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(54) **SYSTEM AND METHOD FOR ORIENTATING CAPTURE OF ULTRASOUND IMAGES**

SYSTEM UND VERFAHREN ZUM AUSRICHTEN DER ERFASSUNG VON ULTRASCHALLBILDERN

SYSTÈME ET PROCÉDÉ D’ORIENTATION DE CAPTURE D’IMAGES ÉCHOGRAPHIQUES

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Description

FIELD OF THE INVENTION

[0001] The present invention relates to mobile handheld ultrasound machines generally and to orientation for correct use in particular.

BACKGROUND OF THE INVENTION

[0002] A medical ultrasound (also known as diagnostic sonography or ultrasonography) is a diagnostic imaging technique based on the application of an ultrasound. It is used to create an image of internal body structures such as tendons, muscles, joints, blood vessels and internal organs.

[0003] Acquiring accurate images in order to perform an effective examination and diagnosis requires placing the ultrasound transducer in an angular position in space with the pertinent organ or body part, as is illustrated in Fig. 1 to which reference is now made. Fig. 1 shows an ultrasound image of an organ of interest 12 taken with a transducer 14. It will be appreciated that the art of navigating transducer 14 to the exact angular position required to achieve the optimal or "canonical" image of organ 12 is crucial to the success of the ultrasound examination. The process typically requires a trained and skilled sonographer.

[0004] For example, in order to perform an echocardiogram, the sonographer has to take images of the heart from various canonical directions, such as four-chamber and two-chamber views. The correct positioning of the transducer is crucial to receiving the optimal view of the left ventricle and consequently to extract the functional information of the heart.

[0005] Mobile ultrasound machines or devices are known in the art, such as the Lumify commercially available from Philips. These mobile ultrasound machines are available in the form of a transducer that communicates with a program downloadable to any portable handheld device such as a smart phone or a tablet.

[0006] The availability of such devices means that ultrasounds may be performed off-site (away from hospitals, etc.) for example, as a triage tool for ambulances or even in the battlefield, at urgent care facilities, nursing homes, etc. without requiring bulky expensive equipment.

[0007] US2015310581 A1 may be considered to disclose a downloadable navigator for a mobile ultrasound unit having an ultrasound probe, implemented on a portable computing device, the navigator comprising: means to receive a non-canonical image of a body part from said mobile ultrasound unit and to generate a transformation, said transformation transforming from a position and rotation associated with a canonical image to a position and rotation associated with said non-canonical image; and a result converter to convert said transformation into orientation instructions for a user of said probe and to provide and display said orientation instructions to said user to change the position and rotation of said probe.

SUMMARY OF THE PRESENT INVENTION

[0008] There is provided, in accordance with a preferred embodiment of the present invention, a downloadable navigator for a mobile ultrasound unit having an ultrasound probe, implemented on a portable computing device. The navigator includes a trained orientation neural network to receive a non-canonical image of a body part from the mobile ultrasound unit and to generate a transformation associated with the non-canonical image, the transformation transforming from a position and rotation associated with a canonical image to a position and rotation associated with the non-canonical image; and a result converter to convert the transformation into orientation instructions for a user of the probe and to provide and display the orientation instructions to the user to change the position and rotation of the probe.

[0009] Moreover, in accordance with a preferred embodiment of the present invention, the navigator also includes a trainer to train the orientation neural network using the canonical image together with non-canonical images taken around the canonical image and transformations to positions and rotations in space associated with the non-canonical images from the canonical image.

[0010] Further, in accordance with a preferred embodiment of the present invention, the trainer includes a training converter to receive IMU (inertia measurement unit) data during training sessions from an IMU mounted on a training probe, the IMU data providing the positions and rotations associated with the non-canonical images and the canonical image, and to convert the positions and rotations to transformations from the position and rotation associated with the canonical image to the position and rotation associated with the non-canonical images.

[0011] Still further, in accordance with a preferred embodiment of the present invention, the trainer includes an untrained orientation neural network and a loss function to train the untrained orientation neural network, the loss function to reduce a distance between a calculated transformation produced by the untrained orientation neural network and a ground truth transformation for each non-canonical image.

[0012] Additionally, in accordance with a preferred embodiment of the present invention, the loss function additionally includes a probability to constrain the calculated transformation to one of a plurality of different canonical orientations.

[0013] Moreover, in accordance with a preferred embodiment of the present invention, the canonical image is one of a plurality of canonical images.

[0014] Further, in accordance with a preferred embodiment of the present invention, the navigator includes a diagnoser to make a diagnosis from a final image generated by the probe when viewing the canonical image.

[0015] Still further, in accordance with a preferred embodiment of the present invention, the portable computing device is one of: a smartphone, a tablet, a laptop, a personal computer, and a smart appliance.

[0016] Additionally, in accordance with a preferred embodiment of the present invention, the navigator includes a set creator to receive a multiplicity of transformations from the trained orientation neural network in response to images from the probe and to generate sets of images and their associated transformations; a sufficiency checker to determine when enough sets have been created; and a trained cyclical canonical view neural network to generate a set of summary cyclical canonical images showing changes in the body part during a body part cycle.

[0017] Moreover, in accordance with a preferred embodiment of the present invention, the navigator includes a cyclical canonical view trainer to train an untrained cyclical canonical view neural network with the sets of images, their associated transformations, and their associated summary cyclical canonical images at each point in the body cycle.

[0018] Further, in accordance with a preferred embodiment of the present invention, the body part cycle is a cardiac cycle.

[0019] Still further, in accordance with a preferred embodiment of the present invention, each set has a single element therein.

[0020] There is provided, in accordance with a preferred embodiment of the present invention, a navigator for a mobile ultrasound unit implemented on a portable computing device having an ultrasound probe. The navigator includes a trained orientation neural network to provide orientation information for a multiplicity of ultrasound images captured around a body part, the orientation information to orient the image with respect to a canonical view of the body part; and a volume reconstructer to orientate the images according to the orientation information, to generate a volume representation of the body part from the oriented images using tomographic reconstruction and to generate a canonical image of the canonical view from the volume representation.

[0021] Moreover, in accordance with a preferred embodiment of the present invention, the navigator includes a sufficiency checker to receive orientations from the trained orientation neural network in response to images from the probe and to determine when enough images have been received; and a result converter to request further images for the trained orientation neural network in response to the sufficiency checker.

[0022] Further, in accordance with a preferred embodiment of the present invention, the navigator includes diagnoser to make a diagnosis from the volume representation of the body part.

[0023] There is provided, in accordance with a preferred embodiment of the present invention, a navigator for a mobile ultrasound unit having an ultrasound probe, implemented on a mobile device. The navigator includes a trained mapping neural network to receive a non-canonical image of a body part from the probe, to map the non-canonical image to a non-canonical map point on a displayable map and to map a multiplicity of canonical images associated with the non-canonical image to canonical map points on the displayable map; and a result converter to display the map marked with canonical and non-canonical map points.

[0024] Moreover, in accordance with a preferred embodiment of the present invention, the trained mapping neural network includes a loss function to ensure that changes in the motion of the probe generate small motions on the displayable map, that distances between images be similar to the distance between map locations and that optimal paths between one canonical image to another be straight, constant speed trajectories.

[0025] Further, in accordance with a preferred embodiment of the present invention, the navigator also includes a diagnoser to make a diagnosis from a final image generated by the probe when a user moves the probe to one of the canonical map points.

[0026] There is provided, in accordance with a preferred embodiment of the present invention, a downloadable navigator for a mobile ultrasound unit having an ultrasound probe, implemented on a mobile device. The navigator includes a set creator to receive images from the probe over time and to generate sets of images; a sufficiency checker to determine when enough sets have been generated; and a cyclical canonical view neural network to generate a set of summary cyclical canonical images showing changes in the body part during a body part cycle.

[0027] Moreover, in accordance with a preferred embodiment of the present invention, the navigator also includes a diagnoser to make a diagnosis from a final image generated by the cyclical canonical view neural network.

[0028] There is provided, in accordance with a preferred embodiment of the present invention, a method for a mobile ultrasound unit having an ultrasound probe, implemented on a portable computing device, the method includes receiving, using a trained orientation neural network, a non-canonical image of a body part from the mobile ultrasound unit and generating a transformation associated with the non-canonical image, the transformation transforming from a position and rotation associated with a canonical image to a position and rotation associated with the non-canonical image; and converting the transformation into orientation instructions for a user of the probe and providing and displaying the orientation instructions to the user to change the position and rotation of the probe.

[0029] Moreover, in accordance with a preferred embodiment of the present invention, the method includes training the orientation neural network using the canonical image together with non-canonical images taken around the canonical image and transformations to positions and rotations in space associated with the non-canonical images from the canonical image.

[0030] Further, in accordance with a preferred embodiment of the present invention, the training includes receiving IMU (inertia measurement unit) data during training sessions from an IMU mounted on a training probe, the IMU data providing the positions and rotations associated with the non-canonical images and the canonical image, and converting the positions and rotations to transformations from the position and rotation associated with the canonical image to the position and rotation associated with the non-canonical images.

[0031] Still further, in accordance with a preferred embodiment of the present invention, the trained mapping neural network includes a loss function to ensure that changes in the motion of the probe generate small motions on the displayable map, that distances between images be similar to the distance between map locations and that optimal paths between one canonical image to another be straight, constant speed trajectories.

[0032] Additionally, in accordance with a preferred embodiment of the present invention, the loss function additionally includes a probability to constrain the calculated transformation to one of a plurality of different canonical orientations.

[0033] Moreover, in accordance with a preferred embodiment of the present invention, the canonical image is one of a plurality of canonical images.

[0034] Further, in accordance with a preferred embodiment of the present invention, the method includes making a diagnosis from a final image generated by the probe when viewing the canonical image.

[0035] Still further, in accordance with a preferred embodiment of the present invention, the portable computing device is one of: a smartphone, a tablet, a laptop, a personal computer, and a smart appliance.

[0036] Additionally, in accordance with a preferred embodiment of the present invention, the method also includes receiving a multiplicity of transformations from the trained orientation neural network in response to images from the probe and generating sets of images and their associated transformations; determining when enough sets have been created; and generating, using a trained cyclical canonical view neural network, a set of summary cyclical canonical images showing changes in the body part during a body part cycle.

[0037] Moreover, in accordance with a preferred embodiment of the present invention, the method also includes training an untrained cyclical canonical view neural network with the sets of images, their associated transformations, and their associated summary cyclical canonical images at each point in the body cycle.

[0038] Further, in accordance with a preferred embodiment of the present invention, the body part cycle is a cardiac cycle.

[0039] Still further, in accordance with a preferred embodiment of the present invention, each set has a single element therein.

[0040] There is provided, in accordance with a preferred embodiment of the present invention, a method for a mobile ultrasound unit implemented on a portable computing device having an ultrasound probe, the method includes providing, using a trained orientation neural network, orientation information for a multiplicity of ultrasound images captured around a body part, the orientation information to orient the image with respect to a canonical view of the body part; and the the images according to the orientation information, generating a volume representation of the body part from the oriented images using tomographic reconstruction and generating a canonical image of the canonical view from the volume representation.

[0041] Moreover, in accordance with a preferred embodiment of the present invention, the method includes receiving orientations from the trained orientation neural network in response to images from the probe and determining when enough images have been received; and requesting further images for the trained orientation neural network in response to the receiving orientations.

[0042] Further, in accordance with a preferred embodiment of the present invention, the method also includes making a diagnosis from the volume representation of the body part.

[0043] There is provided, in accordance with a preferred embodiment of the present invention, a method for a mobile ultrasound unit having an ultrasound probe, implemented on a mobile device. The method includes receiving using a trained mapping neural network, a non-canonical image of a body part from the probe, mapping the non-canonical image to a non-canonical map point on a displayable map and mapping a multiplicity of canonical images associated with the non-canonical image to canonical map points on the displayable map; and displaying the map marked with canonical and non-canonical map points.

[0044] Moreover, in accordance with a preferred embodiment of the present invention, the trained mapping neural network includes a loss function to ensure that changes in the motion of the probe generate small motions on the displayable map, that distances between images are be similar to the straight, constant speed trajectories.

[0045] Further, in accordance with a preferred embodiment of the present invention, the method also includes making a diagnosis from a final image generated by the probe when a user moves the probe to one of the canonical map points.

[0046] There is provided, in accordance with a preferred embodiment of the present invention, a method for a mobile ultrasound unit having an ultrasound probe, implemented on a mobile device. The method includes receiving images from the probe over time and generating sets of images; determining when enough sets have been generated; and generating via a cyclical canonical view neural network, a set of summary cyclical canonical images showing changes in the body part during a body part cycle.

[0047] Moreover, in accordance with a preferred embodiment of the present invention, the method includes making a diagnosis from a final image generated by the cyclical canonical view neural network.

BRIEF DESCRIPTION OF THE DRAWINGS

[0048] The subject matter regarded as the invention is particularly pointed out and distinctly claimed in the concluding portion of the specification. The invention, however, both as to organization and method of operation, together with objects, images, and advantages thereof, may best be understood by reference to the following detailed description when read with the accompanying drawings in which:

Fig. 1 is a schematic illustration of how an ultrasound transducer is placed to capture an image of a body part;
Fig. 2 is a schematic illustration of an ultrasound navigator; constructed and operative in accordance with the present invention;
Figs. 3A and 3B are schematic illustrations of how the navigator of Fig. 2 may aid a non-sonographer orientate probe a transducer in order to capture a suitable image of a body part, constructed and operative in accordance with the present invention;
Fig. 4 is a schematic illustration of the transformation between the orientation of a training probe for a non-canonical image of an organ and its associated canonical image, constructed and operative in accordance with the present invention;
Fig. 5 is a schematic illustration of the training process for an orientation neural network, constructed and operative in accordance with the present invention;
Fig. 6 is a schematic illustration of the elements of the navigator of Fig. 2, constructed and operative in accordance with the present invention;
Fig. 7 is a schematic illustration of the elements of an alternative embodiment to the navigator of Fig. 2, constructed and operative in accordance with the present invention;
Figs. 8A, 8B and 8C are schematic illustrations of the elements and function of an alternative embodiment to the navigator of Fig. 2, constructed and operative in accordance with the present invention;
Figs. 9A and 9B are schematic illustrations of the elements of an alternative embodiment to the navigator of Fig. 2 at training and in operation, constructed and operative in accordance with the present invention; and
Figs. 10A and 10B are schematic illustrations of the elements of an alternative embodiment to the navigator of Figs. 9A and 9B at training and in operation, constructed and operative in accordance with the present invention.

[0049] It will be appreciated that for simplicity and clarity of illustration, elements shown in the figures have not necessarily been drawn to scale. For example, the dimensions of some of the elements may be exaggerated relative to other elements for clarity. Further, where considered appropriate, reference numerals may be repeated among the figures to indicate corresponding or analogous elements.

DETAILED DESCRIPTION OF THE PRESENT INVENTION

[0050] In the following detailed description, numerous specific details are set forth in order to provide a thorough understanding of the invention. However, it will be understood by those skilled in the art that the present invention may be practiced without these specific details. In other instances, well-known methods, procedures, and components have not been described in detail so as not to obscure the present invention.

[0051] Applicants have realized that the ability to use mobile ultrasound machines away from conventional places such as hospitals, means that untrained sonographers or non-sonographers might utilize these machines. However, untrained doctors, first aid providers or even patients themselves do not have the training or knowledge to administer these ultrasounds correctly. It will be appreciated that a different training is required for different organs and body parts.

[0052] Prior art systems such as that described in US Patent Publication No. US2018/0153505 entitled "Guided Navigation of an Ultrasound Probe", published June 7, 2018, and US Patent Publication No. US2016/0143627 entitled "Ultrasound Acquisition Feedback Guidance to a Target View", published May 26, 2016, teach methodologies for determining the deviations between a supplied image and a preferred canonical image of a particular body part for helping the non-sonographer guide his or her transducer to the optimal orientation for capturing a best fit image.

[0053] Applicants have realized that these prior art systems do not provide a complete solution vis-a-vis rotation calculations. Applicants have also realized that these prior art systems are not particularly useful, since they require additional hardware (such as inertial measurement units such as magnetometers, gyroscopes, accelerometers etc.) to aid in determining the location of the non-sonographer's probe. Applicants have realized that a system which does not require additional hardware and which is easily accessible, such as via a download in order to be integrated or used as an overlay with the processing software of the pertinent mobile ultrasound machine, is far more usable. As a result, the present invention operates only with the digital images generated by the ultrasound unit.

[0054] Reference is now made to Fig. 2 which illustrates an ultrasound navigator 100, according to a first embodiment of the present invention, which may be downloaded from a mobile application store 10, such as the Appstore of Apple or Google Play of Google, onto any portable computing device, such as a smartphone, a tablet, a laptop, a personal computer, a smart appliance, etc.

[0055] It will be appreciated that navigator 100 may comprise (as part of the download) a trained orientation neural network 15. Orientation neural network 15 is described in more detail herein below. As discussed herein above, navigator 100 may integrated or used as an overlay with processing software of the pertinent mobile ultrasound machine

[0056] Thus a user 5 may use a transducer or probe 7 (associated with mobile ultrasound unit 8) on patient 9 to supply images of a pertinent body part to navigator 100 and navigator 100 may supply orientation instructions accordingly as to how to orientate probe 7. It will be appreciated that the process may be iterative, with a non-sonographer or user 5 making more than one attempt to correctly orientate probe 7 in order to receive a suitable image. In accordance with a preferred embodiment of the present invention, "orientation" instructions may comprise both position (location in two or three-dimensional space) and rotation information (rotation in 3D space), even though navigator 100 receives only images.

[0057] Reference is now made to Figs. 3A and 3B which illustrate how navigator 100 may aid non-sonographer 5 to orientate probe 7 in order to capture a good image of a particular body part. Fig. 3A shows probe 7, labeled 7A, in the wrong position, i.e. the resultant image, labeled 20A, is not canonical. Fig. 3A additionally includes a set of arrows 21 instructing user 5 to change the rotation of probe 7A. Arrows 21A indicate a 'pitch up' kind of rotation. Fig. 3B shows probe 7B in the newly pitched US orientation and the resultant image 20B, which is better, though still not providing a canonical image. Arrows 21B indicate a new "yaw" rotation may be useful.

[0058] As discussed herein above, navigator 100 receives orientation neural network 15 which may be trained with expert data taken by a skilled sonographer for a particular body part or organ of interest. The training data received may include the canonical image of a particular body part as well as associated non-canonical images and for each, the orientation (i.e. position and rotation) of the sonographer's probe in space. It will be appreciated that this information may be generated using a probe with which an IMU (an inertial measurement unit which may include a magnetometer, a gyroscope, an accelerometer, etc.) is associated. The IMU may determine the orientation of the probe when an image is captured.

[0059] Reference is now made to Fig. 4 which illustrates the transformation between the orientation of a training probe 4c used by a trained sonographer for capturing the canonical image in relation to its orientation when capturing a non-canonical image for an organ. The orientation of training probe 4i when viewing the i^{th} non-canonical image may be defined as a "frame of reference" F_i in space where frame of reference Fi may have the six degrees of freedom (6DoF), corresponding to a three axis system (Q) having three rotations around the axes and three translations along the axes, that an IMU may measure.

[0060] Frames of reference F_i may refer to frame of reference at an origin O, where, for the present invention, the origin may be at the organ and its frame of reference in space may be defined as F_o. For each frame of reference Fi, there may be a transformation Ri from the origin O, where the transformation R_c may be a transformation to the desired orientation, labeled F_c, for viewing the canonical image, as follows:

$$R_c = F_c\, F_o^{-1}$$

$$R_i = F_i\, F_o^{-1} \qquad (1)$$

where F_o^{-1} is the inverse transform of F_o. Thus, a transformation T_i from the canonical pose to the ith non-canonical pose may be $R_iR_c^{-1}$:

$$T_i = R_iR_c^{-1} = F_i\, F_0^{-1}(F_oF_c^{-1}) = F_iF_c^{-1} \qquad (2)$$

[0061] Reference is now made to Fig. 5 which illustrates the training process for orientation neural network 15 using a trainer 30. A skilled sonographer 2 using training probe 4 on a patient 3 may provide both canonical and associated non-canonical images for a particular body part. It will be appreciated that training probe 4 may be associated with an

IMU 6 (an inertial measurement unit which may include a magnetometer, a gyroscope, an accelerometer, etc.) which may determine the orientation F_i of the probe when an image is captured.

[0062] Training converter 22 may receive the orientation data F_i for each image and may determine the transformation $T_i = R_i R_c^{-1}$ from the associated canonical position, as discussed herein above with respect to Fig. 4. Specifically, training converter 22 may take images X from training probe 4 and may process them as necessary. Database 20 may store non-canonical images X_i together with their orientation data F_i and their transformation data T_i. Database 20 may also store canonical images X_c and their associated orientation data F_c. It will be appreciated that there may be multiple canonical images for a body part. For example, the heart has a four chamber canonical image, a two chamber canonical image, etc., and thus, training converter 22 may generate the transformation T_i to each relevant canonical image. It will be appreciated that the relevant canonical image may be provided manually or determined automatically by any suitable algorithm.

[0063] It will be appreciated that the incoming training data to trainer 30 may be a combination of image X_i and its associated ground truth transformation T_i. For each non-canonical image, trainer 30 may learn the positioning transformation for the probe 4 to transform from viewing each canonical image to viewing each non-canonical image. It will be appreciated that the incoming data may comprise data from many different patients 3 so that trainer 30 may learn the changes in images X_i, possibly due to the sex, age, weight, etc., of patient 3 and any other factors which may influence the transformation information between the non-canonical images and the canonical image.

[0064] It will be further appreciated that trainer 30 may be any suitable neural network trainer, such as a convolutional neural network trainer, which may train the network by updating the network to minimize an energy "loss" as determined by a loss function such as a distance between a calculated transformation $S(X_i)$ produced by orientation neural network 15 and the ground truth transformation T_i for image X_i from its associated canonical image. It will be appreciated that transformation $S(X_i)$ begins as an untrained neural network and finishes as a trained neural network.

[0065] The distance function may be any suitable distance function. If there is more than one associated canonical image, orientation neural network 15 may be trained with the ground truth transformation Ti to each non-canonical image. A loss function "Loss" may be calculated as:

$$\text{Loss} = \text{loss}\,(S(X_i), T_i) \qquad (3)$$

[0066] Once orientation neural network 15 is trained, it may generate a transformation T for user probe 7 in response to each incoming image X_i. This transformation may then be inverted or converted to guide user 5 from the orientation for the non-canonical image to the orientation for the canonical image, as described in more detail herein below.

[0067] Reference is now made to Fig. 6 which illustrates the components of navigator 100. Navigator 100 may comprise trained orientation neural network 15, a result converter 40 and a diagnoser 50.

[0068] As discussed herein above, user 5 may randomly place user probe 7 in relation to the desired body part. Trained orientation neural network 15 may provide the transformation T from the associated canonical image to the current non-canonical image of a particular body part. Result converter 40 may invert the generated transformation to provide orientation instructions for probe 7 from the current position and rotation viewing a non-canonical image to a position and rotation to view the associated canonical image. Result converter 40 may provide and display these orientation instructions to user 5 in various ways. It will be appreciated that this process may be iterative until user 5 positions probe 7 correctly (within an error range).

[0069] Result converter 40 may convert the orientation data S(X) produced by trained orientation neural network 15 into an explainable orientation for user 5, for a selected canonical image. Any suitable display may be utilized. An exemplary display is shown hereinabove with reference to Figs. 3A and 3B. It will be appreciated that result converter 40 may use any appropriate interface and may (for example) display colored rotation markings. Moreover, result converter 40 may include elements that enable user 5 to indicate, when there are multiple canonical images for the body part, which canonical image is currently of interest.

[0070] Diagnoser 50 may receive the final canonical image produced by user 5 and may detect any anomalies therein. Diagnoser 50 may be any suitable diagnoser. For example, diagnose 50 may implement the diagnosis method of PCT International Publication WO 2018/136805.

[0071] Applicants have realized that the fact that there are multiple canonical images for a single body part and the fact that there are standard, known motions from one canonical image to another may be utilized to reduce errors in the output of trained orientation neural network 15.

[0072] In this improved embodiment, orientation neural network 15 may be trained to the multiple canonical images. Thus, for each image X_i, there may be multiple calculated transformations. For example, for a pair of canonical images c and c', there may be a pair of calculated transformations $S_c(X_i)$ and $S_c'(X_i)$ for the same image X_i which may have associated ground truth transformations $T_{c,i}$ and $T_{c',i}$.

[0073] Moreover, there is a known motion transformation T_k defined as:

$$T_k = R_c R_{c'}^{-1} \quad (4)$$

where R_c is for canonical image c and $R_{c'}$ is for canonical image c'. These known motions are roughly constant across different subjects and therefore the transformation T_k from one canonical image c to another c' may be utilized to constrain the calculated transformations $S_c(X_i)$ and $S_{c'}(X_i)$ to one of the canonical orientations. To do so, a probability measure P_k may be used to define a maximum likelihood loss term $\log P_k(S_c(X_i)S_{c'}(X_i)^{-1})$ to add to the loss used to train orientation neural network 15, as follows:

$$\text{Loss} = \text{loss}(S_c(X_i), T_{c,i}) + \text{loss}(S_{c'}(X_i), T_{c',i}) - \delta^*\log P_k(S_c(X_i)S_{c'}(X_i)^{-1}) \quad (5)$$

[0074] The probability measure P_k may be determined experimentally by measuring the ground truth transformation T_k between canonical pose c and c' across different subjects. Moreover, there may be multiple probability measures per body part, one for each pair of canonical images for the body part, and each probability measure P_k may define a separate additional term for the loss function.

[0075] In an alternative embodiment, the navigator, here labeled 100', may also comprise a sufficiency checker 60 and a volume reconstructer 70, as is illustrated in Fig 7. to which reference is now made.

[0076] Volume reconstructer 70 may utilize the output of trained orientation neural network 15 and may produce 3D or 4D functions, and/or 3D volumes or 3D space-time volumes of the body parts of interest from the images Xi produced by probe 7. In this embodiment, the images Xi may be considered as cross-sections of the body part of interest.

[0077] Sufficiency checker 60 may check that sufficient cross sections have been received via trained orientation neural network 15 in order to perform the 3D/4D volume reconstruction and may guide user 5 (via result converter 40) accordingly. For example, sufficiency checker 60 may determine when a pre-defined minimal number of images have been taken.

[0078] Upon an indication from sufficiency checker 60, volume reconstructer 70 may generate the 3D/4D volume, after which, reconstructer 70 may pull the relevant canonical views from the generated volume and may provide them to diagnoser 50. It will be appreciated that the canonical views in this embodiment are produced from the generated volume and may or may not have been among the images used to produce the volume.

[0079] Volume reconstructer 70 may utilize tomographic reconstruction, such as that based on inverse Radon transformation or other means, to reconstruct the 3D/4D functions and/or volumes from the images. It will be appreciated that for successful volumatic tomographic reconstruction, it is crucial to know the cross-section's position in 3D space or 4D space-time. Applicants have realized that trained orientation neural network 15 may provide a suggested transformation S(X) for probe 7 for each image taken and that transformation S(X) may be used to rotate the pixels of image Xi from a fixed 2D imaging plane to the 3D orientation Q in space in which probe 4i was positioned when it produced image Xi.

[0080] Volume reconstructer 70 may receive the transformation $S(X_i)$ from trained orientation neural network 15 for each image X_i and may apply the transformation to move the image from an imaging plane (as output from the probe) to a plane defined by the transformation of the probe, producing a rotated cross-section CSi of the body part. Volume reconstructer 70 may then use tomographic reconstruction to build the volume of the body part of interest from the images cross-sections $CS(X_i)$.

[0081] To apply transformation $S(X_i)$, it will first be appreciated that image X_i comprises a set of pixels having a 2D location (x_j,y_j) within the 2D imaging plane and an intensity I_j. Volume reconstructer 70 may apply transformation $S(X_i)$ on a 3D pixel location $(x_j,y_j,0)$ in space to generate an approximation of the 3D orientation Q of image X_i, after which it may apply an operator H to center or scale the orientated image X_i, as follows:

$$Q = H^*S(X_i)^*[x_j,y_j,0]^T \quad (6)$$

[0082] Volume reconstructer 70 may provide the generated canonical image to diagnoser 50 which may then produce a diagnosis from it, as described hereinabove.

[0083] In yet another embodiment, illustrated in Figs. 8A, 8B and 8C to which reference is now made, navigator, here labeled 100", may comprise an image mapping neural network 90. Mapping neural network 90 may map each image X_i onto a 2D plane 92 (Fig. 8B). Fig. 8B shows three exemplary images X_A, X_B and X_D being mapped to three different locations A, B and D on plane 92.

[0084] Result converter, here labeled 42, may display 2D plane 92 to user 5, marking his current location in one color (for example, as a grey dot (shown in Fig. 8C as a shaded dot)) and the location of the canonical images for this body part as dots of other colors (shown in Fig. 8C as numbered circles 1 - 5). Fig. 8C also shows the acquired image X_i and its map 92. Map point $M(X_i)$ may represent non-canonical image X_i on map 92 and the other numbered circles may be canonical map points representing the desired or required canonical views c. User 5 may use trial and error movements of probe 7 to move map point $M(X_i)$ nearer towards the desired circles and mapper 90 may regenerate 2D plane 92 for each new image i from probe 7.

[0085] Applicants have realized that small changes in the motion of probe 7 should generate small motions on 2D plane 92 and that distances between images X_i should be similar to the distance between map locations. Applicants have further realized that optimal paths from one canonical image to another should be straight, constant speed trajectories.

[0086] It will be appreciated that for this embodiment, mapping neural network 90 may be trained using incoming data which may include each image X_i and the image X_c of its associated canonical view.

[0087] Mapping neural network 90 may incorporate a loss function to minimize a distance between a calculated map point $M(X_i)$ currently produced by neural network 90 during training and the associated map point $M(X_c)$ for each canonical view c_j:

$$\text{Loss} = \text{loss}(M(X_i), M(X_{cj})) \qquad (7)$$

[0088] To incorporate an optimal path to the different canonical views, a probability vector $p_{i,j}$ may be added which may define how close the image X_i is on a path to the jth desired canonical image c. The loss function may then be updated to be:

$$\text{Loss} = \text{loss}(M(X_i), \textstyle\sum p_{i,j} M(X_{cj})) \qquad (8)$$

[0089] To preserve distances, the loss function may be updated to be:

$$\text{Loss} = \text{loss}(M(X_i), \textstyle\sum p_{i,j} M(X_{cj})) + \text{loss}(\text{dist}(X_i,X_j), \| M(X_i)\text{-}M(X_j) \|_2) \qquad (9)$$

[0090] It will be appreciated that plane 92 may be either a 2D plane or a 3D volume, as desired. The mapping operations discussed herein above are operative for mapping to a 3D volume as well.

[0091] Applicants have realized that neural networks can be trained not just to generate transformation information but to generate canonical images, given the right kind of training. This might be particularly useful if the input from non-sonographers is expected to be noisy (since they may not have steady enough hands) and/or if it is desired to see, at the canonical view, the body part functioning. For example, ultrasound sonographers regularly provide information about a full cardiac cycle, from systole to distole and back to systole, for cardiac function analysis.

[0092] In yet another embodiment, shown in Figs. 9A and 9B to which reference is now made, navigator 100 may comprise a cyclical canonical view neural network 110, which may be a neural network trained from the output of trained orientation neural network 15. Canonical view cycler 110 may aggregate repeating images to reduce noise and to provide a less noisy summarization of (for example) an organ cycle, such as the cardiac cycle.

[0093] As shown in Fig. 9A, the elements needed for training cyclical canonical view neural network 110 may comprise trained orientation neural network 15, a set creator 112 to create the input to network 110, and a cyclical canonical view trainer 115.

[0094] For this embodiment, skilled sonographer 2 may provide multiple ultrasound images m taken over time as well as multiple images n taken over time at one canonical view pose c. Set creator 112 may receive image X_m from trained orientation neural network 15 along with its associated transformation information $S(X_m)$ and may combine these with their associated image $X_{c,n}$ taken at the canonical view. Skilled sonographer 2 may provide such associations.

[0095] Set creator 112 may then generate triplets $\{[Y_m, Z_m], W_n\}$ where $[Y_m, Z_m]$ are input to cyclical canonical view trainer 115 and W_n is the associated output. Each Y_m may consist of a set of g images where $Y_m = \{X_1, X_2, ...X_g\}$ and Z_m may consist of the transformation information S(X) of the images Y_m such that $Z_m = \{S(X_1), S(X_2)\ S(X_g)\}$. Typically, g may be 10 - 100 images.

[0096] Each pair $[Y_m,Z_m]$ may have a set W_n of associated canonical images X_c taken at the canonical view c at times between 0 and n. The time n may indicate the time within the cardiac cycle. As mentioned herein above, skilled sonographer 2 may indicate the cardiac cycle information and may provide the associated canonical images X_c which will be included in set W_n.

[0097] In this scenario, cyclical canonical view trainer 115 may receive as input general frames Y_m, their approximate transformations Z_m as generated by orientation neural network 15, and their associated cardiac cycle timing n, and may be trained to generate a set of summary images W_n in a canonical view at desired times n. The optimization is:

$$\text{Loss} = \text{loss}(CC_n, W_n) \qquad (10)$$

where CC_n is the output of the cyclical canonical view neural network 110 as it is being trained.

[0098] Cyclical canonical view trainer 115 may generate trained cyclical canonical view neural network 110 for navigator 100 using any appropriate neural network, such as a fully-convolutional network, an encoder-decoder type of network or a generative adversarial network.

[0099] As illustrated in Fig. 9B to which reference is now made, navigator 100‴ may comprise trained orientation neural network 15, a set creator 112' for operation, a sufficiency checker 60', a result converter 40', trained cyclical canonical view neural network 110 and diagnoser 50.

[0100] In operation, non-sonographer 5 may operate probe 7 near the body part of interest over a period of time, at least long enough to cover the desired body part cycle (such as the cardiac cycle). The images from probe 7 may be provided to trained orientation neural network 15 to generate their associated transformations S(X) and to set creator 112' to generate the appropriate sets Y_m and Z_m. Sufficiency checker 60' may check that sets Y_m and Z_m are large enough and may instruct result converter 40' to instruct user 5 either to orientate probe 7 in a desired way or to continue viewing at the current orientation. It will be appreciated that, in this embodiment, non-sonographer 5 does not have to hold probe 7 at exactly the canonical view and thus, the instructions that result converter 40' may provide may be coarser. Cyclical canonical view neural network 110 may generate the summary cyclical, canonical views CC_n from the output of set creator 112'.

[0101] It will be appreciated that this embodiment may also be useful for non-cyclical body parts, particularly for when user 5 may hold probe 7 unsteadily. In this embodiment, each set may have only one or two images therein.

[0102] Applicants have further realized that neural networks can also be trained without the transformation information produced by trained orientation neural network 15. This is shown in Figs. 10A and 10B, which illustrate a system similar to that of Figs. 9A and 9B, but without trained orientation neural network 15. As a result, for training (Fig. 10A) a set creator 113 may create Y_m from images X_i and may create W_n from canonical images X_c at times n. Cyclical canonical view trainer 115 may generate cyclical canonical view neural network 110 using equation (10).

[0103] At runtime (Fig. 10B), a set creator 113' may create Y_m from images X_i and cyclical canonical view neural network 110 may generate the summary views CC_n.

[0104] It will be appreciated that the present invention may provide a navigator for non-sonographers to operate a mobile ultrasound machine without training and without any additional hardware other than the ultrasound probe. Thus, the navigator of the present invention receives ultrasound images as its only input. It will further be appreciated that this may enable non-sonographers to perform ultrasound scans in many non-conventional scenarios, such as in ambulances, in the battlefield, at urgent care facilities, nursing homes etc.

[0105] Moreover, the present invention may be implemented in more conventional scenarios, such as part of conventional machines used in hospital or clinic environments, which may also be implemented on carts.

[0106] Unless specifically stated otherwise, as apparent from the preceding discussions, it is appreciated that, throughout the specification, discussions utilizing terms such as "processing," "computing," "calculating," "determining," or the like, refer to the action and/or processes of a general purpose computer of any type such as a client/server system, mobile computing devices, smart appliances or similar electronic computing device that manipulates and/or transforms data represented as physical, such as electronic, quantities within the computing system's registers and/or memories into other data similarly represented as physical quantities within the computing system's memories, registers or other such information storage, transmission or display devices.

[0107] Embodiments of the present invention may include apparatus for performing the operations herein. This apparatus may be specially constructed for the desired purposes, or it may comprise a general-purpose computer or a client/server configuration selectively activated or reconfigured by a computer program stored in the computer. The resultant apparatus when instructed by software may turn the general purpose computer into inventive elements as discussed herein. The executable instructions may define the inventive device in operation with the computer platform for which it is desired. Such a computer program may be stored in a computer accessible storage medium which may be a non-transitory medium, such as, but not limited to, any type of disk, including optical disks, magnetic-optical disks, read-only memories (ROMs), volatile and non-volatile memories, random access memories (RAMs), electrically programmable read-only memories (EPROMs), electrically erasable and programmable read only memories (EEPROMs), magnetic or optical cards, Flash memory, disk-on-key or any other type of media suitable for storing electronic instructions and capable of being coupled to a computer system bus.

[0108] The processes and displays presented herein are not inherently related to any particular computer or other apparatus. Various general-purpose systems may be used with programs in accordance with the teachings herein, or it may prove convenient to construct a more specialized apparatus to perform the desired method. The desired structure for a variety of these systems will appear from the description below. In addition, embodiments of the present invention are not described with reference to any particular programming language. It will be appreciated that a variety of programming languages may be used to implement the teachings of the invention as described herein.

[0109] While certain features of the invention have been illustrated and described herein, many modifications, substitutions, changes, and equivalents will now occur to those of ordinary skill in the art.

Claims

1. A downloadable navigator (100) for a mobile ultrasound unit (8) having an ultrasound probe (7), implemented on a portable computing device, the navigator comprising:

   a trained orientation neural network (15) to receive a non-canonical image of a body part from said mobile ultrasound unit (8) and to generate a transformation associated with said non-canonical image, said transformation transforming from a position and rotation associated with a canonical image to a position and rotation associated with said non-canonical image; and
   a result converter (40) to convert said transformation into orientation instructions for a user (5) of said probe (7) and to provide and display said orientation instructions to said user (5) to change the position and rotation of said probe (7).

2. The navigator according to claim 1 and comprising a trainer (30) to train said orientation neural network using said canonical image together with non-canonical images taken around said canonical image and transformations to positions and rotations in space associated with said non-canonical images from said canonical image.

3. The navigator according to claim 2 and wherein said trainer (30) comprises a training converter (22) to receive inertia measurement unit, IMU, data during training sessions from an IMU (6) mounted on a training probe (4c), said IMU data providing said positions and rotations associated with said non-canonical images and said canonical image, and to convert said positions and rotations to transformations from said position and rotation associated with said canonical image to said position and rotation associated with said non-canonical images.

4. The navigator according to claim 2 and wherein said trainer (30) comprises an untrained orientation neural network and a loss function to train said untrained orientation neural network, said loss function to reduce a distance between a calculated transformation produced by said untrained orientation neural network and a ground truth transformation for each non-canonical image.

5. The navigator according to claim 4 wherein said loss function additionally includes a probability to constrain said calculated transformation to one of a plurality of different canonical orientations.

6. The navigator according to claim 1 and also comprising:

   a set creator (112, 112') to receive a multiplicity of transformations from said trained orientation neural network (15) in response to images from said probe (7) and to generate sets of images and their associated transformations;
   a sufficiency checker (60, 60') to determine when enough sets have been created; and
   a trained cyclical canonical view neural network (110) to generate a set of summary cyclical canonical images showing changes in said body part during a body part cycle.

7. The navigator according to claim 6 and also comprising a cyclical canonical view trainer (115) to train an untrained cyclical canonical view neural network with said sets of images, their associated transformations, and their associated summary cyclical canonical images at each point in said body part cycle.

8. The navigator according to claim 6 wherein said body part cycle is a cardiac cycle.

9. The navigator according to claim 6 wherein each set has a single element therein.

10. A method for a mobile ultrasound unit (8) having an ultrasound probe (7), implemented on a portable computing device, the method comprising:

receiving, using a trained orientation neural network (15), a non-canonical image of a body part from said mobile ultrasound unit (8) and generating a transformation associated with said non-canonical image, said transformation transforming from a position and rotation associated with a canonical image to a position and rotation associated with said non-canonical image; and
converting said transformation into orientation instructions for a user (5) of said probe (7) and providing and displaying said orientation instructions to said user (5) to change the position and rotation of said probe (7).

11. The method according to claim 10 and comprising training said orientation neural network using said canonical image together with non-canonical images taken around said canonical image and transformations to positions and rotations in space associated with said non-canonical images from said canonical image.

12. The method according to claim 11 and wherein said training comprises receiving inertia measurement unit, IMU, data during training sessions from an IMU (6) mounted on a training probe (4c), said IMU data providing said positions and rotations associated with said non-canonical images and said canonical image, and converting said positions and rotations to transformations from said position and rotation associated with said canonical image to said position and rotation associated with said non-canonical images.

13. The method according to claim 10 and also comprising:

receiving a multiplicity of transformations from said trained orientation neural network (15) in response to images from said probe (7) and generating sets of images and their associated transformations;
determining when enough sets have been created; and
generating, using a trained cyclical canonical view neural network, a set of summary cyclical canonical images showing changes in said body part during a body part cycle .

14. The method according to claim 13 and also comprising training an untrained cyclical canonical view neural network with said sets of images, their associated transformations, and their associated summary cyclical canonical images at each point in said body part cycle.

15. The method according to claim 13 wherein said body part cycle is a cardiac cycle.

16. The method according to claim 13 wherein each set has a single element therein.

Patentansprüche

1. Herunterladbarer Navigator (100) für eine mobile Ultraschalleinheit (8) mit einer Ultraschallsonde (7), die auf einer tragbaren Rechenvorrichtung implementiert ist, der Navigator umfassend:

ein trainiertes neuronales Orientierungsnetzwerk (15) zum Empfangen eines nicht-kanonischen Bildes eines Körperteils von der mobilen Ultraschalleinheit (8) und zum Erzeugen einer Transformation, die mit dem nicht-kanonischen Bild assoziiert ist, wobei die Transformation von einer Position und Drehung, die mit einem kanonischen Bild assoziiert ist, in eine Position und Drehung, die mit dem nicht-kanonischen Bild assoziiert ist, transformiert, und
einen Ergebniskonverter (40) zum Umwandeln der Transformation in Orientierungsanweisungen für einen Benutzer (5) der Sonde (7) und zum Bereitstellen und Anzeigen der Orientierungsanweisungen für den Benutzer (5), um die Position und Drehung der Sonde (7) zu ändern.

2. Navigator nach Anspruch 1, umfassend einen Trainer (30), um das neuronale Orientierungsnetzwerk unter Verwendung des kanonischen Bildes zusammen mit nicht-kanonischen Bildern, die um das kanonische Bild herum aufgenommen wurden, und Transformationen zu Positionen und Drehungen im Raum, die mit den nicht-kanonischen Bildern aus dem kanonischen Bild assoziiert sind, zu trainieren.

3. Navigator nach Anspruch 2, wobei der Trainer (30) einen Trainingskonverter (22) umfasst, um Daten einer Inertialen Messeinheit, IMU, während Trainingssitzungen von einer IMU (6), die an einer Trainingssonde (4c) montiert ist, zu empfangen, wobei die IMU-Daten die Positionen und Drehungen bereitstellen, die mit den nicht-kanonischen Bildern und dem kanonischen Bild assoziiert sind, und um die Positionen und Drehungen in Transformationen von der Position und Drehung, die mit dem kanonischen Bild assoziiert sind, zu der Position und Drehung, die mit den nicht-kanonischen Bildern assoziiert sind, umzuwandeln.

4. Navigator nach Anspruch 2, wobei der Trainer (30) ein untrainiertes neuronales Orientierungsnetz und eine Verlustfunktion zum Trainieren des untrainierten neuronalen Orientierungsnetzes umfasst, wobei die Verlustfunktion einen Abstand zwischen einer berechneten Transformation, die durch das untrainierte neuronale Orientierungsnetz erzeugt wird, und einer Ground-Truth-Transformation für jedes nicht kanonische Bild reduziert.

5. Navigator nach Anspruch 4, wobei die Verlustfunktion zusätzlich eine Wahrscheinlichkeit beinhaltet, die berechnete Transformation auf eine von einer Vielzahl von unterschiedlichen kanonischen Orientierungen einzuschränken.

6. Navigator nach Anspruch 1, ferner umfassend:

   einen Satzerzeuger (112, 112'), um eine Vielzahl von Transformationen von dem trainierter neuronalen Orientierungsnetzwerk (15) als Reaktion auf Bilder von der Sonde (7) zu empfangen und Sätze von Bildern und deren assoziierter Transformationen zu erzeugen,
   einen Suffizienz-Prüfer (60, 60'), um zu bestimmen, wann genug Sätze erzeugt worden sind, und
   ein trainiertes neuronales Zyklische-Kanonische-Sicht-Netzwerk (110), um einen Satz von summarischen zyklischen kanonischen Bildern zu erzeugen, die Änderungen in dem Körperteil während eines Körperteilzyklus zeigen.

7. Navigator nach Anspruch 6, ferner umfassend einen Zyklische-Kanonische-Sicht-Trainer (115), um ein nicht trainiertes neuronales Zyklische-Kanonische-Sicht-Netzwerk mit den Sätzen von Bildern, ihren assoziierten Transformationen und ihren assoziierten summarischen zyklischen kanonischen Bildern an jedem Punkt in dem Körperzyklus zu trainieren.

8. Navigator nach Anspruch 6, wobei der Körperteilzyklus ein Herzzyklus ist.

9. Navigator nach Anspruch 6, wobei jeder Satz ein einzelnes Element darin aufweist.

10. Verfahren für eine mobile Ultraschalleinheit (8) mit einer Ultraschallsonde (7), die auf einer tragbaren Rechenvorrichtung implementiert ist, das Verfahren umfassend:

   Empfangen, unter Verwendung eines trainierten neuronalen Orientierungsnetzwerkes (15), eines nicht-kanonischen Bildes eines Körperteils von der mobilen Ultraschalleinheit (8) und Erzeugen einer Transformation, die mit dem nicht-kanonischen Bild assoziiert ist, wobei die Transformation von einer Position und Drehung, die mit einem kanonischen Bild assoziiert ist, in eine Position und Drehung, die mit dem nicht-kanonischen Bild assoziiert ist, transformiert, und
   Umwandeln der Transformation in Orientierungsanweisungen für einen Benutzer (5) der Sonde (7) und Bereitstellen und Anzeigen der Orientierungsanweisungen für den Benutzer (5), um die Position und Drehung der Sonde (7) zu ändern.

11. Verfahren nach Anspruch 10, umfassend das Trainieren des neuronalen Orientierungsnetzwerkes unter Verwendung des kanonischen Bildes zusammen mit nicht-kanonischen Bildern, die um das kanonische Bild herum aufgenommen wurden, und Transformationen zu Positionen und Drehungen im Raum, die mit den nicht-kanonischen Bildern aus dem kanonischen Bild assoziiert sind.

12. Verfahren nach Anspruch 11, wobei das Trainieren das Empfangen von Daten einer Inertialen Messeinheit, IMU, während Trainingssitzungen von einer IMU (6), die an einer Trainingssonde (4c) montiert ist, wobei die IMU-Daten die Positionen und Drehungen bereitstellen, die mit den nicht-kanonischen Bildern und dem kanonischen Bild assoziiert sind, und Umwandeln der Positionen und Drehungen in Transformationen von der Position und Drehung, die mit dem kanonischen Bild assoziiert sind, zu der Position und Drehung, die mit den nicht-kanonischen Bildern assoziiert sind, umfasst.

13. Verfahren nach Anspruch 10, ferner umfassend:

   Empfangen einer Vielzahl von Transformationen von dem trainierter neuronalen Orientierungsnetzwerk (15) als Reaktion auf Bilder von der Sonde (7) und Erzeugen von Sätzen von Bildern und deren assoziierter Transformationen,

Bestimmen, wann genug Sätze erzeugt worden sind, und
Erzeugen, unter Verwendung eines trainierten neuronalen Zyklische-Kanonische-Sicht-Netzwerkes, eines Satzes von summarischen zyklischen kanonischen Bildern, die Änderungen in dem Körperteil während eines Körperteilzyklus zeigen.

14. Verfahren nach Anspruch 13, ferner umfassend das Training eines nicht trainierten neuronalen Zyklische-Kanonische-Sicht-Netzwerkes mit den Sätzen von Bildern, ihren assoziierten Transformationen und ihren assoziierten summarischen zyklischen kanonischen Bildern an jedem Punkt in dem Körperzyklus.

15. Verfahren nach Anspruch 13, wobei der Körperteilzyklus ein Herzzyklus ist.

16. Verfahren nach Anspruch 13, wobei jeder Satz ein einzelnes Element darin aufweist.

Revendications

1. Navigateur téléchargeable (100) pour une unité mobile à ultrasons (8) ayant une sonde à ultrasons (7) implémentée dans un dispositif de calcul portable,
le navigateur comprenant :

- un réseau neuronal d'orientation entraîné (15) pour recevoir une image non canonique d'une partie du corps, d'une unité mobile à ultrasons (8) et pour générer une transformation associée à cette image non canonique, cette transformation convertissant une position et une rotation associées à une image canonique en une position et une rotation associées à cette image non-canonique, et
- un convertisseur de résultat (40) pour convertir la transformation en instructions d'orientation pour l'utilisateur (5) de la sonde (7) pour fournir et afficher ces instructions d'orientation à l'utilisateur (5) pour changer la position et la rotation de cette sonde (7).

2. Navigateur selon la revendication 1, et comprenant :

- un entraîneur (30) pour entraîner le réseau neuronal d'orientation en utilisant l'image canonique avec les images non-canoniques prises autour de cette image canonique et les transformations en positions et rotations dans l'espace associées à ces images non-canoniques à partir de l'image canonique.

3. Navigateur selon la revendication 2,
dans lequel
l'entraîneur (30) comprend un convertisseur d'entraînement (22) pour recevoir d'une unité de mesure inertielle IMU, des données pendant les sessions d'entraînement de l'unité IMU (6) montée sur une sonde d'entraînement (4c), cette donnée IMU fournissant les positions et les rotations associées aux images non-canoniques et à l'image canonique pour convertir les positions et les rotations pour les transformer à partir de la position et de la rotation associées à l'image canonique, en positions et rotations associées aux images non-canoniques.

4. Navigateur selon la revendication 2,
dans lequel
l'entraîneur (30) comprend un réseau neuronal d'orientation non entraîné et une fonction de perte pour entraîner le réseau neuronal d'orientation non-entraîné, cette fonction de perte réduisant la distance entre une transformation calculée produite par le réseau neuronal d'orientation non-entraîné et une transformation de base vraie pour chaque image non-canonique.

5. Navigateur selon la revendication 4,
dans lequel
la fonction de perte comprend par addition, une probabilité pour contraindre la transformation calculée selon l'une de l'ensemble des différentes orientations canoniques.

6. Navigateur selon la revendication 1,
comprenant également :

- un créateur d'ensembles (112, 112') pour recevoir une multiplicité de transformations du réseau neuronal

d'orientation entraîné (15) en réponse aux images de la sonde (7) et pour générer des jeux d'image et leurs transformations associées,
- un vérificateur de suffisance (60, 60') pour déterminer si suffisamment de jeux d'images ont été créés, et
- un réseau neuronal de vue canonique cyclique entraîné (110) pour générer un jeu d'images canoniques cycliques en résumé montrant les modifications de la partie corporelle pendant un cycle de partie corporelle.

7. Navigateur selon la revendication 6,
comprenant également
un entraîneur de vues canoniques cycliques (115) pour entraîner un réseau neuronal de vues canoniques cycliques non-entraîné avec des jeux d'images, leurs transformations associées et leurs images canoniques cycliques résumées, associées en chaque point de ce cycle de partie corporelle.

8. Navigateur selon la revendication 6,
selon lequel
le cycle de partie corporelle est un cycle cardiaque.

9. Navigateur selon la revendication 6,
dans lequel
chaque jeu a un élément unique.

10. Procédé pour une unité mobile d'ultrasons (8) ayant une sonde à ultrasons (7), implémenté dans un dispositif de calcul portable, le procédé consistant à :

- recevoir en utilisant un réseau neuronal d'orientation entraîné (15), une image non-canonique d'une partie corporelle de l'unité d'ultrasons mobile (8) et générer une transformation associée à cette image non-canonique, cette transformation transformant une position et une rotation associées à l'image canonique en une position et une rotation associées à l'image non-canonique, et
- convertir cette transformation en instructions d'orientation pour l'utilisateur (5) de la sonde (7) et fournir et afficher les instructions d'orientation pour cet utilisateur (5) pour modifier la position et la rotation de la sonde (7).

11. Procédé selon la revendication 10,
consistant à entraîner le réseau neuronal d'orientation en utilisant l'image canonique avec les images non canoniques prises autour de cette image canonique et les transformations en positions et rotations dans l'espace associé aux images non canoniques à partir de l'image canonique.

12. Procédé selon la revendication 11,
selon lequel
l'entraînement consiste à recevoir d'une unité de mesure inertielle, IMU, des données au cours des cessions d'entraînement à partir de l'unité IMU (6) montée sur une sonde d'entraînement (4c), ces données IMU fournissant les positions et les rotations associées aux images non-canoniques et l'image canonique et convertissant les positions et les rotations en transformations à partir de la position et de la rotation associées à l'image canonique en positions et rotations associées aux images non-canoniques.

13. Procédé selon la revendication 10 et consistant en outre à :

- recevoir une multiplicité de transformations du réseau neuronal d'orientation entraîné (15) en réponse aux images de la sonde (7) et générer des jeux d'image et de leurs transformations associées,
- déterminer s'il y a assez de jeux d'images qui ont été créés, et
- générer en utilisant un réseau neuronal de vision canonique cyclique entraîné, un jeu d'images canoniques cycliques résumées, montrant les changements de la partie corporelle au cours d'un cycle de partie corporelle.

14. Procédé selon la revendication 13,
selon lequel en outre
entraîner un réseau neuronal de vue canonique cyclique non entraîné avec les jeux d'images, leurs transformations associées et les images canoniques cycliques en résumé, associées à chaque point de ce cycle de partie corporelle.

15. Procédé selon la revendication 13,
selon lequel

le cycle de partie corporelle est un cycle cardiaque.

16. Procédé selon la revendication 13, dans lequel chaque jeu a un seul élément.

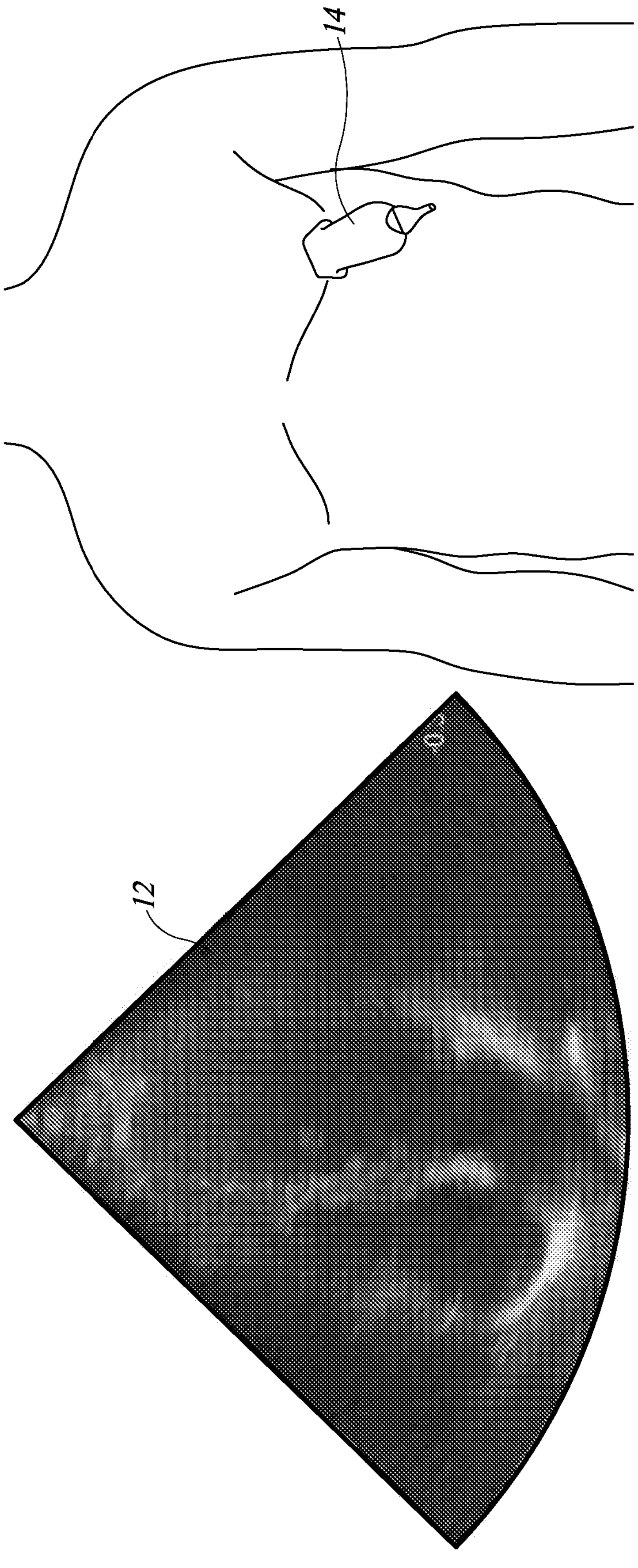
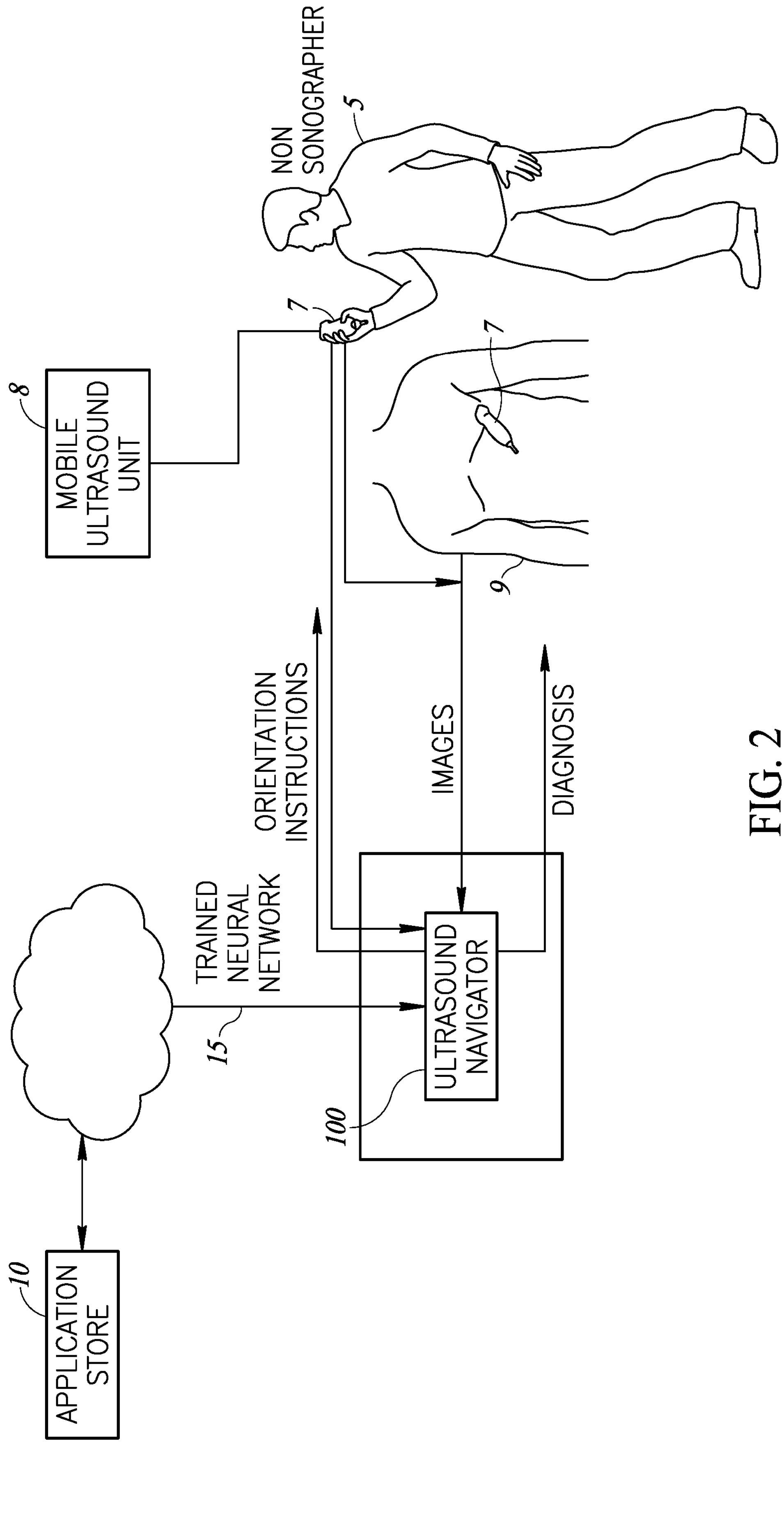


FIG. 1



NON SONOGRAPHER
5
7
8
MOBILE ULTRASOUND UNIT
7
9
ORIENTATION INSTRUCTIONS
IMAGES
DIAGNOSIS
TRAINED NEURAL NETWORK
15
ULTRASOUND NAVIGATOR
100
10
APPLICATION STORE

FIG. 2

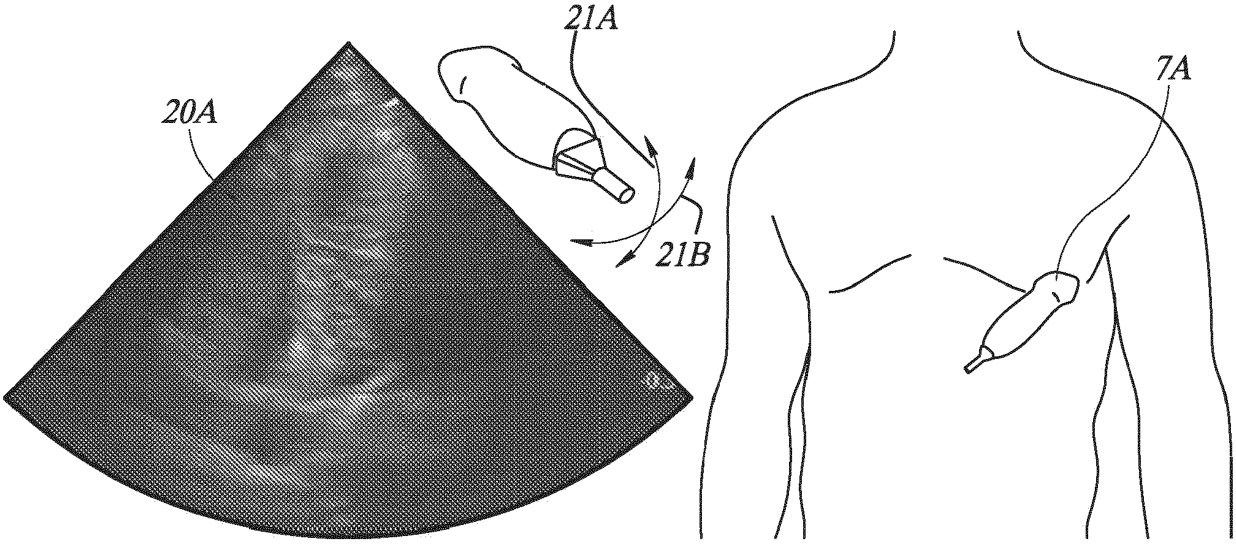


FIG. 3A

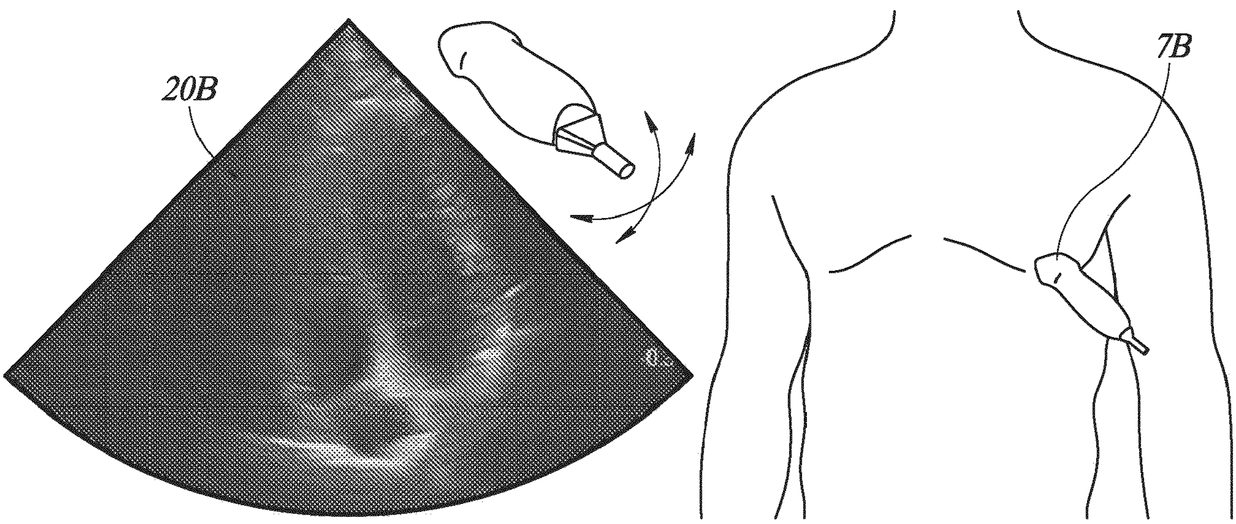


FIG. 3B

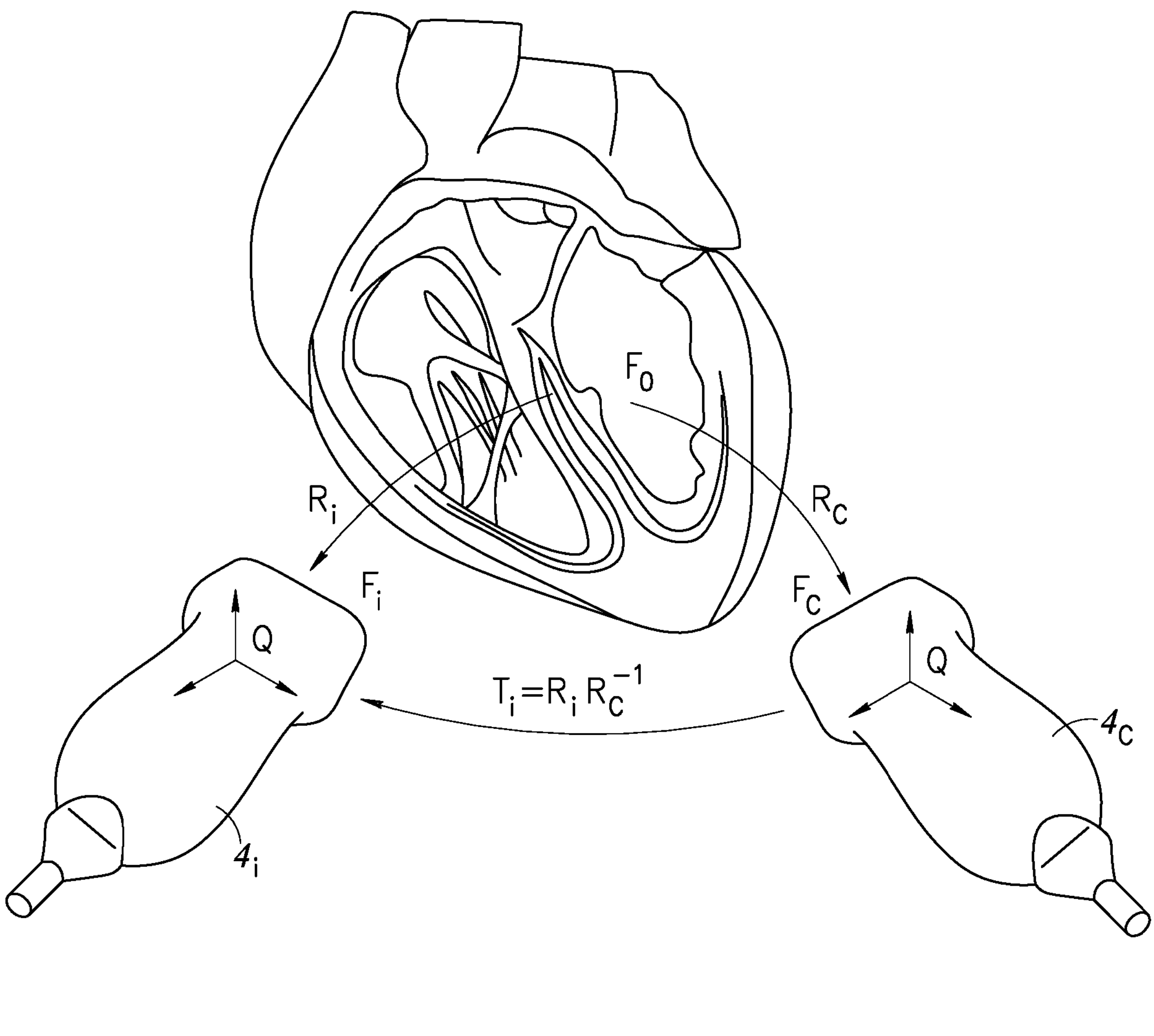


FIG. 4

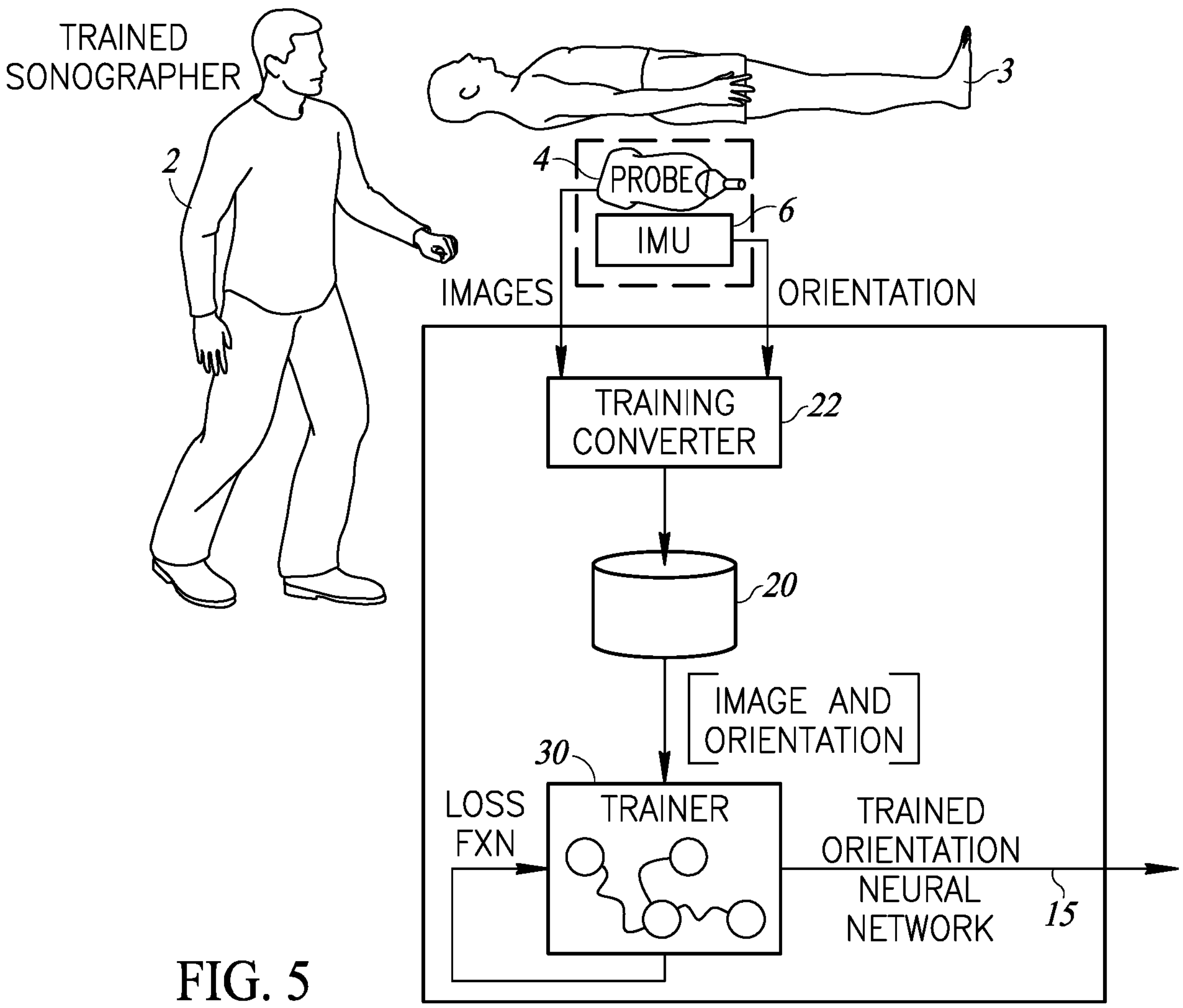

TRAINED
SONOGRAPHER
2
3
4
PROBE
6
IMU
IMAGES
ORIENTATION
TRAINING
CONVERTER
22
20
IMAGE AND
ORIENTATION
30
LOSS
FXN
TRAINER
TRAINED
ORIENTATION
NEURAL
NETWORK
15

FIG. 5

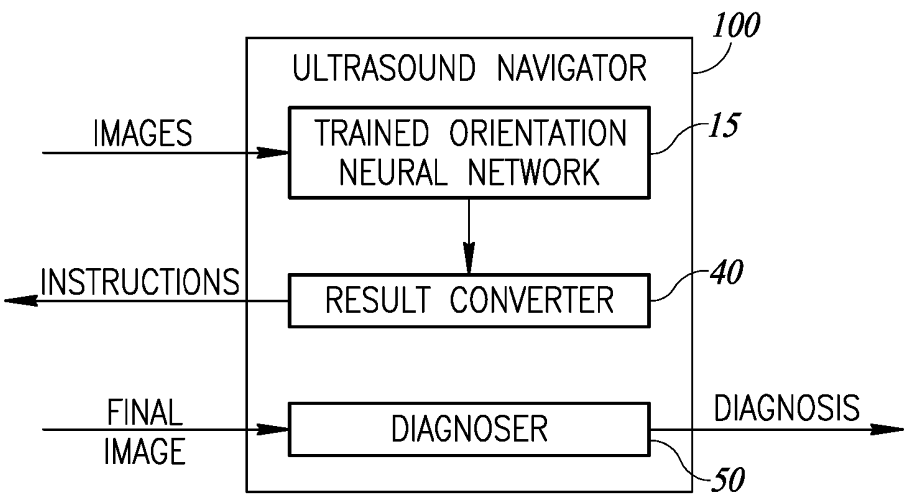

100
ULTRASOUND NAVIGATOR
IMAGES
TRAINED ORIENTATION
NEURAL NETWORK
15
INSTRUCTIONS
RESULT CONVERTER
40
FINAL
IMAGE
DIAGNOSER
DIAGNOSIS
50

FIG. 6

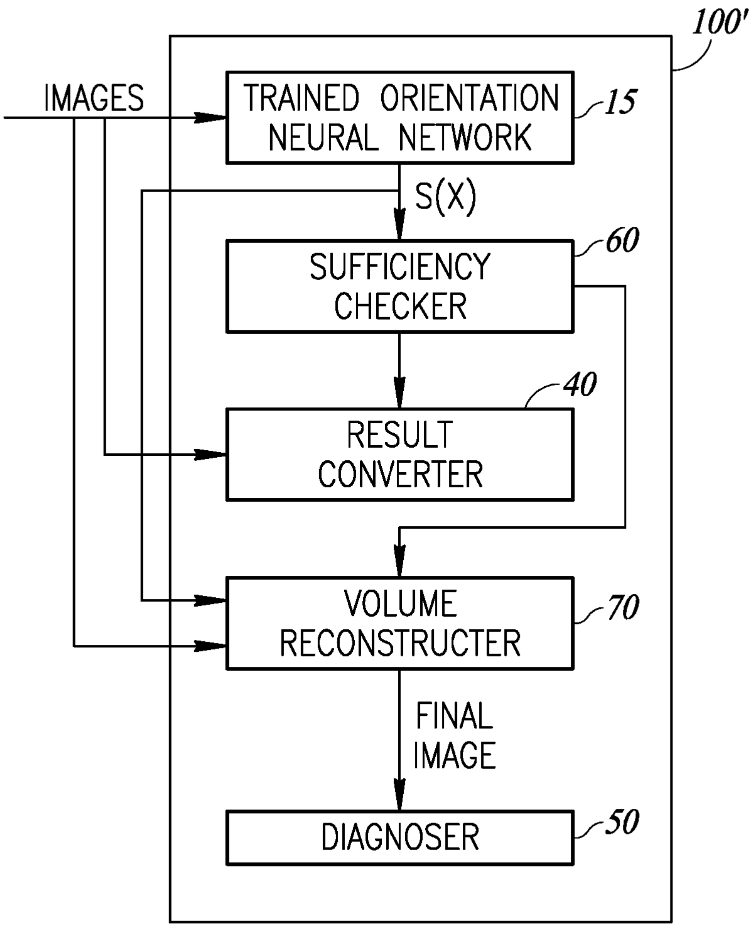

100'
IMAGES
TRAINED ORIENTATION NEURAL NETWORK
15
S(X)
SUFFICIENCY CHECKER
60
RESULT CONVERTER
40
VOLUME RECONSTRUCTER
70
FINAL IMAGE
DIAGNOSER
50

FIG. 7

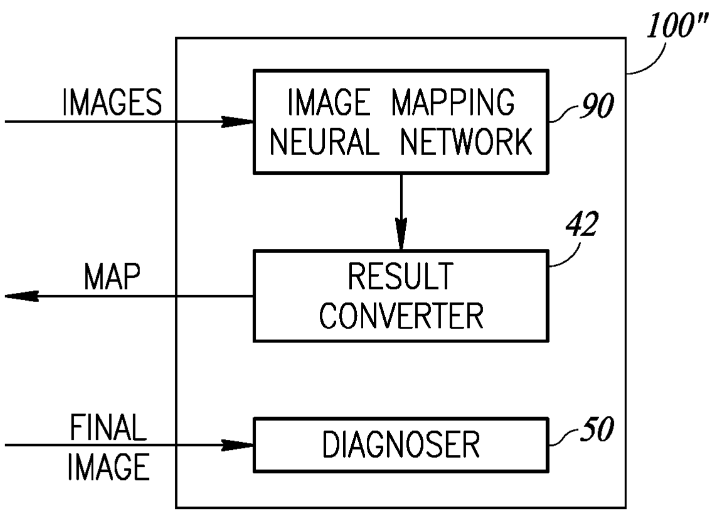

100"
IMAGES
IMAGE MAPPING NEURAL NETWORK
90
RESULT CONVERTER
42
MAP
FINAL IMAGE
DIAGNOSER
50

FIG. 8A

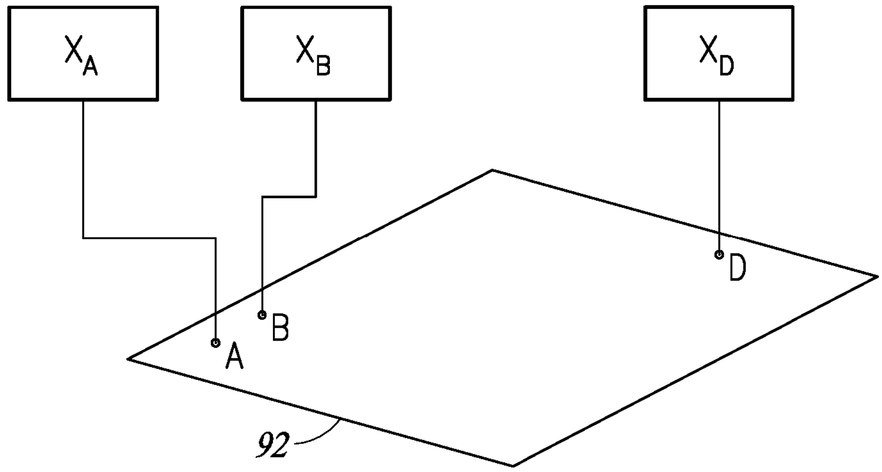


FIG. 8B

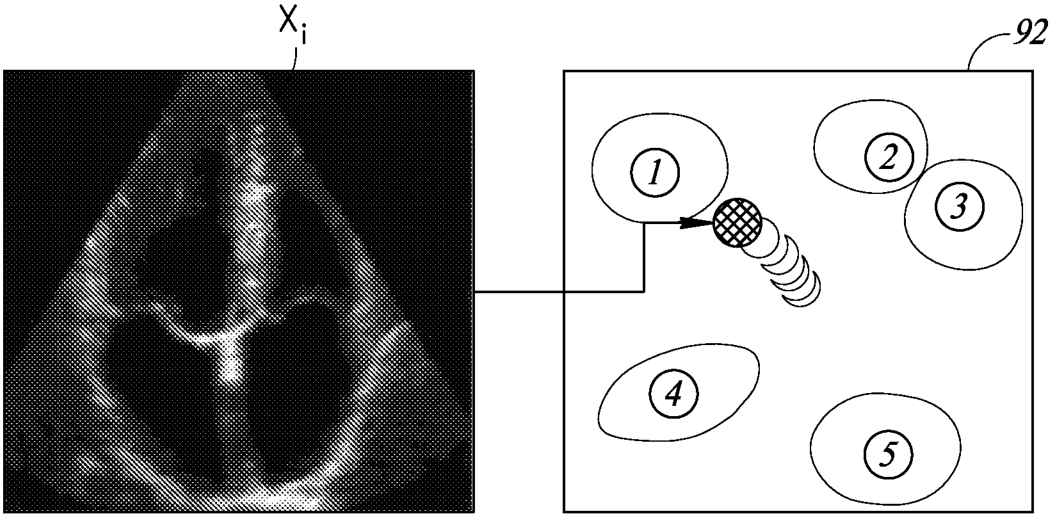


FIG. 8C

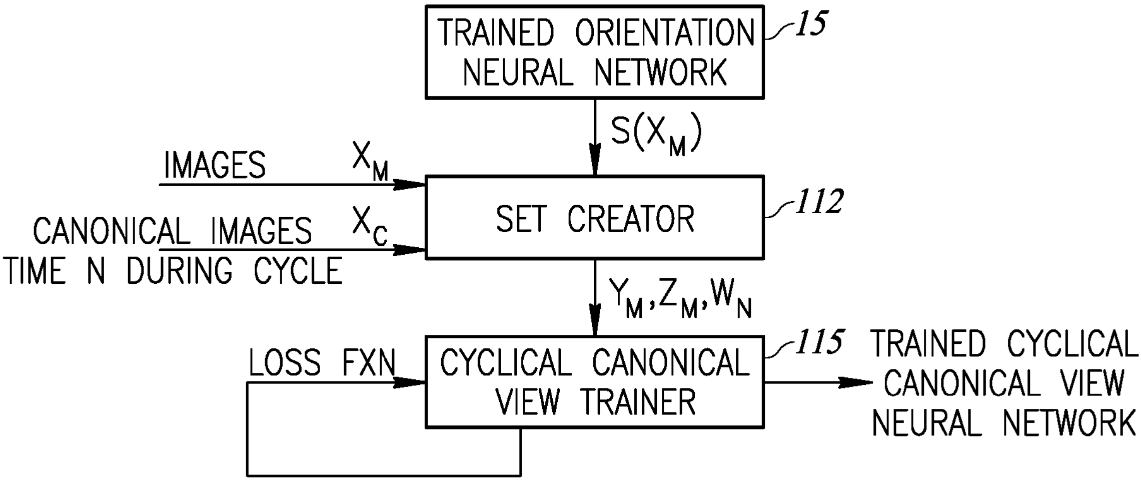

TRAINED ORIENTATION NEURAL NETWORK
15
S(X_M)
IMAGES X_M
SET CREATOR
112
CANONICAL IMAGES X_C
TIME N DURING CYCLE
Y_M, Z_M, W_N
LOSS FXN
CYCLICAL CANONICAL VIEW TRAINER
115
TRAINED CYCLICAL CANONICAL VIEW NEURAL NETWORK

FIG. 9A

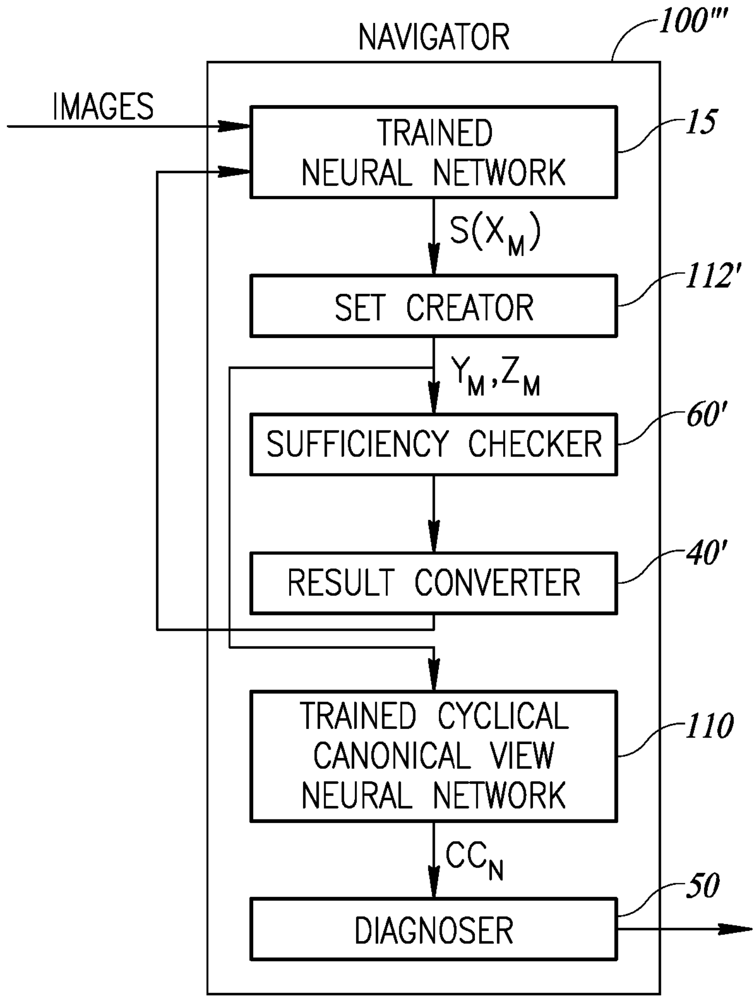

NAVIGATOR
100'''
IMAGES
TRAINED NEURAL NETWORK
15
S(X_M)
SET CREATOR
112'
Y_M, Z_M
SUFFICIENCY CHECKER
60'
RESULT CONVERTER
40'
TRAINED CYCLICAL CANONICAL VIEW NEURAL NETWORK
110
CC_N
DIAGNOSER
50

FIG. 9B

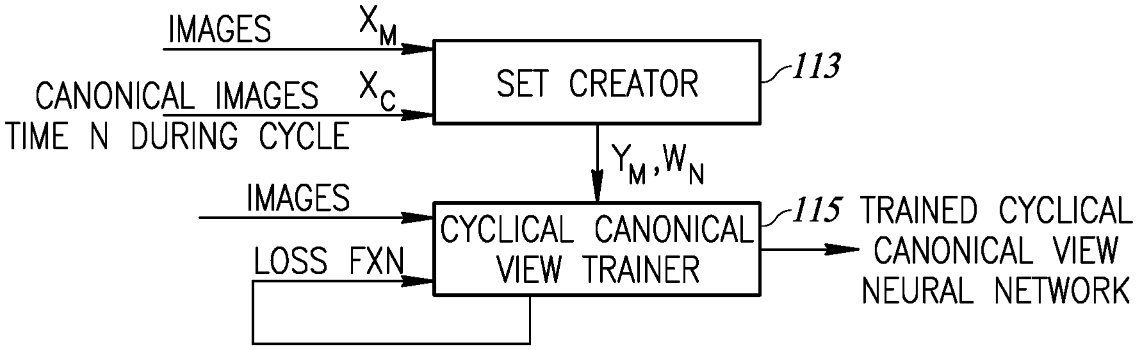


FIG. 10A

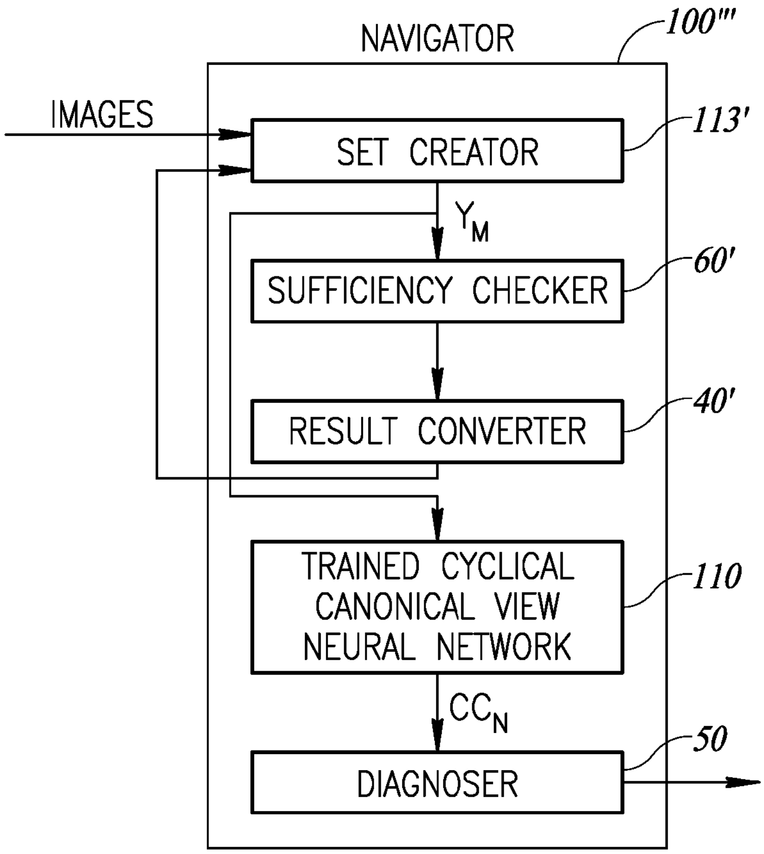


FIG. 10B

REFERENCES CITED IN THE DESCRIPTION

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- US 20180153505 A **[0052]**
- US 20160143627 A **[0052]**
- WO 2018136805 A **[0070]**