visible chambers in 2D TTE, with or without contrast. The chamber contours are overlaid to the clip, and relevant clinical metrics are reported in the summary table. AI-enabled image-based end diastolic and end systolic frame selection allow support for ECG-free workflows.




Based on the automated analysis of three clips (A2C, A3C, A4C), 2D Heart[AI] displays LV longitudinal segmental strain curves and bull's eye plot of peak systolic strain.

estimation of end-diastolic and end-systolic frames are defined as the frames in which the left ventricle has maximal (resp. minimal) visible area. Proper identification therefore requires examining and understanding the content of the clip.

The AI system performing this task is trained to consider the full sequence of frames, and recognize the motion patterns associated with the systolic (resp. diastolic) phase during which the visible area of the left ventricle is decreasing (resp. increasing). The image frames separating systolic and diastolic phases are then selected as the key frames of interest.

The system is based on a combination of convolutional neural networks for the analysis of the content of individual frames; and recurrent neural networks and convolutional neural networks for the analysis of sequences of frames. It performs the task purely based on imaging data, without the need of an ECG signal: thus, it guarantees a consistent performance regardless of the availability or quality of an ECG recording.

AI-powered selection of end-diastolic and end-systolic frames for 2D TTE with and without Physio (A4C, A3C, A2C) was accurate in 80% of the verification data sets [10].

## Contour the blood pool

The goal of contouring is the quantification of geometrical and functional features of the heart chambers. This is achieved first and foremost by clearly differentiating regions in the image representing the blood pool inside the chamber, from other regions representing the myocardial wall, or other background structures.

Image segmentation is the operation by which AI algorithms perform such differentiation. A convolutional neural network is trained to assign the proper label to each pixel in the image, assigning it either to the blood pool region, or to the myocardium (or background). However, this is not sufficient to allow the automatic quantification of measurements such as segmental strains, which are intrinsically defined based on anatomical fiducials. Knowing the localization of such fiducials in the image allows understanding of the heart chambers: their position, orientation and scale, as well as the relative position of different segments (apical vs. basal, septal vs. lateral).

The convolutional neural network is equipped with a second arm, trained to segment regions in the image corresponding to the location of three landmarks for each chamber: two of them on the annulus of the heart valve constituting the tips of the chamber contour; and one of them representing the apex or roof of the chamber. By training both arms of the convolutional neural network to jointly perform their complementary segmentation tasks, consistency of the results is enforced: ensuring that the blood pool region extends

**Spotlight: Heart Failure**

AI-enabled automated workflow to improve efficiency in diagnosis and management of heart failure.

up to the position of the anatomical fiducials, while in turn the fiducials are localized in proximity of regions identified as blood pool.

By performing chamber contouring at the automatically detected end-diastolic and end-systolic frames (thanks to AI-based key frame identification), 2D Heart$^{AI}$ produces semi-automated volume and ejection fraction estimation. LV end diastolic and end systolic volumes have 98% correlation with the estimates provided by the consensus of 4 sonographers on 45 clips, for all supported cardiac views (A2C, A3C, A4C), with or without contrast agent (i.e., LVO) [8] [11].

## Quantify chamber mechanics

The basis for quantification of myocardial mechanics is the identification of image patterns in the clip, which are associated to the position of the myocardium and its motion over time. If the observed structures, as they move, remain in the path of the sound waves captured by the echo probe, their motion can be reconstructed from the motion of the corresponding image patterns.

When considering 2D TTE images, some of the challenges of this approach are immediately evident. Depending on the probe position and orientation, as well as the relative motion of the probe itself with respect to the body of the patient, the target region of myocardium may not be visible in all frames – therefore its motion may not be observable at all times.

2D Heart$^{AI}$ combines the solid foundation of traditional computer vision methods for speckle tracking, namely estimation of optical flow and block matching, with motion constraints derived from the AI-based image segmentation. The shape of the chamber contour is defined in end systolic and end diastolic frames by 2D Heart$^{AI}$ autocontouring. These contours then guide the speckle tracking algorithm, providing multiple key frames at which the position of the contour is known exactly.

The problem of reconstructing the full motion of the chamber contour is then broken down in multiple sub-problems, each dealing with the motion of the chamber contour between consecutive key frames. In the first sub-problem, the motion field is defined as the combination of the forward motion of the end diastolic contour towards the end of the cardiac cycle, and the backward motion of the end systolic contour towards the beginning of the heart cycle. Analogously for the second sub-problem, focusing on the motion field in the diastolic phase.

2D Heart$^{AI}$ is designed to support contour tracking both in 2D TTE clips with and without contrast opacification. The GLS curves have an average 97% correlation coefficient with curves produced by 4 sonographers on 45 clips, for all supported cardiac views (A4C, A3C, A2C), with and without contrast agent (i.e., LVO) [12].

# 4D Heart$^{AI}$

## 3D echocardiography holds the promise of single-stop, efficient and accurate whole heart analysis. 4D Heart$^{AI}$ helps to master it.

The value of 3D echocardiography for heart function estimation is increasingly recognized and demonstrated by its endorsement in clinical guidelines for the evaluation of ventricular size and function. 3D strain imaging may be preferred over 2D to fully characterize complex ventricular mechanics, as seen for instance in heart failure patients, thanks to its superior capability to quantify rotational dynamics.

The possibility of observing the entirety of the chamber in a single imaging window is an important asset for the accurate determination of volumes and ejection fraction, without relying on geometric assumptions or having to correct for foreshortening. Combined with real-time acquisition of the heart motion, with no stitching artifacts, this gives a unique opportunity to visualize and analyze the heart as an interconnected system, in which the dynamics of each chamber is interacting with the dynamics of the whole. The new matrix array transducers 5Z1 and Z6T support 11,404,800 processing channels and 384 physical channels, acquiring and enabling simultaneous viewing of three-dimensional images in real-time with up to 250 volumes per second.

Leveraging the advanced imaging capabilities of the new probes, 4D Heart$^{AI}$ allows visualization and interpretation of the heart as a unified structure, whose function is determined by the synergy of the individual components.

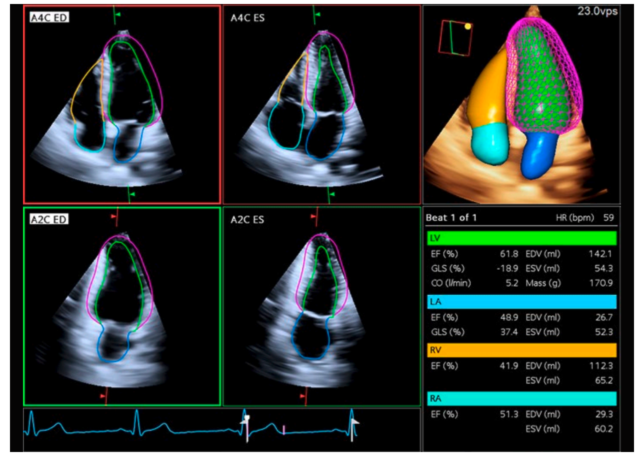
4D Heart$^{AI}$ leverages AI technologies to robustly identify the 3D shape of the chambers and track their motion during the heart cycle, and incorporates clinical experts' knowledge through large databases of annotations and based on state-of-the-art artificial intelligence techniques.

## Optimal extraction of planar views

An effective way to visualize the anatomical structures captured in the volume acquired by the 3D probe is to generate planar views consistent with the 2D echocardiography protocol (e.g., apical and parasternal short axis). This allows reviewing of the image content in a familiar format and helps standardize the analysis workflow. Additionally, optimized 2D data visualization can be useful to efficiently review the geometry of the heart chamber, minimizing user interactions with the 3D shape which require more complex and time consuming gestures.

**Spotlight:**
**Heart Failure**

AI-powered 4D whole heart analysis for complex myocardial mechanics typical of heart failure.



AI-automated 4-chamber analysis for EF, GLS. Control points for the LV epicardium are shown as the nodes of the triangular mesh in purple in the top right quadrant.

From a 3D acquisition it is possible to extract 2D views with minimal foreshortening and tied to the anatomical structures of interest. This requires, however, being able to identify anatomical fiducials such as the roof or apex of each chamber, as well as the shape and mutual position of the inflow and outflow orifices.

4D Heart$^{AI}$ leverages to this effect a deep reinforcement learning technique to train multiple AI agents to look for the anatomical fiducials in 3D space. Each AI agent learns an optimal decision policy, that defines a step-by-step procedure to move from the center of the volume to the position of the desired fiducial. At each step in its path, the AI agent uses the local appearance of the image as input to decide the next move. To increase efficiency and robustness, the AI agent takes steps of decreasing length as it gets closer to the target location – moving quicker in the initial steps and more precisely in the final steps.

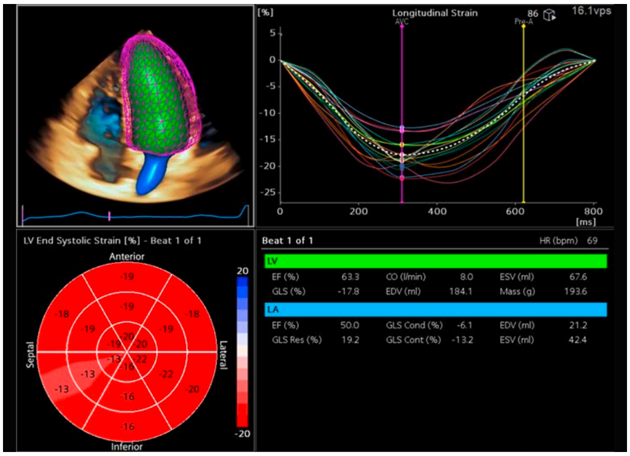
4D Heart$^{AI}$ has a 98%* MPR Identification and Alignment accuracy [22]. The evaluated views included standard apical and short axis view, as well as context-specific 2D views to simplify data review and contour editing for atria and the right ventricle.

## Contour the blood pool

The image segmentation task is achieved by a trained convolutional neural network analogous to the one powering 2D Heart$^{AI}$. Specialized instances of the network are trained to identify each visible chamber in 3D TTE and TEE. A GPU-powered implementation enables multi-chamber 3D segmentation in seconds.

Leveraging the automatic detection of multiple anatomical fiducials using deep reinforcement learning, 4D Heart$^{AI}$ builds a representation of each chamber using a multitude of control points. Based on the position of the fiducials, a local reference system for each chamber is consistently defined. Control points are then associated to their position on the chamber wall in longitudinal, radial and circumferential directions. Corresponding control points are positioned in the same anatomical region of the myocardium, for any heart analyzed by 4D Heart$^{AI}$. This supports easy inter-subject comparison of chamber anatomy via statistical shape analysis. Additionally, the chamber walls can be dynamically subdivided in 18 segments for the left ventricle according to the definitions proposed by the American Heart Association.

**Average*




4D mechanics, segmental strain, bull's eye plot. In the top left quadrant, the 2D view of the data is automatically defined for optimal visualization (foreground) of the mid inferolateral segment selected in the bull's eye plot.

4D Heart$^{AI}$ using both TTE and TEE has a up to 96% accuracy rate for detecting LV ED and ES volumes between manual contours and 4D Heart$^{AI}$ [14].

## Quantify chamber mechanics

4D Heart$^{AI}$ extends the approach used by 2D Heart$^{AI}$ to support comprehensive 4D mechanics quantification. The speckle tracking algorithm combines the estimation of optical flow from time- and space-varying image intensity with motion constraints provided by the AI-based segmentation and landmark detection algorithms. The motion is reconstructed between a pair of consecutive image key frames (e.g., end-diastolic and end-systolic) by combining the forward tracking of contour points (e.g., from their and diastolic position), with the backward tracking of contour points (e.g., from their systolic position).

The motion of each control point on the chamber contour is analyzed independently. The deformation of the myocardial tissue in the neighborhood of each control point is estimated by considering the motion of multiple neighbor points. This leads to the evaluation of the Lagrange strain tensor in each control point, providing a measure of how the myocardium locally changes its configuration with respect to the reference or resting state.

Leveraging the local reference system built for each chamber based on the automatically detected anatomical fiducials, three orthonormal axes are defined for each control point, representing the longitudinal, radial and circumferential directions. The radial direction is defined as normal to the chamber contour and oriented towards its axis. The longitudinal direction is defined as locally tangent to the chamber contour, and oriented towards the apex. The circumferential direction is defined as locally tangent to the LV contour, and orthogonal to the first two axes.

All the quantities describing the motion of control points (displacement, velocity, strain) are finally projected along the axes of the local reference system to obtain longitudinal, radial and circumferential point-wise estimates. Global or segmental quantities are computed as the integral average of point-wise estimates over the region of interest (respectively, the entire myocardial wall or an individual segment).

4D Heart$^{AI}$ using both TTE and TEE has a up to 96% accuracy rate for detecting LV ED and ES volumes between manual contours and 4D Heart$^{AI}$ [23].

# AI Measure

The AI Measure feature covers a set of semi-automated cardiac measurements for Doppler, 2D, and M-mode based on AI technologies

### Abbreviations

| | |
|---|---|
| **AI** | Artificial Intelligence |
| **HMSL** | Hierarchical Marginal Space Learning |
| **LV** | Left ventricle |
| **MSL** | Marginal Space Learning |
| **PHD** | Probabilistic, hierarchical and discriminant framework |

The main purpose of this feature is to improve efficiency, consistency, and robustness of routine cardiac measurements. AI Measure tools increase clinical confidence by reducing intra-operator variability and increasing accuracy and reproducibility regardless of the level of experience. This feature will also drastically reduce exam time needed to complete exams and streamline workflows. In addition, AI Measure also reduces the number of keystrokes required to complete a cardiac exam.

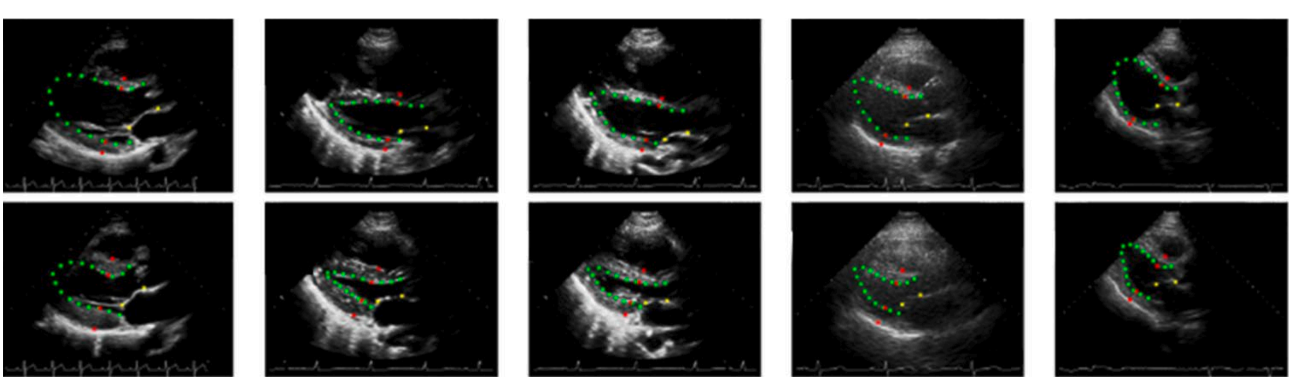
Although the measurement contours are 89% accepted by clinical users without editing [21], the system always allows the user to adjust the contour before confirmation.

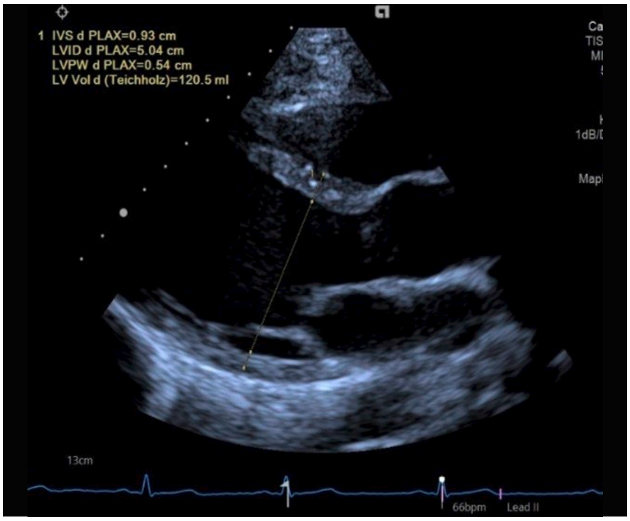
AI Measure generates contours of several types based on the user selected measurement. Some are simple like dots or lines, others more complex like polylines and traces. These contours imitate the contours a clinician could draw in manual mode. Measurement values are subsequently derived from the shapes and positions of the contours by deterministic algorithms. From one measurement contour multiple measurements can be calculated. AI Measure supports 42 measurements enabled by contours generated by 15 models leveraging several AI algorithms based on supervised learning strategy. The algorithms fall into 3 groups:

- B-mode (2D)
- M-mode
- Doppler

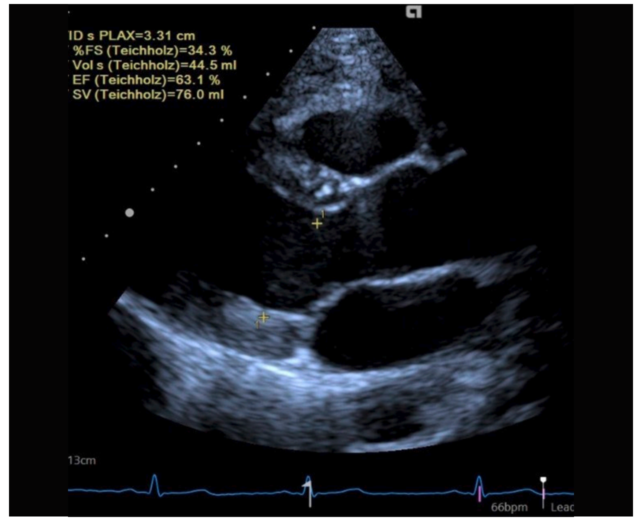
## B-mode

Sonographers compute the LV measurements by marking key points in a PLAX ED (End Diastole) image or a PLAX ES (End Systole) image to identify the IVSd (interventricular septum end-diastole), LVIDd (LV internal dimension






B-mode measurement contour for ED (polyline)




B-mode measurement contour for ES (two points)

end diastole), LVPWd (left ventricular posterior wall thickness end-diastole), and LVIDs (LV internal dimension end systole) measurements. Ideally, the key points all lie along a single line in the 2D B-mode image. However, manual placements may not fall exactly on a line. The AI Measure B-mode algorithm automatically finds the four landmark points on a straight line in a given PLAX image. The PLAX image may be either an ED or ES frame. Note that for an ES frame, only two points out of 4 are used to compute the LVIDs. However, finding the points by observing only the local region around the points is difficult due to occlusion or noise. To overcome this limitation, the principle heart structures of left ventricle, mitral valve, and aortic valve are utilized to find the measurement landmark points.

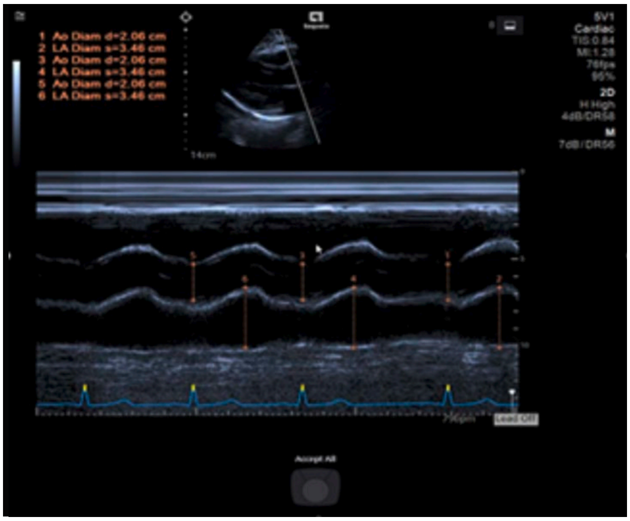
The deployed algorithm proposed by JinHyeong et al. [1] employs supervised learning-based techniques to generate models using annotated training data. The training data consists of PLAX images collected at ED and ES. The images are annotated by an expert who manually draws a contour of the LV and marks the four key landmark points. The LV annotation contour is defined using a series of points distributed uniformly along the LV endocardium.

The algorithm first detects and localizes the LV structure including mitral valve and aortic valve which is relatively stable in PLAX view. The LV structure detector is trained using the Hierarchical Marginal Space Learning (HMSL) approach proposed by Zheng et al. [2] and Sofka et al. [3]. The main advantage of the HMSL algorithm is to speed-up the object detection time by dividing the search space into location, angle and size sequentially rather than scanning the entire search space. Each detector in HMSL is trained using Probabilistic Boosting Tree [5].

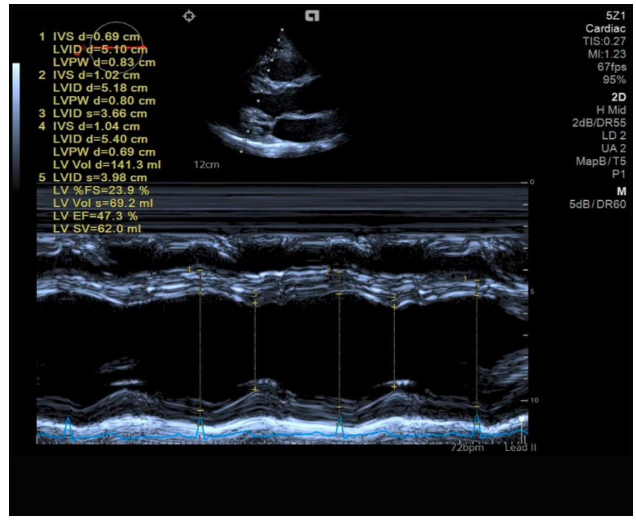
The candidates identified by the object detection component are passed to the shape inference component. The shape inference algorithm infers the best possible shape of LV and the measurement landmark points inside each candidate image patch.

The LV candidates and their measurement landmark points are used to train the warping detector which not only excludes the outliers from the candidates but also provides probabilities that support selection of the final solution.

The final component of the algorithm is used to further refine the landmarks by utilizing the temporal motion of the heart structure. A pseudo anatomic M-mode image is constructed by stacking one dimensional B-mode images from the time window around the ED frame (or the ES frame) using the line defined by the four landmark points. The algorithm of landmark detection in anatomic M-mode [4] is used to refine the landmark points.




Aortic root measurements




Left ventricle measurements

## M-mode

The M-mode echocardiogram is a spatial-temporal image slice of the human heart captured by an ultrasound device. Unlike regular B-mode echocardiography that uses multiple interrogation beams, M-mode echocardiography uses a single interrogation beam and hence achieves an enhanced temporal and spatial (along the single line) resolution. It is often used in clinical practices to assess the functionality of anatomic structures inside the heart such as the left ventricle and the aortic root as its high image quality allows accurate measurement and captures subtle motion.

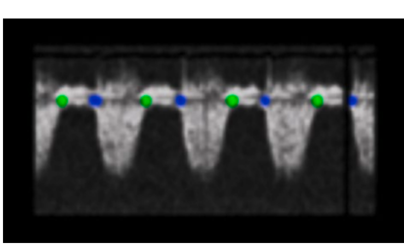
The algorithm generating contours for obtaining M-mode measurements also employs knowledge-based imaging technologies which can learn the expert’s knowledge from the training image set and corresponding annotations. Based on the models constructed from the learning stage, the algorithm determines location of the landmark points for the measurements of left ventricle and aortic root.

As shown in the figures above, from the M-mode echocardiogram, the algorithm detects a cohort of four landmarks on the lines corresponding to ED/ES whose positions are provided as input.

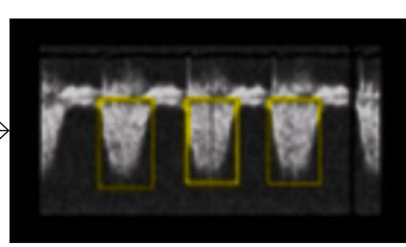
## Doppler

Doppler echocardiography is widely used to assess cardiovascular functionalities such as valvular regurgitation and stenosis. The Doppler effect is employed to determine blood flow (or structure) direction and relative velocity. The acquired Doppler echo-cardiogram is a velocity-time image.

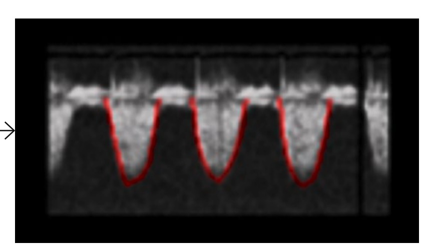
**Sequence example of results of a sequence/hierarchy of detectors**



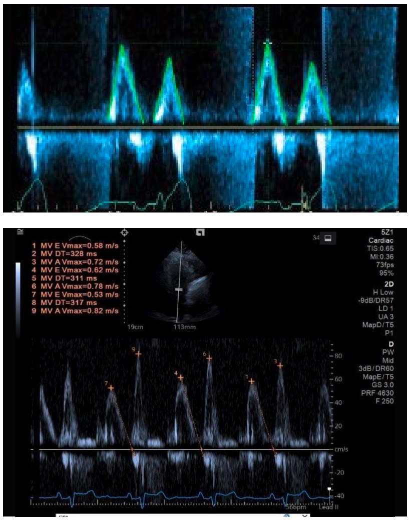
Left & Right root detector



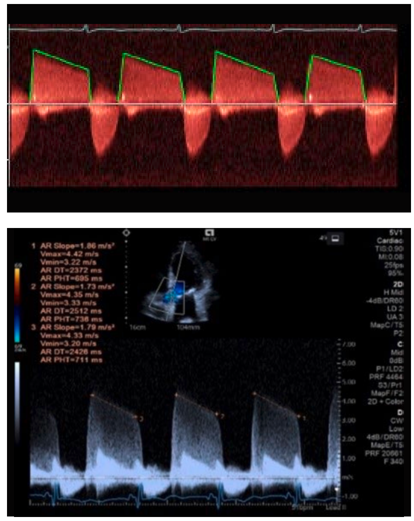
Box detector



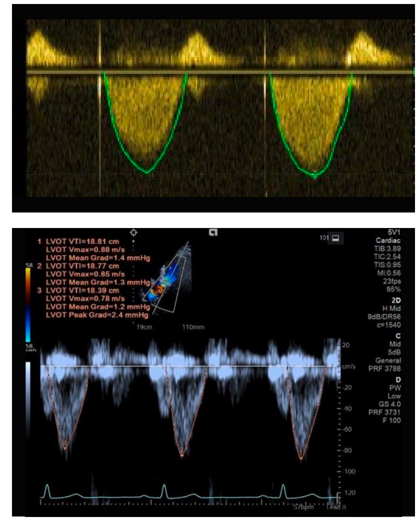
Warping detector



Triangles



Quadrilaterals



Curves

In M-mode images, the detection algorithm detects only a cohort of landmarks. However, for Doppler measurements the same PHD Framework algorithm detects parameters of more complex structures.

The measurement contours in the product:

- Triangles (for Mitral inflow measurements)
- Quadrilaterals (for Aortic regurgitation measurements)
- Curves (e.g. LVOT measurements)

## The PHD Framework

The probabilistic, hierarchical and discriminant (PHD) framework that was proposed by S. K. Zhou et al. [6] is utilized. To detect the right parameters for different measurement contours for M-mode and Doppler from the properties of PHD Framework allows very fast detection of various deformable anatomic structures found in M-mode and Doppler echocardiograms.

The PHD Framework uses a hierarchy of detectors that are discovering the best configuration of parameters of primitives so that the detection probability is maximized. The hierarchy of detectors is important, because early results simply stops evaluation of the rest of the classifiers in the hierarchy saving computation time.

The specific hierarchy of detectors in the PHD Framework used for M-mode (cohort of landmarks) and for Doppler (Triangles, Quadrilaterals, and Curves) are listed below.

**Cohort**

- A cohort of landmarks
  1. N independent landmark detectors (where N is number of landmarks)
  2. Warping detector

- Triangles
  1. Box detector
  2. Peak detector

- Quadrilaterals
  1. Left & Right root detector
  2. Box detector
  3. Left peak detector
  4. Warping detector

- Curves
  1. Left & Right root detector
  2. Box detector
  3. Warping detector

89%* of the time the AI Measure (B-mode, Doppler and M-mode) were acceptable/accurate to the user [15].

**Average*

# AI Assist

AI technology takes ease-of-use to the next level. AI Assist placement of color Doppler boxes and Spectral Doppler gates is a leap forward in transthoracic echocardiogram workflow.

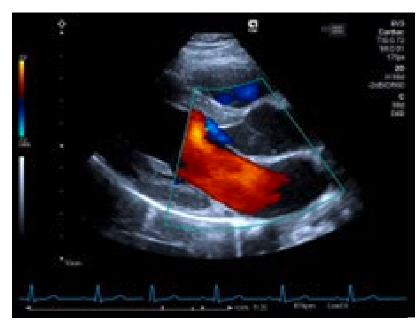
Transthoracic echocardiography is a basic part of most cardiac evaluations. It provides information about cardiac structure and function, establishes diagnosis, and guides therapy. A workflow improvement for such a frequently performed foundational examination provides benefits that accrue over many patients.

A typical Echo exam requires 100's of keystrokes, and takes 40–45 minutes to complete. A typical sonographer performs about 8 exams per day but demand is higher. About 90% of sonographers report repetitive motion injuries, which is far more than any other imaging modality [13]. The dexterity required to position the transducer and simultaneously manipulate the system controls calls for a skilled user.

AI Assist is a workflow improvement that reduces keystrokes, reduces exam time, reduces repetitive motions, and increases exam standardization and repeatability. AI Assist for 12 standard Echocardiogram views has a 99% accuracy rate for proper view classification and Doppler placement on 23 anatomical and hemodynamic targets [7]. In real-time, as the sonographer scans, a single button press places the color Doppler box and/or the spectral Doppler cursor on a selected anatomy region within the cardiac view. Placement is supported for a total of 23 view+anatomy locations. Color box placement is 98% accurate [16] and PW/CW cursor placement is 95% accurate-meaning no adjustment or only minor adjustment needed [17].

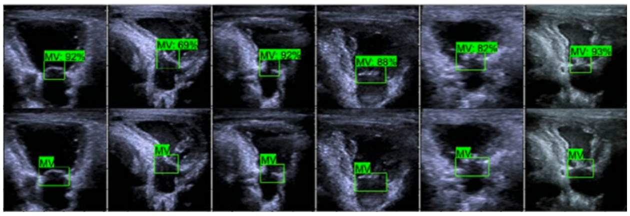
## The sonographer is in control

AI Assist simplifies the clinician's workflow without getting in the way. The sonographer can adjust any AI placement by simply using the traditional user interface controls to transition seamlessly to manual control. The system will return to performing AI placement with a single button press.

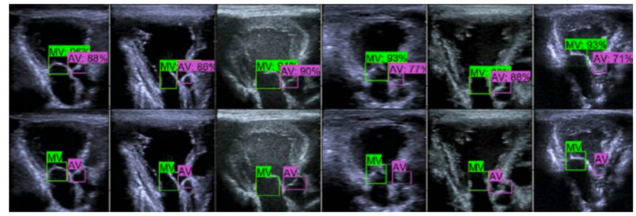



### Spotlight: Transthoracic echocardiogram

AI-powered workflow enables faster exam completion and reduces repetitive stress motions.



Apical 2 Mitral Valve Object Detection AI bounding boxes (top row) and ground truth annotations (bottom row). The AI model confidence score is given as a percentage. (Note: images are presented in acoustic acquisition format).



Apical 3 Mitral Valve (green) and Aortic Valve (purple) Object Detection AI bounding boxes (top row) and ground truth annotations (bottom row). The AI model confidence score is given as a percentage.

## Leverage AI technology

AI Assist leverages advances in the field of AI, specifically the computer vision techniques of Image Classification and Object Detection. A deep convolutional neural network for Image Classification is trained to identify standard TTE cardiac views. Additional deep learning networks perform Object Detection to identify locations of important anatomical regions in each view. For example, in the Apical 4 Chamber view, AI Assist can place the color Box and/or spectral Doppler cursor appropriately for the mitral valve, tricuspid valve and pulmonary vein. The feature leverages the computational power of NVIDIA GPU and Intel CPU hardware and software to integrate the AI algorithms into the live scanning workflow.

## Focus on capturing the right images

Point-and-shoot cameras with automatic focusing have helped make all of us better photographers. We now can concentrate our attention on the subject and composition of the image rather than the mechanics of setting up the camera. AI Assist aspires to take the ultrasound system a step closer to being like a point-and-shoot camera. Providing assistance in repetitive tasks in the TTE exam allows the sonographer to focus more attention on capturing the right images.

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**[7]** 11658871-ETP-001-01 **** overall accuracy 1732/1745 -> 99.26% Accuracy (Pg. 3)

**[8]** 023_2D4dhEART-aUTO-V-rEFsTS pages 2, 3

**[9]** 11658867-ETP-001-01 – Accuracy and Verification Test Report p 13

**[10]** 11658867-ETP-001-01 – Accuracy and Verification Test Report p 4 – Average for all views

**[11]** 11668553-EPI-001-01 – Algorhythm Study Report Strainguage pg 29 &31

**[12]** 11658867-ETP-001-01 – Accuracy and Verification Test Report p 4- Average for all views

**[13]** Ultrasound. 2015 Nov; 23(4): 224–230. Published online 2015 Jun 30. doi: 10.1177/1742271X15593575

**[14]** 11668552-EPI-001-02 – Algorhythm Study Report Unified Heart pg 23 & 24

**[15]** 11658748-ETP-001-01 – eSieMeasure Accuracy and Verification Report pg. 5 – Average

**[16]** 11668550-EPI-001-01 – Algorithm Study Report p 26 – Average accuracy for all views

**[17]** 11668550-EPI-001-01 – Algorithm Study Report p 27 – Average accuracy for all views

**[18]** 023_2D4DHeart-Auto-v-RefStd page 4

**[19]** 023_2D4DHeart-Auto-v-RefStd page 13

**[20]** https://www.siemens-healthineers.com/magnetic-resonance-imaging/technologies-and-innovations/deep-resolve

**[21]** ESieMeasure Accuracy and Verification Report pg 5

**[22]** Accuracy and Verification Report pg 7

**[23]** Algorhythm Study Report Unified Heart pg 23 & 24

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[1] *Personalization of diagnosis, therapy selection and monitoring, after care and managing health.*

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