(54) **Computerized characterization of cardiac motion in medical diagnostic ultrasound**

Computerisierte Kennzeichnung der Herzbewegung in einem medizinisch diagnostischen Ultraschall

Caractérisation informatique de mouvement cardiaque dans un ultrason de diagnostic médical

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Description

BACKGROUND

5   **[0001]**   This present invention relates to characterizing cardiac motion from ultrasound information.
[0002]   Being a non-invasive and cost effective modality, ultrasound is usually the initial method to quantify cardiac mechanics in a non-invasive manner. Recent developments in the field of echocardiography allow the cardiologist to quantify cardiac strain in a non-invasive manner. However, most existing methods for measuring myocardial strain are limited to measurements in one or two dimensions.
10   **[0003]**   The myocardium changes during a cardiac cycle. The volume of the ventricular wall itself may remain relatively consistent during the cardiac cycle, such with a change less than 5%. Since myocardial tissue is virtually incompressible, the tissue deforms in all three dimensions simultaneously. Therefore, it is important to compute the cardiac motion in three-dimensions.
[0004]   Given the recent progress on real-time ultrasound imaging, unstitched volumetric data can be captured in a
15   high volume rate, which allows quantification of cardiac strain and other parameters in three-dimensions. For example, the estimation and analysis of cardiac motion provides important information for the elasticity and contractility of the myocardium. Although visual wall motion scoring is the clinically established method for assessment of regional myocardial function, this methodology may be variable between observers. To quantify from a sequence of volumes (e.g., 3D+t or 4D), manual tracing becomes burdensome.
20   **[0005]**   US2005/0059876 discloses systems and methods for automated assessment of regional myocardial function using wall motion analysis methods that analyze various features/parameters of patient information (image data and non-image data) obtained from medical records of a patient. US 2006/0064007 A1 discloses the tracking of ventricle motion to evaluate the degree of ischemia and infarction in ultrasound heart data.

25   BRIEF SUMMARY

[0006]   By way of introduction, the preferred embodiments described below include methods, computer readable media and systems for computerized characterization of cardiac wall motion. Quantities for cardiac wall motion are determined from a four-dimensional (i.e., 3D + time) sequence of ultrasound data. The quantities are determined with minimal user
30   input. A processor automatically processes the volume data to locate the cardiac wall through the sequence and calculate the quantity from the cardiac wall position or motion. Various machine learning is used for locating and tracking the cardiac wall, such as using a motion prior learned from training data for locating and the motion prior, speckle tracking, boundary detection, and mass conservation cues for tracking with another machine learned classifier.
[0007]   Where the sequence extends over multiple cycles, the cycles are automatically divided for independent tracking
35   of the cardiac wall. Independent tracking in each cycle may reduce or avoid inaccuracies due to drift. The cardiac wall from one cycle may be used to propagate to another cycle for initializing the independent tracking. The tracked cardiac wall from a plurality of cycles may be fused temporally to enhance tracking accuracy and robustness.
[0008]   Particular and preferred aspects of the invention are set out in the accompanying independent and dependent claims.
40   **[0009]**   The present invention is defined by the following claims, and nothing in this section should be taken as a limitation on those claims. Further aspects and advantages of the invention are discussed below in conjunction with the preferred embodiments.

BRIEF DESCRIPTION OF THE DRAWINGS

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[0010]   The components and the figures are not necessarily to scale, emphasis instead being placed upon illustrating the principles of the invention. Moreover, in the figures, like reference numerals designate corresponding parts throughout the different views.

50   Figure 1 is a block diagram of one embodiment of a system for characterizing cardiac motion from ultrasound information;
Figure 2 is a flow chart diagram of one embodiment of a method for characterizing cardiac motion from ultrasound information;
Figure 3 shows an example sequence of medical diagnostic ultrasound images representing one embodiment of a
55   method for characterizing cardiac motion from ultrasound;
Figure 4 shows an example sequence of medical diagnostic ultrasound images over a plurality of cycles and a corresponding example graph showing volume through the sequence;
Figure 5 shows an example multi-planar reconstruction and three-dimensional rendering of medical diagnostic

ultrasound images with an overlay of a located myocardium;
Figure 6 illustrates tracking of a heart wall through a plurality of heart cycles according to one embodiment;
Figure 7 is a graphical representation of one embodiment of meshes representing the myocardium through two heart cycles and a corresponding example atlas; and
Figure 8 is a graphical representation of a coordinate system relative to the heart.

DETAILED DESCRIPTION OF THE DRAWINGS AND PRESENTLY PREFERRED EMBODIMENTS

[0011] To quantitatively detect wall-motion abnormalities of the left ventricle (LV), automated analysis of LV wall motion may be preferred to visual assessments. Cardiac motion is quantified by recovering the three-dimensional (3D) non-rigid deformation of the ventricular wall from 3D+t ultrasound images or frames of data. Robust multi-cycle ventricular wall motion tracking on volumetric ultrasound data is provided. By using knowledge-based 3D+t myocardial function assessment, automated cardiac quantification is provided. Myocardial mechanics, such as an atlas based representation, are determined with a multi-model, learning-based motion estimation using high frame rate volumetric ultrasound data.

[0012] Given the recent progress on real-time ultrasound imaging, high frame rate volumetric ultrasound images or frames of data may be acquired over multiple cardiac cycles. Detecting motion in three-dimensions may be more useful than the more arbitrary motion detection in one or more planes. The estimation and analysis of cardiac motion may provide important information for the quantification of the elasticity and contractility of the myocardium. Detecting motion over multiple cycles may be more useful than over a single cycle, especially where drift in tracking is avoided.

[0013] Multiple types of information, such as image gradients, boundary detection and motion prediction, are fused to achieve a robust tracking on 3D+t ultrasound sequences. The use of these types of information may allow efficient, high speed performance, such as tracking at 1 second per frame for volumetric ultrasound data on a 3.0GHz personal computer (PC) machine.

[0014] Detection of wall-motion abnormalities of the left ventricle (LV) provides important information on myocardial (dys-)function in a variety of clinical settings, and is widely accepted as a predictor for non-ischemic cardiomyopathy and coronary artery disease. Boosted by automatic detection and tracking techniques, 3D non-rigid deformation of the myocardium may be recovered from 3D+t ultrasound data, allowing for statistical atlases of cardiac motion on a large population. Normal and diseased myocardial motion patterns may be automatically detected, and the severity of a disease determined using the statistical atlases of myocardial deformation parameters based on statistical indices, such as Hotelling's t-square score, to measure the deviation from healthy cardiac motion patterns. A learning-based method automatically estimates the 3D displacements and velocities of the myocardial motion.

[0015] In one embodiment, a fully automatic method and system estimates the 3D non-rigid deformation of the whole myocardium on instantaneous volumetric ultrasound data using database-guided detection and information fusion-based tracking. Global and regional myocardial mechanics are estimated based on the tracking result. The quantified mechanics may include parameters such as volume, velocity, displacement, twist, torsion, strain, strain rate, principal strain, radius, curvature, contraction front mapping (CFM), relaxation front mapping (RFM), and Coronary Map. The mechanics may be reported in graphical, parametric, chart, numerical, and/or bull's eye representations. The parameters may be projected to the local heart coordinate system (e.g., the longitudinal (meridional) DL, radial (transmural) DR, and circumferential DC directions).

[0016] Quantified mechanics parameters may be fused with other imaging modalities, such as coronary CT (Computed Tomography) data, to enhance visualization quality and diagnostic confidence of physicians.

[0017] While discussed herein for use on the myocardium or left ventricle with ultrasound data, the approach may be considered a general framework. This general framework may be applied to other portions of the heart and/or other organs. The general framework may be applied to other imaging modalities, such as x-ray, computed tomography, or magnetic resonance imaging. The systems, methods and instructions herein may instead or additionally be used for other cyclical or repetitive motion characterization, such as analysis of diaphragm motion or a gait while jogging. In yet other embodiments, non-medical analysis is performed using the methods, systems, or instructions disclosed herein, such as analysis of turbine blade vibrations or structural reaction to environmental conditions (e.g., bridge variation due to wind). The medical imaging cardiac example is used herein.

[0018] Automatic semantic processing provides myocardial mechanics. Tracing and tracking are integrated using specific knowledge of the anatomy involved for full myocardial mechanics computation from 3d+t volumetric ultrasound images. A fully automatic system is provided with information fusion-based robust tracking and comprehensive parameter estimation of myocardium mechanics. The automated system includes automatic initialization of myocardial boundaries and multi-planar reconstruction (MPR) planes in the first frame by real-time detection. Automatic tracking of the myocardium motion and estimation of clinical cardiac parameters in three-dimensional space is provided. Information from multiple cues, such as speckle tracking, boundary detection, mass conservation, and/or motion prior, are fused into a single Bayesian objective function to achieve accurate and robust tracking of the whole myocardium volume. Efficient optimization, such as manifold learning, is used to achieve high speed.

[0019] Automatic temporal adjustment is provided for when ECG is not available or not correct. Boundary detection and motion prediction are combined with image intensity to prevent drifting in multiple cardiac cycles.

[0020] In one embodiment, the process proceeds through a number of actions. In a first action, automatic temporal segmentation is provided. When ECG information is not available or not correct, pre-processing automatically estimates one or more key frames (e.g., end diastole (ED) and/or end systole (ES)).

[0021] In a second action, automatic data navigation is provided. To be compatible with two-dimensional (2D) analysis, standard multi-planar reformatted planes (MPRs) (e.g., apical four chamber, apical two chamber, apical three chamber, and short axis views) are extracted from the 3D volumetric data automatically.

[0022] In a third action, automatic tracking initialization is provided. The initial endocardial and epicardial boundaries of the left ventricle (LV) are obtained using a marginal space learning (MSL) classifier. Other classifiers may be used.

[0023] In a fourth action, ventricular wall motion tracking is provided. The 3D deformation of the myocardial wall is captured by fusing the information from multiple cues, including speckle tracking, boundary detection and motion prior.

[0024] This framework may have advantages as compared to mere image registration or optical flow tracking. Boundary detection and motion prediction are combined with image intensity information to prevent drifting. The improved tracking accuracy and robustness may better track ventricular wall motion reliably in multiple cardiac cycles. Efficient optimization may achieve high speed performance. Initialization (e.g., location of the endocardial wall in one frame) is automatic. Automatic temporal segmentation may be used to report the number of heart beats, the number of frames in each beat, and the indices of end-diastolic (ED) and end-systolic (ES) frames.

[0025] Figure 1 shows a system 10 for characterizing cardiac motion. The system 10 includes a processor 12, a memory 14, a transducer 18, and a display 16. Additional, different or fewer components may be provided. In one embodiment, the system 10 is a medical diagnostic imaging system, such as an ultrasound imaging system. As or after frames of data representing a patient's heart in three-dimensions are acquired, the system 10 automatically characterizes the cardiac motion of the heart. As an ultrasound imaging system, the system 10 includes a transmit beamformer, receive beamformer, B-mode detector, Doppler detector, harmonic response detector, contrast agent detector, scan converter, filter, combinations thereof, or other now known or later developed medical diagnostic ultrasound system components. In other embodiments, the system 10 is a computer, workstation or server. For example, a local or remote workstation without the transducer 18 receives ultrasound data and characterizes cardiac motion.

[0026] The transducer 18 is a piezoelectric or capacitive device operable to convert between acoustic and electrical energy. The transducer 18 is an array of elements, such as a multi-dimensional or two-dimensional array. Alternatively, the transducer 18 is a wobbler for mechanical scanning in one dimension and electrical scanning in another dimension.

[0027] The system 10 uses the transducer 18 to scan a volume. Electrical and/or mechanical steering allows transmission and reception along different scan lines in the volume. Any scan pattern may be used. In one embodiment, the transmit beam is wide enough for reception along a plurality of scan lines. In another embodiment, a plane, collimated or diverging transmit waveform is provided for reception along a plurality, large number, or all scan lines.

[0028] Ultrasound data representing a volume is provided in response to the scanning. The ultrasound data is beamformed, detected, and/or scan converted. The ultrasound data may be in any format, such as polar coordinate, Cartesian coordinate, a three-dimensional grid, two-dimensional planes in Cartesian coordinate with polar coordinate spacing between planes, or other format. The ultrasound data may be of any type, such as B-mode, flow mode, Doppler mode, contrast agent, harmonic, or other ultrasound modes of imaging.

[0029] The ultrasound data is grouped into frames. Each frame includes the ultrasound data sufficient to detect values for the voxels representing the volume of the patient. For B-mode, the ultrasound data includes samples from the receive scan lines. The ultrasound data is beamformed or detected. For Doppler, the ultrasound data may include samples from a plurality of reception events performed along each scan line or estimated velocity or energy samples for each scan line. Each frame of data represents the volume at a given time. Different frames represent substantially the same volume at different times. Substantially accounts for unintended patient or sonographer movement and/or movement caused by the heart cycle.

[0030] The processor 12 is one or more general processors, digital signal processors, application specific integrated circuits, field programmable gate arrays, servers, networks, digital circuits, analog circuits, combinations thereof, or other now known or later developed device for processing medical ultrasound data. The processor 12 implements a software program, such as code generated manually or programmed or a trained classification system. For example, the processor 12 is a classifier implementing a graphical model (e.g., Bayesian network, factor graphs, or hidden Markov models), a boosting base model, a decision tree, a neural network, combinations thereof or other now known or later developed algorithm or training classifier. The classifier is configured or trained for distinguishing between the desired groups of states or to identify options and associated probabilities. The processor 12 may implement multiple classifiers with or without further programming to identify the left ventricle, track motion of the heart, and/or calculate parameters.

[0031] The processor 12 performs machine learning and/or applies a machine-learned algorithm. For example, the processor 12 applies a probabilistic model to detect the myocardium and/or to track the myocardium. The probabilistic model is a machine-learned classifier. Any classifier may be applied, such as a model-based classifier or a learned

classifier (e.g., classifier based on machine learning). For learned classifiers, binary or multi-class classifiers may be used, such as Bayesian or neural network classifiers. In one embodiment, a binary boosting classifier with a tree and cascade structure is used. A single class or binary classifier, collection of different classifiers, cascaded classifiers, hierarchal classifier, multi-class classifier, model-based classifier, classifier based on machine learning, or combinations thereof may be used. Multi-class classifiers include CART, K-nearest neighbors, neural network (e.g., multi-layer perceptron), mixture models, or others. A probabilistic boosting tree may be used. Error-correcting output code (ECOC) may be used. The classifier is instructions, a matrix, a learned code, or other software and/or hardware for distinguishing between information in frames of ultrasound data.

[0032] The classifier may include a plurality of models or classifiers (e.g., detectors) operable together or independently. For example, different probabilistic models are trained, such as one for detecting the myocardium in a given frame of ultrasound data and another for tracking the myocardium between frames. The tracking model may use the output of the detection model. The probabilistic models may be joint or dependent.

[0033] For application, the processor 12 calculates features for classification. The same or different features are used for classification in each stage. For example, features are calculated for each frame of data from the data itself for detecting the myocardium. Other features, such as the output of the detection, features from the data itself, and/or other types of information in a fusion for tracking, are calculated for tracking. Using a machine-trained translation classifier, the features are used to rule out hypotheses and/or select a hypothesis corresponding to the location of the myocardium.

[0034] In one embodiment for detection and/or tracking, the features are three-dimensional features. 3D data is used to calculate the features. The window function defining the data is a cube, but may have other volume shapes. The window is translated, rotated, and scaled as part of searching for an anatomy. The same or different sized windows are used for different anatomies.

[0035] Any features may be used. Different types of features may be used for the same classifier, or all of the features are of a same type for a given classifier. In one embodiment, Haar wavelet-like and/or steerable features are calculated. The features represent directional gradients. Haar wavelet-like features represent the difference between different portions of a region. Any number of features may be used, such as tens, hundreds, or thousands. The machine learning process may operate to determine a desired subset or set of features to be used for a given classification task. In one embodiment, the type of features used is gradient features. For example, the "steerable" features described by Zheng, et al. in "Fast Automatic Heart Chamber Segmentation from 3D CT Data Using Marginal Space Learning and Steerable Features," Proc. Int'l Conf. on Computer Vision, pp. 1-8, 2007, are used. Other types of features may alternatively or additionally be used.

[0036] The ultrasound data may be processed prior to calculating features. For example, the gradients throughout the frame are calculated. The features are determined from the gradient information. As another example, low, high, or bandpass filtering is applied.

[0037] The classifier is trained from a training data set using a computer. Any number of expert annotated sets of ultrasound data is used. For example, about 200 hundred ultrasound sequences representing the whole or at least a majority of the myocardium are annotated. The annotation is a line, points, curves or volumes (e.g., a mesh or surface) associated with myocardium boundary. The annotation is provided for each frame of data. This large number of annotations allows use of a probabilistic boosting tree to learn relevant features over a large pool of 3D Haar features and/or steerable features. Both features may be efficiently computed and be effective as a feature space for boosting classifiers. Other features may be used. Each classifier uses the data sets and annotations specific to the anatomy being classified.

[0038] In one embodiment, the classifier is a knowledge-based probabilistic model, such as marginal space learning using a hierarchical search. A database of known cases is collected for machine learning, providing a database-driven knowledge-based approach. For training data, three-dimensional context information is preserved and guides the detection process. Knowledge is embedded in large annotated data repositories where expert clinicians manually indicate the anatomies. The known cases may be spatially aligned or registered, such as by aligning the coordinate system to the heart. The detected boundary may be scaled and/or aligned to a model or otherwise normalized. The detectors are trained on a large number of annotated 3D ultrasound volumes. The classifier learns various feature vectors for distinguishing between a desired anatomy and information not being detected. In alternative embodiments, the classifier is manually programmed.

[0039] The probabilistic boosting tree (PBT) unifies classification, recognition, and clustering into one treatment. For example, the detection and/or tracking classifiers are trained as a probabilistic boosting tree. The classifier is a tree-based structure with which the posterior probabilities of the presence of the anatomy of interest are calculated from given data. Each detector not only provides a binary decision for a given sample, but also a confidence value associated with the decision. The nodes in the tree are constructed by a combination of simple classifiers using boosting techniques, such as disclosed by Tu, "Probabilistic Boosting-Tree: Learning Discriminative Models for Classification, Recognition, and Clustering," Proc. Int'l Conf. on Computer Vision, pp 1589-1596, 2005.

[0040] The classifier is trained and applied as a machine-trained marginal space detection and/or fused information tracking classifier. The resulting machine-trained classifiers are applied as a detector of the myocardium in a given frame

and tracking the myocardium between frames.

[0041] The processor 12 is operable to calculate cardiac related information, such as calculating area, volume, identifying cardiac cycle time periods, determining spatial parameter values as a function of time, strain, elasticity, twist, torsion, and/or characterize cardiac motion. In one embodiment, the processor 12 implements a model or trained classification system (i.e., the processor is a classifier) programmed with desired thresholds, filters or other indicators of class. For example, the processor 12 or another processor tracks one or more points and calculates spatial parameter values for each point in a model. For example, the characterization processes, systems or instructions used in U.S. Patent Publication No. 2005-0059876, the disclosure of which is incorporated herein by reference, are used. One method is described which characterizes the motion of each segment of the heart on a scale of 1-5, as per guidelines from the American Society of Echocardiography. The classification may be performed using the motion information described above.

[0042] The memory 14 is a non-transitory computer readable storage media. Computer readable storage media include various types of volatile and non-volatile storage media, including but not limited to random access memory, read-only memory, programmable read-only memory, electrically programmable read-only memory, electrically erasable read-only memory, flash memory, magnetic tape or disk, optical media and the like.

[0043] The memory 14 stores the ultrasound frame or image data. The data is stored for or during processing by the processor 12. For example, ultrasound data is a sequence of B-mode images or frames representing a myocardium at different times. The sequences are in a clip stored in a CINE loop, DICOM images or other format. The ultrasound data is input to the processor 12 or the memory 14.

[0044] The memory 14 may store data representing instructions executable by a programmed processor, such as the processor 12, for characterizing cardiac motion from ultrasound information. The automatic or semiautomatic operations discussed herein are implemented, at least in part, by the instructions. In one embodiment, the instructions are stored on a removable media drive for reading by a medical diagnostic imaging system or a workstation networked with imaging systems. An imaging system or work station uploads the instructions. In another embodiment, the instructions are stored in a remote location for transfer through a computer network or over telephone communications to the imaging system or workstation. In yet other embodiments, the instructions are stored within the imaging system on a hard drive, random access memory, cache memory, buffer, removable media or other device.

[0045] The instructions are for characterizing cardiac motion from ultrasound information. The functions, acts or tasks illustrated in the figures or described herein are performed by the programmed processor 12 executing the instructions stored in the memory 14 or a different memory. The functions, acts or tasks are independent of the particular type of instructions set, storage media, processor or processing strategy and may be performed by software, hardware, integrated circuits, film-ware, micro-code and the like, operating alone or in combination. Likewise, processing strategies may include multiprocessing, multitasking, parallel processing and the like.

[0046] The display 16 is a CRT, LCD, plasma, projector, monitor, printer, or other display device for presenting an image and/or quantities to the user. The display 16 may be configured by the output of the processor 12 to display information to the user.

[0047] Figure 2 shows a method for computerized characterization of cardiac motion from ultrasound data. Figure 3 shows another embodiment of the method with respect to representative ultrasound medical images. Additional, different or fewer acts than shown may be used. For example, act 24 is not performed. Act 26 may not be performed where the sequence represents a single cycle or less or where the tracking is to be performed through multiple cycles without countering drift or with continuous, uniform processing. In another example, act 34 is not performed and an image is generated instead. The image represents the volume within the patient, such as being a rendering of the volume from one or more viewing directions or an MPR image.

[0048] The acts are performed in the order shown. Act 32 represents acts 28 and 30 being performed for different heart cycles, so is performed in parallel, before, or after acts 28 and 30. In other embodiments, the acts are performed in a different order.

[0049] In act 20, a sequence of frames of ultrasound data are obtained. The frames represent a volume of a patient at different times. The frames are acquired by scanning the patient with ultrasound. The frames may be obtained in real time with the scanning. As the scanning occurs for a subsequent frame of data, the most recently acquired frame of data is processed. The frames are obtained while the patient is still being scanned and/or while the patient is still being examined in a given visit. Alternatively, the frames are acquired from a memory or transfer where the scan occurred previously in an examination no longer occurring.

[0050] In an example embodiment, the 4D ultrasound sequences are acquired with a medical diagnostic ultrasound scanner with the average volume size of size $200 \times 200 \times 140$ voxels and resolution of 1mm in the x, y and z directions. Each frame is detected data representing the volume. Any frame rate is used, such as 15 or more frames a second or heart beat. The sequence is over a portion of a heart cycle, over multiple cycles, or any length. Other volume sizes, resolutions, and/or frame rates may be used.

[0051] In act 22, one or more frames in the heart cycle are identified. For example, an end-diastolic and/or end-systolic

frame is identified. Since the different frames represent different times, the different frames are associated with different phases of the heart cycle. One or more frames may correspond to a given phase of the heart cycle. For example, one frame represents the volume at the end-diastolic time. Since time separates frame acquisition, two frames may overlap or represent the closest times to the desired phase. One may be selected, an interpolation frame may be formed, or the

5   frames may be averaged.

[0052] In one embodiment, ECG information is used to determine the frames associated with phases. For multi-cycle data, the number of heart beats, the number of frames in each beat, and the indices of end-diastolic (ED) and end-systolic (ES) frames may be used. However, the ECG information might be unavailable or incorrect in some data. The frames of ultrasound data may be used to determine the frames for particular phases.

10   **[0053]** The frames representing the heart at the desired phases are determined from the volume within the myocardium. The left ventricle chamber expands and contracts throughout the heart cycle. The volume enclosed by the myocardium, as opposed to the volume of the myocardium, is plotted over time (see Figure 4).

[0054] In one embodiment, the volume is calculated by detecting the myocardium. Any boundary detection may be used. For example, the detection discussed below for act 28 as part of tracking is performed for each frame of data to

15   calculate volume. This detection relies on knowledge of the myocardium resulting from machine-learning. The knowledge is used as a motion prior. Instead of asking the user to manually select the number of cardiac cycles and the indices of key frames (ED or ES), the endocardial boundary of the left ventricle (LV) is detected in each frame using a learning-based approach. Any learning based approach for boundary detection may be used.

[0055] Given three spatial dimensions, time, and a large number of voxels in each volume, the dimensionality of the

20   data for detecting the boundary is high. In one embodiment, the dimensionality is reduced. The data is combined or processed to have fewer variables. For example, the identity of the myocardium is performed using relative relationships of points rather than absolute coordinates. A boundary may be represented as a mesh. Rather than using the x, y, z (Cartesian) coordinates of each possible point on the mesh, the point's location relative to other points is used. The relative location is maintained while reducing the dimensionality. In alternative embodiments, the dimensionality is not

25   reduced.

[0056] The tissue boundary may have one or more gaps. The gaps are closed by curve fitting or interpolation. Alternatively, the gaps are identified and the tissue boundary is closed by connecting a flat or curved surface between the tissue boundary points closest to the gap. The region enclosed by the boundary is the cavity volume. For each frame in the sequence, the volume is calculated.

30   **[0057]** A volume curve is computed based on the detected LV boundaries. The volume over time may be low pass filtered. The variation in volume indicates relative cycle timing. The end-diastolic phase corresponds to a maximum volume of the left ventricle, and the end-systolic phase corresponds to a minimum volume of the left ventricle. The indices of end-diastolic (ED) and end-systolic (ES) frames are selected as the local peaks and valleys of the volume curve. The number of cardiac cycles is also set as the number of ED-ES pairs.

35   **[0058]** In act 24, multi-planar reconstruction or reformatting planes (MPR) are detected. Any standardized or non-standard viewing plane relative to the heart may be detected. For example, standard heart views include the apical four chamber plane (A4C), apical two chamber plane (A2C), apical three chamber plane (A3C), and one or more short axis planes (e.g,. short axis middle plane (SAXM)). Standard views are used to visualize the cardiac structures and are the starting point of many echocardiographic examinations. To automate the clinical workflow and facilitate the subsequent

40   processing tasks, such as ventricular wall motion tracking, standard cardiac MPR planes may be automatically detected from a 3D volume. The planes may be detected for one or more of the frames.

[0059] The views are detected from features. Three or more features of the heart (e.g., valves, chamber apex, or other features) are identified from the frame of data. Using a model of the heart indicating the spatial position of the planes relative to the heart orientation represented by the locations of the detected features, the positions of the planes relative

45   to the volume represented by the frame of data are determined.

[0060] In one embodiment, another machine-trained classifier is used to detect the planes or views. A learning-based method may achieve fast, accurate, and consistent MPR detection. Any machine-trained classifier may be used, such as disclosed in U.S. Published Patent Application No. 20090074280.

[0061] In act 26, the sequence of frames is divided into cycles. In a two-cycle example, the sequence is divided into

50   first and second heart cycles. The division is based on the volume within the myocardium. Using ED frames as the beginning of a heart cycle, the peaks in the volume indicate the beginning of each cycle. The variation of the volume, such as shown in the example of Figure 4, indicates the different cycles. Other beginning phases may be used.

[0062] Given the cardiac cycle and phase information estimated in act 22, the input ultrasound sequence is split into individual cardiac cycles. Figure 4 shows an example division. The separation allows for independent tracking through

55   each cycle to prevent or limit the drifting over a long sequence. Division of the cycles provides for tracking in act 30 performed differently between cycles (inter-cycle tracking) than for within each cycle (inner-cycle tracking). Acts 28 and 30 represent the inner cycle tracking for one cycle. Act 32 represents inner-cycle tracking for other cycles. Tracking of additional cycles may be provided.

[0063] In act 28, a processor identifies a myocardium in one or more frames. For example, the heart wall is located in the ED frame, SD frame and/or last frame before the next cycle. Tracking is initialized by detecting the myocardial boundaries of the left ventricle (LV). Both the endocardial and epicardial boundaries are detected, but just one boundary may be identified in other embodiments.

[0064] The frame includes ultrasound data representing the heart wall in three dimensions, so the myocardium is located as a three-dimensional boundary, surface or mesh. For example, the pose (i.e., position, orientation, and scale) and shape of the LV are estimated. The LV for the whole myocardium is located. To reduce processing, the three-dimensional boundary may be tessellated into a 3D mesh.

[0065] The boundary is identified automatically, such as without user input. The processor identifies the boundary from the ultrasound data of the frame with or without data from other frames. The identification is performed in real-time with the acquisition. The user configures the system to perform heart scanning prior to activation. Upon activation, the scanning occurs and the boundary is identified without further user input.

[0066] The processor identifies the boundary using a classifier or detector. Features may be identified using image processing. In one embodiment, the processor identifies the boundary using a machine-trained classifier. For example, marginal space learning (MSL) is used to create a classifier for identifying the boundary. The 3D detector is trained with training data, such as a pre-annotated database of 668 or other number of volumetric ultrasound frames. The training database is manually annotated by clinical experts to provide the ground-truth segmentation.

[0067] The MSL is trained using a probabilistic boosting-tree (PBT). Any types of features from the ultrasound data may be used. In one example, steerable features are used. Haar, Haar-like or other features may alternatively or additionally be used. The data represents intensities, but may be gradient data or subject to other pre-processing. The features are calculated from the ultrasound data, such as centering a window or kernel over each location and determining the steerable features for each window position. The learned detector may then use steerable features for subsequently obtained frames (e.g., the frame or frames determined in act 22) to identify the boundary.

[0068] The machine-trained 3D detector locates the pose, including the position X =(x, y, z), orientation θ =(α, β, γ) and scale S =(sx,sy,sz), of the LV. Control points representing the mesh are positioned using the detector. The detector represents a model of the anatomy where the model is fit by application of the matrix to the ultrasound data. The fitting locally deforms the model. The local deformations of the myocardial boundaries are estimated based on the posterior distribution pi(X|I) of each control point (i.e., mesh location) on the surface. The posterior distribution is learned as part of the machine training of the 3D detector using the steerable features and the probability boosting-tree (PBT). Given an input volume, the mean LV shape is aligned to the detected pose or data. The model (i.e., mean LV shape) is deformed to locate the best boundary candidate using the trained boundary detector for each point of the model along the normal directions.

[0069] Figure 5 shows example detected boundaries overlaid on MPR B-mode images (first four medical images) and a three-dimensional rendering (last medical image). Both the endocardial and epicardial boundaries of the left ventricle (LV) are detected. The volumetric ultrasound data is acquired from a cardiomyopathy patient. Automatically detected multi-planar reformatted planes (MPRs) include, from left to right: (a) apical four chamber plane, (b) apical three chamber plane, (c) apical two chamber plane, and (d) short axis middle plane. In the three-dimensional rendering, the boundaries are overlaid as meshes.

[0070] The heart or other anatomy identified in act 28 is for initializing the tracking. For tracking in one temporal direction through the sequence, the boundary is identified in one frame. For tracking from different temporal directions, the boundary is initialized in two or more frames. For example, the boundaries in the first and last frames of the sequence are identified. The boundary may then be tracked in forward and reverse directions through the portion of the sequence of the given cycle.

[0071] The machine-trained detector of act 28 represents a motion prior. The knowledge from the learning provides the typical myocardium position for different phases. For each phase, a classifier is trained and used. Alternatively, the same classifier detects the boundary at any phase.

[0072] In one embodiment, the motion prior information is used throughout a cycle to determine the volume in act 26. In another embodiment, the motion prior is used for initializing the tracking in act 28. Combinations of these uses may be provided.

[0073] In yet another embodiment, the motion prior is also or alternatively used as an input feature for tracking in act 30. For example, the myocardium is located through the sequence with the machine-learned detector (motion prior). The knowledge of the probabilities, as fit to the data of each frame, indicates the location or local offset based on the motion prior. The machine-learned knowledge of the heart wall represented in training data is used to identify or locally warp the boundary in real-time with the scanning.

[0074] To reduce the amount of data processing for detecting the boundary, manifold learning with K-means clustering may be used. The motion prior is computed offline using manifold learning and hierarchical K-means clustering from a large number of training sequences with a single cardiac cycle each. The temporal deformations are first aligned by 4D generalized procrustes analysis. The scale is normalized and the model aligned to the data. The aligned high-dimensional

motion vectors (i.e., coordinates of the boundary) are mapped to a low-dimensional embedding using the ISOMAP or other algorithm. Motion prior modes are finally extracted by hierarchical K-means clustering in the low-dimensional embedding space. For real-time application, the motion prior is used to identify or limit the location represented by data based on local deformation.

[0075] The initialization of act 28 is performed using the detector for one cycle. For another cycle, the initialization may not rely on the motion prior. The machine-learned knowledge is not used. Instead, the tracked boundary from the temporally adjacent cycle is propagated in time (e.g., interpolated) to indicate an initial boundary position. For example, the boundary in the last from of one cycle is propagated to the first frame of the next cycles. Alternatively, the same initialization may be used for other cycles.

[0076] In act 30, the processor estimates non-rigid deformation of a myocardium through the sequence. The estimation is through a cycle or portion of a cycle. In alternative embodiments, the estimation is through more than a cycle.

[0077] The estimation tracks the boundary from one frame to another frame. This frame-to-frame tracking progresses through the sequence. The motion of the heart wall, such as the myocardium, is determined. The motion may be determined by differences between absolute positions of the heart wall in different frames.

[0078] The motion prior alone may be used to reduce drift and account for individual patient variation from the motion prior, the estimation uses information in addition to or instead of the motion prior. For example, another machine-learned model of the myocardium is used to locate the myocardium in each frame. The estimation is performed using different features, type of machine-learned classifier, or combinations thereof. In order to estimate myocardium strain, dense tracking of the cardiac motion establishes the inter-frame correspondences for each point on the 3D mesh initialized in act 28. This task is particularly challenging for the ultrasound data because of the noise and missing data.

[0079] Instead of removing the speckle noise, which might potentially lose discriminative features, information from multiple cues is fused into another machine-trained classifier. The additional machine-learned knowledge is used to track based on a plurality of cues. For example, the cues include the motion prior information (i.e., heart wall boundary or local deformation detected from each frame of ultrasound data as discussed above for act 28), speckle tracking, boundary detection, and mass conservation. Image quality measurements based on image intensities and speckleness scores are integrated in a weighted likelihood estimation to handle noise and signal dropouts in ultrasound data. These cues are used as input feature vectors. The feature vectors may be processed, such as filtered, prior to input. Additional, different, or fewer cues may be provided. For example, Haar, steerable or other features are also input. Other types of gradient or non-gradient features may be used.

[0080] By using the motion prior, two machine-learned classifiers are used for tracking. The first deforms a representative model to the data of each frame based on learned posterior probabilities. The result is a mesh of detected positions of the boundary in the frame. The mesh is input to another machine-trained classifier with other features to track the boundary between frames. The boundary in a given frame of the sequence is based on the mesh, but may be different than the motion prior mesh depending on the other features. The mesh may be input as absolute coordinates of the control points or may use the manifold learning and be input as relative locations. The motion prior mesh represents the shape of the myocardium.

[0081] In one embodiment, the other machine-trained classifier implements a Bayesian objective function. The motion prior is used in a Bayesian objective function with speckle tracking, boundary detection, and mass conservation. The Bayesian objective function is represented as:

$$\arg\max_{X_t} p(X_t|Y_{0:t}) = \arg\max_{X_t} p(Y_t|X_t)p(X_t|Y_{0:t-1}) \qquad (1)$$

where $Y_{0:t} = Y_0,..., Y_t$ are the measurements (e.g., steerable or Haar features) from the input image sequence $I_{0:t} = I_0,...,I_t$. For clarity, X_t denotes a concatenation of the mesh point positions, $X_t = [X_1,...,X_n]$, which are estimated at the current time instant t (i.e., output of the motion prior or other machine-trained detector for the given frame), and n is the total number (e.g., 700-800) of points in the mesh model.

[0082] Assuming the Markovian structure of the motion, equation 1 is solved in a recursive manner.

$$\arg\max_{X_t} p(X_t|Y_{0:t}) = \arg\max_{X_t} p(Y_t|X_t) \int p(X_t|X_{t-1}) \, p(X_{t-1}|Y_{0:t-1}) \qquad (2)$$

To maximize the accuracy and robustness of the tracking performance, the likelihood term $p(Y_t|X_t)$ is computed from both boundary detection and speckle template matching cues as follows, $p(Y_t|X_t) = (1-\lambda_k)p(y_b|X_t)+\lambda_k p(T_t|X_t)$, where T_t

is the speckle pattern template (i.e., window or kernel for matching the speckle pattern from one frame to another frame) and λ_k is the weighting coefficient of the matching term. In the first term, $p(y_b|X_t)$ is the posterior distribution of the myocardial boundaries learned as the boundary detector using the steerable features and the probabilistic boosting-tree (PBT). The second term $p(T_t|X_t)$ is obtained by a logistic function, $1/(1+e^{-\|It(Xt)-Tt\|2})$ based on speckle matching:

$$\|I_t(X_t) - T_t\|^2 = \sum_{i,j,k} I_t(X_t + (i, j, k)) - T_t(i, j, k))^2 \qquad (3)$$

where i, j, and k are the pixel-wise shift in the x, y, and z directions, respectively. λ_k is computed based on the speckleness measure as follows,

$$\lambda_k = 1/(1+e^{-fc(It(Xt), Tt)}), \ f_c(I_t(X_t), T_t) = cov(I_t(X_t), T_t)/\sigma(I_t(X_t))\sigma(T_t) \qquad (4)$$

where $cov(I_t(X_t), T_t)$ is the intensity covariance between the image block $I_t(X_t)$ centered at X_t and the speckle template T_t. $\sigma(I_t(X_t))$ and $\sigma(T_t)$ are the intensity variance of the image block $I_t(X_t)$ and the speckle template T_t, respectively. Any block size may be used, such as $11 \times 11 \times 11$. Any search region may be used. In one embodiment, the search region is limited, such as over a range of $7 \times 7 \times 7$. To handle the temporal image variation, the speckle template T_t is updated using the image intensities $I_t(X_{t-1})$ from the previous frame t - 1. The template changes for each pair of frames between which the boundaries are tracked.

[0083] The prediction term in Equation 1, $p(X_t|X_{t-1})$, is the transition probability function $^\wedge p(X_t|X_{t-1})$ augmented by an incompressibility constraint. $p(X_t|X_{t-1})= {}^\wedge p(X_t|X_{t-1})p(fV (X_t) - fV (X_{t-1}))$, where fV (X) is the volume enclosed by the mesh X and $^\wedge p(X_t|X_{t-1})$ is learned directly from the training data set. $p(fV (X_t) - fV (X_{t-1}))$ is modeled as a zero mean Gaussian distribution $N(0, \sigma_V)$ based on the training data.

[0084] The Bayesian function or other machine-learned classifier is used for tracking within a sequence. For example, the machine-learned classifier is used use to determine the location of the myocardium in each frame throughout a heart cycle. Inner-cycle motion tracking estimates cardiac motion.

[0085] To prevent or limit drifting, the ventricular wall motion is tracked in both forward and backward directions based on learned motion priors. For example, the boundary is initialized in both the first and last frames of the sequence. The tracking is performed in forward and reverse temporal directions. The tracking may be to adjacent frames, such that half the sequence uses the forward tracked boundary and the other half uses the reverse tracked boundary. Alternatively, both forward and reverse tracking are performed over the entire sequence. As a result, two boundaries are provided for each frame. The two boundaries are averaged, interpolated, otherwise combined, or used to select one.

[0086] Since two machine learned classifiers are used for boundary detection given the input volumetric sequence, both an optical flow tracker and a boundary detection tracker are used. By including both approaches, temporal consistency and smooth motion may more likely be assured, and drifting and outliers may be avoided. The optical flow tracker directly computes the temporal displacement for each point from one frame to the next (e.g., speckle tracking). Initialized by one-step forward prediction, the detection tracker obtains the deformations in each frame with maximal probability. The results are then fused into a single estimate by averaging the computed deformations and the procedure is repeated until the full 4D model is estimated for the complete sequence. In this way, the collaborative trackers complement each other, as the optical flow tracker provides temporally consistent results and its major issue of drifting is addressed by the boundary detection along with the one-step forward prediction.

[0087] The 3D correlation in equation 3 is computationally expensive. To achieve a fast processing, the speed of estimation in equation 3 may be improved using:

$$I_t(X_t) - T_t{}^2 = I_t(X_{t-1} + \Delta X) - T_t{}^2 \qquad (5)$$

where ΔX is the point displacement between two frames. Let $D_t = I_t(X_{t-1})-T_t$ be the concatenation of the intensity difference at each point between the current frame of data (image I_t) and the template T_t and $G_t=(\partial I_t(X_{t-1})/\partial X$ be the image gradients of I_t at X_{t-1}. Equation 5 is rewritten using the first order Taylor expansion:

$$\|D_t + G_t \Delta X\|^2 = D_t^T D_t + 2 D_t^T G_t \Delta X + \Delta X^T G_t^T G_t \Delta X \qquad (6).$$

[0088] Because of the acquisition nature of the ultrasound data, noise and signal dropouts may introduce artifacts. A regularization term based on a non-orthogonal projection may reduce the artifacts. The regularization term is as follows:

$$\hat{X} = \bar{X} + Vsqrt(C)q, \ q = sqrt(C)V^T(X - \bar{X}) \qquad (7)$$

where X is the mean shape, V is the matrix of concatenated eigenvectors, and q is a parametric vector describing the non-rigid warp. C is a diagonal weighting matrix whose diagonal entries are defined by a logistic function: $C(i,i) = l/(1+e^{-\lambda_i \, ilt(Xt(i))})$ where each weight λ_i is learned from the training data. Since each diagonal element in the weighting matrix C has a small value on low intensity values, a small weight on the regions with missing data and signal drop-outs in the volumetric ultrasound images results.

[0089] Consequently, the objective function (equation 2) may be rewritten as:

$$\arg\max_{q_t} p(q_t|Y0{:}t) = \arg\max_{q_t} p(Y_t|q_t) \int p(q_t|q_{t-1}) \, p(q_{t-1}|Y_{0:t-1}) \quad (8),$$

which may be solved recursively. The 3D correlation in equation 6 may be computed as follows:

$$\|D_t + G_t \Delta X\|^2 = D_t^T D_t + 2 D_t^T G_t \Delta q + \Delta q^T G_t^T G_t \Delta q \qquad (9).$$

where $G_t = G_t Vsqrt(C)$. Because $D^T D_t$, $D^T G_t$, and $G^T G_t$ are independent of Δq, these terms may be pre-computed to speed up the computation.

[0090] In practice, the number of warp parameters, n_q, is much less than the number of mesh points n. For example, n_q may be 150 while n is 771. The computational cost to solve equation 8 is much less than the original objective function in equation 2. The 3D correlation in equation 2 is an O(mn) operation where m (e.g., 7) is the search range in the x, y, and z directions, while equation 8 has a complexity of $O(nn_q)$ only. A high speed performance may be achieved, such as an average processing time on a 3.0GHz PC machine of less than 1 second per frame for a 3D+t ultrasound sequence with the volume size of $200 \times 200 \times 140$.

[0091] In alternative embodiments, other tracking may be used. For example, the tracking may rely on boundary detection (e.g., local deformation estimation guided by the motion prior fitting) alone. As another example, an image process without machine-trained classifier is used. Speckle tracking alone may be provided. In one embodiment, the tracking disclosed in U.S. Patent Publication No. 2004-0208341, filed March 7, 2004, is used, the disclosure of which is incorporated herein by reference. The tracking is performed by image analysis. For example, speckle or tissue is tracked using correlation or minimum sum of differences calculations. The best match of data for or surrounding each location is identified in subsequent images. As another example, a snake-based tracker is used. The endocardial contour for the inner border of the left ventricle wall and/or the epicardial contour for the outer border of the left ventricle wall are identified. The boundary is tracked between images based on minimum stress or distortion of the previous boundary. The relationship between the two boundaries may be used to assist in the snake-based tracker. Other now known or later developed tracking methods may be used.

[0092] As represented in act 32, the tracking for an additional cycle is performed independently. The myocardium is tracked through each cycle separate from other cycles. Act 30 is performed for each cycle without continuing tracking from the other cycle. The tracking of the frames of one cycle is independent of the tracking of the frames of another cycle and vice versa.

[0093] The initialization for the other cycle may be dependent on the previous cycle while the tracking is not. The locations or mesh of the myocardium in the last or adjacent frame of one cycle is propagated to the first or adjacent frame from the other cycle. For example, the myocardium in a first (e.g., ED frame) of a subsequent cycle is initialized by propagation of the myocardium or motion from the closest (e.g., last) frame in the previous cycle. As illustrated in Figure 6, the boundary in frame t1, the last frame in cycle 1, is propagated to the ED frame, the first frame in cycle 2. Because of the cyclic motion pattern of each cycle, the ED frame of the second cycle may also be initialized by propagating

the motion from the ED frame of the first cycle. Propagation is performed by interpolation. Data matching or speckle tracking may be used for initialization in the other sequence.

[0094] This inter-frame connection is provided without use of the motion prior. The initialization is based on other cues. Alternatively, the motion prior is used. In other embodiments, the initialization of the tracking for each cycle is independent of information form other cycles.

[0095] In act 34, one or more cardiac parameters are calculated. The parameters are variables, such as any myocardial mechanical characteristic. For example, volume, displacement, velocity, twist, torsion, strain, strain rate, principal strain, radius, curvature, contraction front map, relaxation front map, coronary map, or combinations thereof are calculated. One or more values or quantities are calculated for the parameters. For maps or other parametric displays, values are calculated for different locations (e.g., different segments and/or control points of the mesh).

[0096] The parameters are calculated based on the tracking. The change in position over time (e.g., motion or velocity) or the absolute position may be used to determine the parameter. By tracking the non-rigid deformation through a sequence, information (e.g., volume) based on the absolute position may be calculated for the desired phase or phases.

[0097] The calculation occurs without user input. For example, the user configures the system to scan a volume of a patient and to provide values or displays for one or more specific parameters. The system scans, detects the boundary, tracks the boundary, and calculates the values without further input. In alternative embodiments, user input during the process is provided.

[0098] The sequences from different cycles may be normalized as a function of time. Similarly, frames of data associated with each cardiac cycle may be normalized to a common cardiac cycle by re-plotting as function of time. The normalized or extracted image data is used to calculate values for one or more parameters. Cardiac motion may be classified as a function of the values. For example, tissue motion timing, Eigen motion, curvature, local ejection-fraction ratio and/or bending energy are used to identify normal, abnormal or a type of abnormal operation. The local ejection-fraction ratio may indicate local cardiac contraction abnormalities.

[0099] In one embodiment, the myocardial motion pattern is quantized using statistical atlases of deformation. To facilitate the analysis, the tracking result X is temporally aligned to a reference cycle length. For example, 16 frames per cycle are provided in a set cycle length). The cycle's length is based on particular cardiac phases, such as ED and SD. The 4D generalized procrustes analysis is used to align all resampled motion vectors to remove the translation, rotation and scaling in the global coordinate systems, while keeping the shape variations and motion patterns inside the motion vectors.

[0100] The aligned motion sequence of the detected mesh is then projected to a low-dimensional space using manifold learning, such as ISOMAP. Because the actual number of constraints that control the LV motion are much less than the original dimensionality, the aligned 3D shape vectors lie on a low-dimensional manifold. In the low-dimensional manifold, geodesic distance is used to measure the similarities. Unsupervised manifold learning is capable of discovering the nonlinear degrees of freedom that underlie complex natural observations. ISOMAP embeds the nonlinear manifold into a low-dimensional subspace. Figure 7 shows two temporally aligned LV motion sequences with 16 frames per cardiac cycle. Figure 7 also shows several LV motion representations in a low dimensional space on a graph. For example, the high dimensional motion displacement vectors of a cardiac cycle are projected to a 2-dimensional parametric space, where each point in the resulting 2-dimensional space represents the deformation magnitude of a certain frame relative to its neighboring frames. In the graph, the low-dimensional representation leads to a natural clustering of motion patterns. These patterns may be used to analyze motion abnormalities.

[0101] A statistical index of the cardiac motion sequence is calculated. The motion displacement distribution is estimated locally in time and space based on the Hotelling's T-square statistic. For each frame (X,t) in the temporally aligned motion sequences, the average μ and covariance W of myocardial displacements (dX,t) for a set of healthy volunteers is computed. Motion abnormalities are then computed for each individual by calculating a statistical distance to the displacement distribution of the atlas population as follows:

$$d^2 = (dX - \mu)^T W^{-1} (dX - \mu).$$

[0102] In other embodiments, displacement and/or velocity are calculated. Given the tracking result X, displacements and velocities are computed in the three-dimensional space. The displacement and velocity are determined relative to the heart. As represented in Figure 8, a local heart coordinate system describes the LV deformation. The three directions of the heart are defined as longitudinal (meridional) DL, radial (transmural) DR, and circumferential DC. Each point position X is then projected from the Cartesian coordinate system to the local cardiac coordinate system, $X^I = (X^{(L)}, X^{(R)}, X^{(C)})$. The longitudinal and radial displacements are computed as $Z_t^{(L)} = X_t^{(L)} - X_{t-1}^{(L)}$ and $Z_t^{(R)} = X_t^{(R)} - X_{t-1}^{(R)}$, respectively. The circumferential displacements is computed as the rotation angle, $Z^{(C)} = \arccos(<DR_t, OR_{t-1}>)$, where $<, >$ denotes the dot product. $Z^{(C)}$ is defined as positive if the rotation is counter-clockwise viewed from the apex, and

negative if clockwise. The velocity is computed as dividing the displacements by the acquisition time step t_f of the input 3D+t ultrasound sequence.

[0103] Other parameters may be calculated. Any display of the values for the calculated parameters may be used, such as a text value, a graph, or modulation of a spatial image.

[0104] While the invention has been described above by reference to various embodiments, it should be understood that many changes and modifications can be made without departing from the scope of the invention. It is therefore intended that the foregoing detailed description be regarded as illustrative rather than limiting, and that it be understood that it is the following claims that are intended to define the scope of this invention.

Claims

1. A method for calculating a myocardial mechanical property using computerized characterization of cardiac motion from ultrasound data in an automatic manner, the method comprising:

    obtaining (20) a sequence of frames of ultrasound data, the frames representing a volume of a patient at different times;
    identifying (28), with a processor (12), a myocardium in a first frame;
    estimating (30), with the processor (12), non-rigid deformation of the myocardium through the sequence by volumetrically tracking the indentified myocardium from the first frame to a second frame of the sequence of frames using a discriminative classifier, wherein the classifier distinguishes between the left ventricle myocardium and other information in a frame based on a machine-learned model of the image intensity and/or speckle patterns specific to the left ventricle myocardium, wherein the machine-learned model is trained by machine processing of annotated training data of known cases, using machine-learning to select learned features, and wherein the machine-learned model comprises a motion prior of typical myocardium positions for different phases of the cardiac cycle learned from the known cases using the machine-learning;
    calculating (34), with the processor (12), a first myocardial mechanical quantity as a function of the non-rigid deformation, the quantity computed in both a Cartesian coordinate system and a local heart coordinate system.

2. The method of claim 1 further comprising:
    determining (22) an end-diastolic or end-systolic frame as a function of a volume within the myocardium, wherein the volume is based on the motion prior.

3. The method of claim 1 wherein obtaining (20) comprises scanning the patient and wherein identifying (28) comprises identifying (28) in real time with the scanning.

4. The method of claim 1 wherein identifying (28) comprises locating with the motion prior.

5. The method of claim 4 wherein identifying (28) and estimating (30) reduce dimensionality by maintaining relative location information and avoiding use of absolute coordinates.

6. The method of claim 1 wherein estimating (30) comprises using the motion prior in a Bayesian objective function with integration of a plurality of cues, including myocardium boundary detection, speckle tracking and mass conservation.

7. The method of claim 1 wherein estimating (30) comprises volumetric tracking between pairs of the frames in a forward direction and volumetric tracking between the pairs of frames in a reverse direction, the forward and reverse directions being temporal directions through the sequence, and comprises combining the trackings from the forward and reverse directions for the same pairs.

8. The method of claim 1 further comprising dividing (26) the sequence into first and second heart cycles based on a volume within the myocardium, wherein identifying (28) for the first heart cycle comprises identifying (28) with the motion prior, wherein identifying (28) for the second heart cycle comprises identifying (28) with propagation of myocardium locations from a first frame of the first heart cycle to a second frame of the second heart cycle, and wherein estimating (30) comprises volumetric tracking the myocardium through the first and second heart cycles independently.

9. The method of claim 1 wherein calculating (34) comprises calculating (34) volume, displacement, velocity, twist,

torsion, strain, strain rate, principal strain, radius, curvature, contraction front map, relaxation front map, coronary map, or combinations thereof from the estimate of the non-rigid deformation of the myocardium, the calculating (34) occurring in both the Cartesian coordinate system and the local heart coordinate system without user input for tracing or tracking;

fusing the quantity with another imaging modality.

10. The method of claim 1 further comprising detecting (24) multi-planar reconstruction planes with an additional machine-trained classifier.

11. The method of claim 1, wherein estimating comprises:

tracking (30) as a function of a speckle tracking with the speckle patterns, boundary detection, mass conservation, and a motion prior;
combining a detection score from the machine-learned model with a plurality of scores, including a speckle tracking score, a mass conservation score, and a motion prediction score;
determining (22) the non-rigid deformation of the myocardium over time as a function of the combining.

12. The method of claim 11 wherein the tracking comprises tracking with first machine-learned knowledge specific to a left ventricle myocardium with the speckle tracking, boundary detection, mass conservation, and motion prior as input features, the motion prior comprises second machine-learned knowledge.

13. The method of claim 11 wherein propagating comprises performing the tracking from the first frame to the second frame without the motion prior.

14. The method of claim 1 further comprising locating the myocardium through the sequence with a machine-learned detector, and wherein identifying (28) comprises identifying (28) as a function of variation in a volume of the heart over time, the volume calculated from the myocardium located through the sequence.

15. A non-transitory computer readable storage media (14) having stored therein data representing instructions which, when executed by a processor (12), causes the processor to carry out the method of any one of claims 1 to 14.

Patentansprüche

1. Verfahren zum Berechnen einer mechanischen Myokard-Eigenschaft unter Verwendung einer computergestützten Kennzeichnung der kardialen Bewegung aus Ultraschalldaten in einer automatischen Weise, wobei das Verfahren umfasst:

Gewinnen (20) einer Folge von Rahmen von Ultraschalldaten, wobei die Rahmen ein Volumen eines Patienten zu verschiedenen Zeiten repräsentieren;
Identifizieren (28) eines Myokards in einem ersten Rahmen mit einem Prozessor (12);
mit dem Prozessor (12), Abschätzen (30) der nicht-starren Verformung des Myokards durch die Folge hindurch durch volumetrisches Verfolgen des identifizierten Myokards aus dem ersten Rahmen bis zu einem zweiten Rahmen der Folge von Rahmen und der Verwendung eines diskriminativen Klassifikators, wobei der Klassifikator zwischen dem Myokard des linken Ventrikels und anderen Informationen in einem Rahmen unterscheidet, auf der Basis eines maschinell erlernten Modells der Bildintensität und/oder Specklemuster, die spezifisch für das Myokard des linken Ventrikels sind, wobei das maschinell erlernte Modell durch maschinelle Verarbeitung von kommentierten Trainingsdaten von bekannten Fällen trainiert wird, wobei das maschinelle Lernen verwendet wird, um erlernte Merkmale zu wählen, und wobei das maschinell erlernte Modell eine Bewegung vor typischen Myokard-Positionen für verschiedene Phasen des kardialen Zyklus umfasst, die von den bekannten Fällen unter Verwendung des maschinellen Lernens erlernt wurden;
mit dem Prozessor (12), Berechnen (34) einer ersten myokardialen mechanischen Größe als Funktion der nicht-starren Verformung, der Größe, die sowohl in einem kartesischen Koordinatensystem als auch in einem lokalen Herz-Koordinatensystem berechnet wird.

2. Verfahren nach Anspruch 1, das ferner umfasst:
Bestimmen (22) eines end-diastolischen oder end-systolischen Rahmens als Funktion eines Volumens innerhalb des Myokards, wobei das Volumen auf der vorherigen Bewegung beruht.

3. Verfahren nach Anspruch 1, wobei das Gewinnen (20) das Scannen des Patienten umfasst und wobei das Identifizieren (28) das Identifizieren (28) in Echtzeit beim Scannen umfasst.

4. Verfahren nach Anspruch 1, wobei das Identifizieren (28) das Lokalisieren bei der vorherigen Bewegung umfasst.

5. Verfahren nach Anspruch 4, wobei das Identifizieren (28) und das Abschätzen (30) die Dimensionalität durch Aufrechterhalten der relativen Ortsinformationen und das Vermeiden der Verwendung von absoluten Koordinaten reduziert.

6. Verfahren nach Anspruch 1, wobei das Abschätzen (30) die Verwendung der vorherigen Bewegung in einer Bayesschen Objektivfunktion mit Integration von mehreren Programmaufrufen umfasst, einschließlich Feststellung der Myokardgrenzen, Speckle-Verfolgung und Massenerhaltung.

7. Verfahren nach Anspruch 1, wobei das Abschätzen (30) das volumetrische Verfolgen zwischen Paaren von Rahmen in einer Vorwärtsrichtung und volumetrisches Verfolgen zwischen den Paaren von Rahmen in einer umgekehrten Richtung umfasst, wobei die Vorwärts- und Rückwärtsrichtungen zeitweilige Richtungen durch die Folge sind und das Kombinieren der Verfolgungen aus der Vorwärts-und Rückwärts-Richtung für dieselben Paare umfasst.

8. Verfahren nach Anspruch 1, das ferner das Aufteilen (26) der Folge in erste und zweite Herzzyklen umfasst, das auf einem Volumen innerhalb des Myokards beruht, wobei das Identifizieren (28) für den ersten Herzzyklus das Identifizieren (28) mit der vorherigen Bewegung umfasst, wobei das Identifizieren (28) für den zweiten Herzzyklus das Identifizieren (28) bei Fortschreiten von Myokardorten von einem ersten Rahmen des ersten Herzzyklus zu einem zweiten Rahmen des zweiten Herzzyklus umfasst, und wobei das Abschätzen (30) das unabhängige volumetrische Verfolgen des Myokards durch den ersten und zweiten Herzzyklus umfasst.

9. Verfahren nach Anspruch 1, wobei das Berechnen (34) das Berechnen (34) von Volumen, Verschiebung, Geschwindigkeit, Drehung, Torsion, Belastung, Belastungsrate, Hauptbelastung, Radius, Krümmung, vorderes Herz-Kartenfenster, Relaxations-Kartenfenster, koronare Karte oder Kombinationen derselben aus der Abschätzung der nicht-starren Verformung des Myokards umfasst, wobei das Berechnen (34) sowohl im kartesischen Koordinatensystem als auch im lokalen Herz-Koordinatensystem ohne Nutzereingabe zum Verfolgen auftritt; Verbinden der Größe mit einem weiteren Bildgebungsverfahren;

10. Verfahren nach Anspruch 1, das ferner das Feststellen (24) von multiplanaren Rekonstruktionsebenen mit einem weiteren maschinell erlernten Klassifikator umfasst.

11. Verfahren nach Anspruch 1, wobei das Abschätzen umfasst:

Verfolgen (30) als Funktion einer Speckle-Verfolgung mit den Speckle-Mustern, Feststellung von Grenzen, Massenerhalt und einer vorherigen Bewegung;
Kombinieren eines Feststellungspunktwertes aus dem maschinell erlernten Modell mit mehreren Punktwerten, einschließlich eines Speckle-Verfolgungs-Punktwertes, eines Massenerhaltungs-Punktwertes und eines Bewegungs-Vorhersage-Punktwertes;
Bestimmen (22) der nicht-starren Verformung des Myokards über der Zeit als Funktion des Kombinierens.

12. Verfahren nach Anspruch 11, wobei das Verfolgen das Verfolgen mit erstem maschinell erlerntem Wissen, das spezifisch für ein Myokard des linken Ventrikels mit Speckle-Verfolgung ist, Massenerhalt und vorherige Bewegung als Eingabe-Merkmale, wobei die vorherige Bewegung zweites maschinell erlerntes Wissen umfasst.

13. Verfahren nach Anspruch 11, wobei das Fortschreiten das Ausführen der Verfolgung vom ersten Rahmen zum zweiten Rahmen ohne die vorherige Bewegung umfasst.

14. Verfahren nach Anspruch 1, das ferner das Lokalisieren des Myokards durch die Folge mit einem maschinell angelernten Detektor umfasst, und wobei das Identifizieren (28) das Identifizieren (28) als Funktion einer Variation in einem Volumen des Herzens im Verlauf der Zeit umfasst, wobei das Volumen aus dem Myokard berechnet wird, das durch die Folge lokalisiert wird.

15. Nicht-flüchtiges computerlesbares Speichermedium (14), das darin Daten gespeichert hat, die Anweisungen repräsentieren, welche bei Ausführung durch einen Prozessor (12) bewirken, dass der Prozessor das Verfahren nach

einem der Ansprüche 1-14 ausführt.

Revendications

1. Procédé de calcul d'une propriété mécanique myocardique utilisant une caractérisation informatisée d'un mouvement cardiaque à partir de données ultrasonores d'une manière automatique, le procédé comprenant les étapes consistant à :

   obtenir (20) une séquence de trames de données ultrasonores, les trames représentant un volume d'un patient à des instants différents ;
   identifier (28), à l'aide d'un processeur (12), un myocarde dans une première trame ;
   estimer (30), à l'aide du processeur (12), une déformation non rigide du myocarde à travers la séquence en suivant de manière volumétrique le myocarde identifié de la première trame à une seconde trame de la séquence de trames en utilisant un classificateur discriminant, dans lequel le classificateur fait la distinction entre le myocarde du ventricule gauche et d'autres informations dans une trame sur la base d'un modèle par apprentissage machine de l'intensité d'image et/ou de motifs de tavelure spécifiques au myocarde du ventricule gauche, dans lequel le modèle par apprentissage machine est formé par traitement machine de données de formation annotées de cas connus, utilisant un apprentissage machine pour sélectionner des caractéristiques apprises, et dans lequel le modèle par apprentissage machine comprend un mouvement antérieur des positions typiques du myocarde pour différentes phases du cycle cardiaque apprises à partir des cas connus en utilisant un apprentissage machine ;
   calculer (34), à l'aide du processeur (12), une première quantité mécanique myocardique en fonction de la déformation non rigide, la quantité étant calculée à la fois dans un système de coordonnées cartésien et dans un système de coordonnées du coeur local.

2. Procédé selon la revendication 1, comprenant en outre :
   la détermination (22) d'une trame télédiastolique ou télésystolique en fonction d'un volume dans le myocarde, le volume étant basé sur le mouvement antérieur.

3. Procédé selon la revendication 1, dans lequel l'obtention (20) comprend le balayage du patient et dans lequel l'identification (28) comprend l'identification (28) en temps réel à l'aide du balayage.

4. Procédé selon la revendication 1, dans lequel l'identification (28) comprend une localisation avec le mouvement antérieur.

5. Procédé selon la revendication 4, dans lequel l'identification (28) et l'estimation (30) réduisent la dimensionnalité en maintenant des informations relatives de localisation et en évitant l'utilisation de coordonnées absolues.

6. Procédé selon la revendication 1, dans lequel l'estimation (30) comprend l'utilisation du mouvement antérieur dans une fonction objective bayésienne avec intégration d'une pluralité de répliques, incluant une détection de limites du myocarde, un suivi de tavelures et une conservation de la masse.

7. Procédé selon la revendication 1, dans lequel l'estimation (30) comprend un suivi volumétrique entre des paires de trames dans une direction avant et un suivi volumétrique entre les paires de trames dans une direction inverse, les directions avant et inverse étant des directions temporelles à travers la séquence, et comprend de combiner les suivis à partir des directions avant et inverse pour les mêmes paires.

8. Procédé selon la revendication 1, comprenant en outre la division (26) de la séquence en premier et second cycles cardiaques sur la base d'un volume dans le myocarde, l'identification (28) pour le premier cycle cardiaque comprenant l'identification (28) avec le mouvement antérieur, l'identification (28) pour le second cycle cardiaque comprenant l'identification (28) avec une propagation de localisations du myocarde d'une première trame du premier cycle cardiaque à une seconde trame du second cycle cardiaque, et l'estimation (30) comprenant un suivi volumétrique du myocarde indépendamment à travers les premier et second cycles cardiaques.

9. Procédé selon la revendication 1, dans lequel le calcul (34) comprend le calcul (34) d'un volume, d'un déplacement, d'une vitesse, d'un entortillement, d'une torsion, d'une contrainte, d'un taux de contrainte, d'une contrainte principale, d'un rayon, d'une courbure, d'une carte frontale de contraction, d'une carte frontale de relaxation, d'une carte

coronaire, ou de combinaisons de ceux-ci à partir de l'estimation de la déformation non rigide du myocarde, le calcul (34) se produisant à la fois dans le système de coordonnées cartésien et le système de coordonnées du coeur local sans entrée utilisateur pour le dépistage ou le suivi ;

fusionner la quantité avec une autre modalité d'imagerie.

10. Procédé selon la revendication 1, comprenant en outre la détection (24) de plans de reconstruction multi-plans avec un classificateur fomé par machine supplémentaire.

11. Procédé selon la revendication 1, dans lequel l'estimation comprend les étapes consistant à :

suivre (30) en fonction d'un suivi de tavelures avec les motifs de tavelure, une détection de limites, une conservation de la masse, et un mouvement antérieur ;

combiner un score de détection provenant du modèle par apprentissage machine avec une pluralité de scores, incluant un score de suivi de tavelures, un score de conservation de la masse, et un score de prédiction de mouvement ;

déterminer (22) la déformation non rigide du myocarde dans le temps en fonction de la combinaison.

12. Procédé selon la revendication 11, dans lequel le suivi comprend le suivi avec une première connaissance par apprentissage machine spécifique à un myocarde du ventricule gauche avec le suivi de tavelures, une détection de limites, une conservation de la masse, et un mouvement antérieur comme caractéristiques d'entrée, le mouvement antérieur comprenant une seconde connaissance par apprentissage machine.

13. Procédé selon la revendication 11, dans lequel la propagation comprend la réalisation du suivi de la première trame à la seconde trame sans le mouvement antérieur.

14. Procédé selon la revendication 1, comprenant en outre la localisation du myocarde à travers la séquence à l'aide d'un détecteur par apprentissage machine, et dans lequel l'identification (28) comprend l'identification (28) en fonction d'une variation d'un volume du coeur dans le temps, le volume étant calculé à partir du myocarde localisé à travers la séquence.

15. Support de stockage lisible par ordinateur non transitoire (14) dans lequel sont stockées des données représentant des instructions qui, lorsqu'elles sont exécutées par un processeur (12), amènent le processeur à exécuter le procédé selon l'une quelconque des revendications 1 à 14.

FIG. 1

FIG. 2
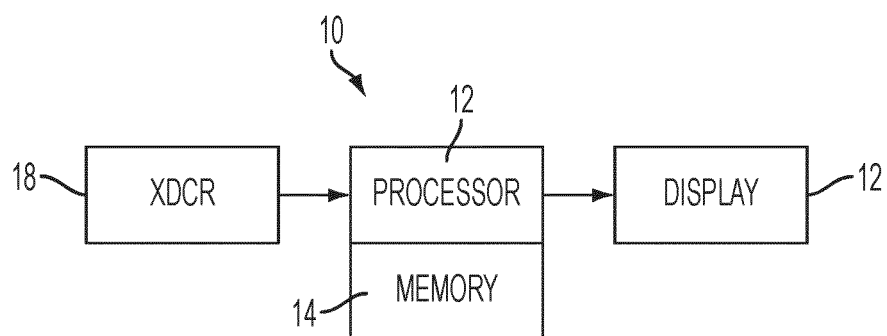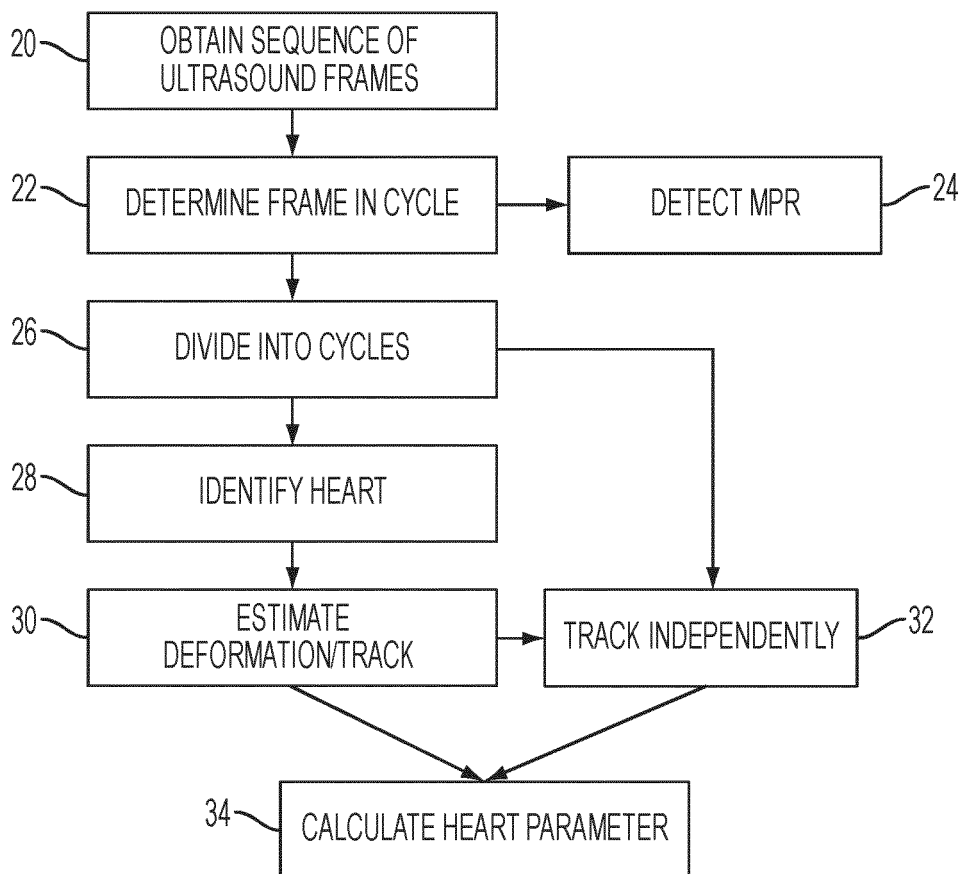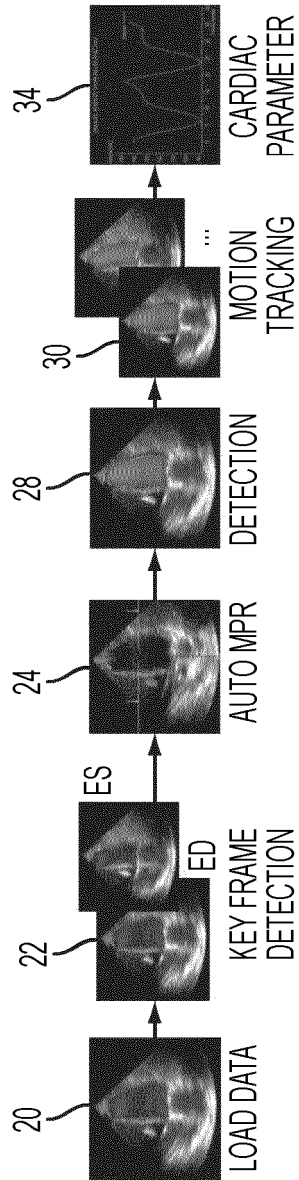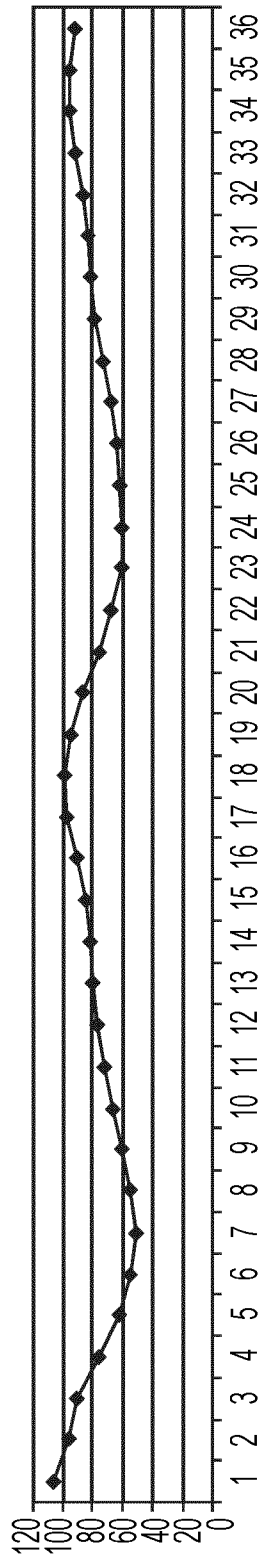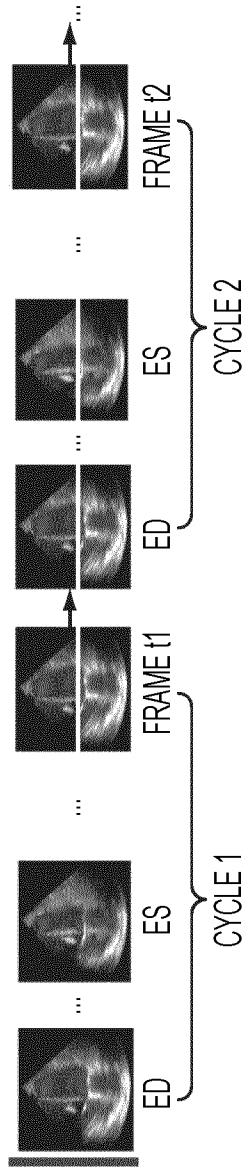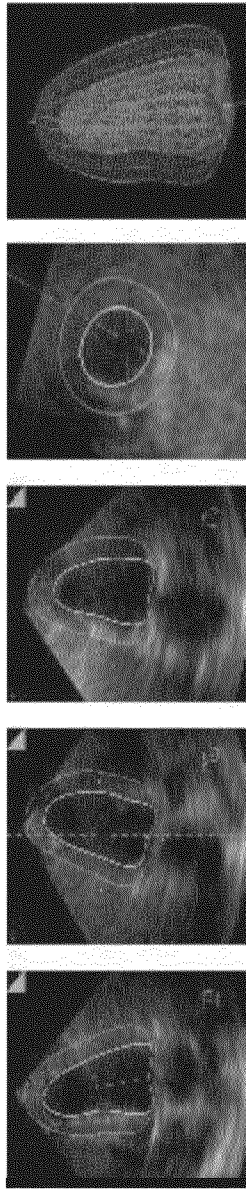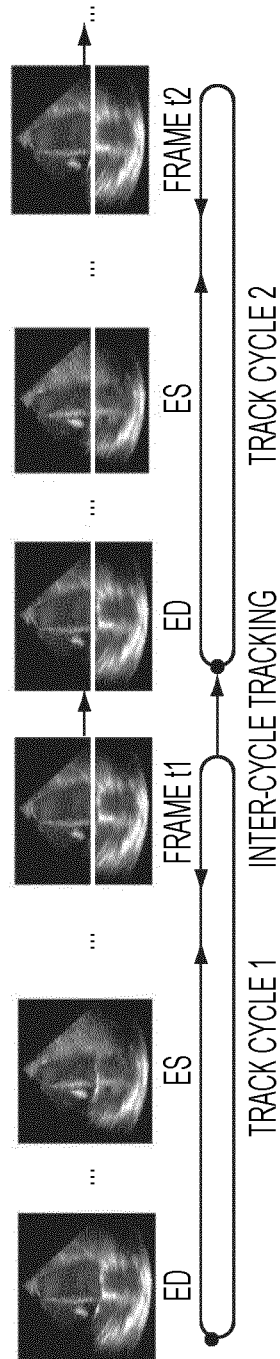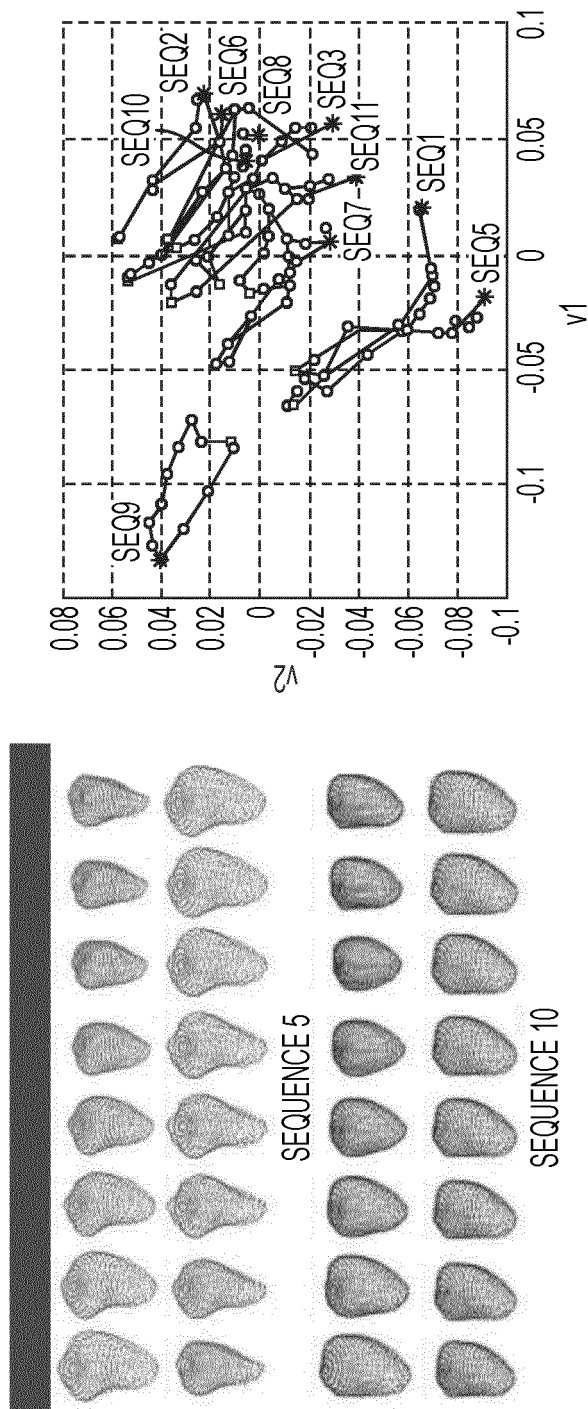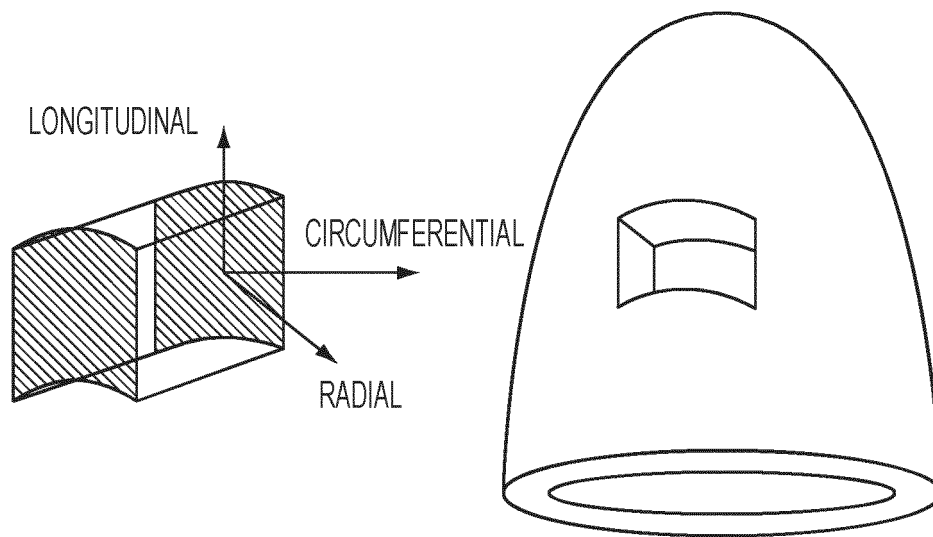
FIG. 3

FIG. 4

FIG. 5

FIG. 6

FIG. 7

FIG. 8

REFERENCES CITED IN THE DESCRIPTION

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专利名称(译)	医学诊断超声中心脏运动的计算机表征		
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其他公开文献	EP2434454A3 EP2434454A2		
外部链接	Espacenet		

摘要(译)

提供了心脏壁运动的计算机表征。从四维（即，3D +时间）超声数据序列确定（34）心脏壁运动的量。处理器（12）自动处理体积数据以通过序列定位（28）心脏壁并计算（34）来自心脏壁位置或运动的量。各种机器学习用于定位（28）和跟踪（30）心脏壁，例如使用从训练数据中学习的运动，用于初始定位心脏壁和运动先前，散斑跟踪，边界检测和质量守恒线索。用于跟踪另一台机器学习的分类器。在序列延伸多个循环的情况下，循环被自动分割（26）以独立跟踪心脏壁。来自一个循环的心壁可用于将（32）传播到另一个循环以初始化跟踪。每个周期中的独立跟踪（32）可以减少或避免由于漂移引起的不准确性。

$$\arg\max_{X_t} p(X_t|Y_{0:t}) = \arg\max_{X_t} p(Y_t|X_t) p(X_t|Y_{0:t-1}) \qquad (1)$$