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

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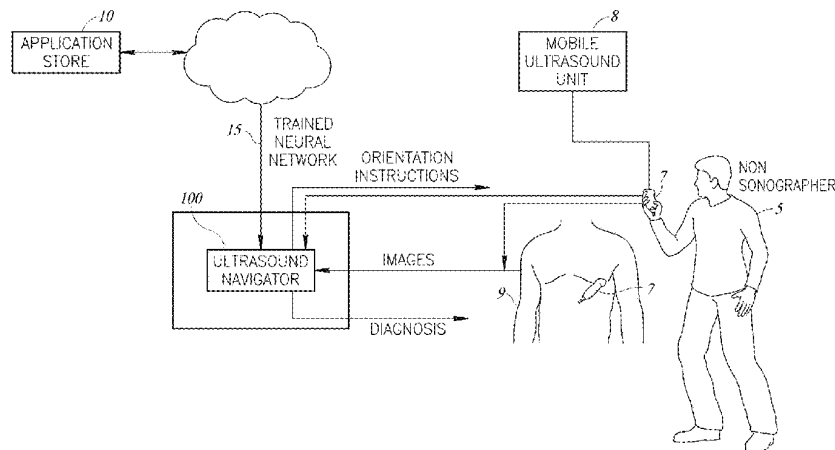
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(57) **ABSTRACT**

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.

24 Claims, 9 Drawing Sheets



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A61B 8/13 (2006.01)
G09B 23/28 (2006.01)
G06T 3/60 (2006.01)
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G16H 30/40 (2018.01); *G06T 2207/10132*
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2207/20084 (2013.01); *G06T 2207/30048*
 (2013.01)
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A61B 8/58; *A61B 8/585*; *G06N 3/08*;
G06T 1/20; *G06T 11/003*; *G06T*
2207/10132; *G06T 2207/20081*; *G06T*
2207/20084; *G06T 2207/30048*; *G06T*
3/20; *G06T 3/60*; *G06T 7/0012*
 See application file for complete search history.

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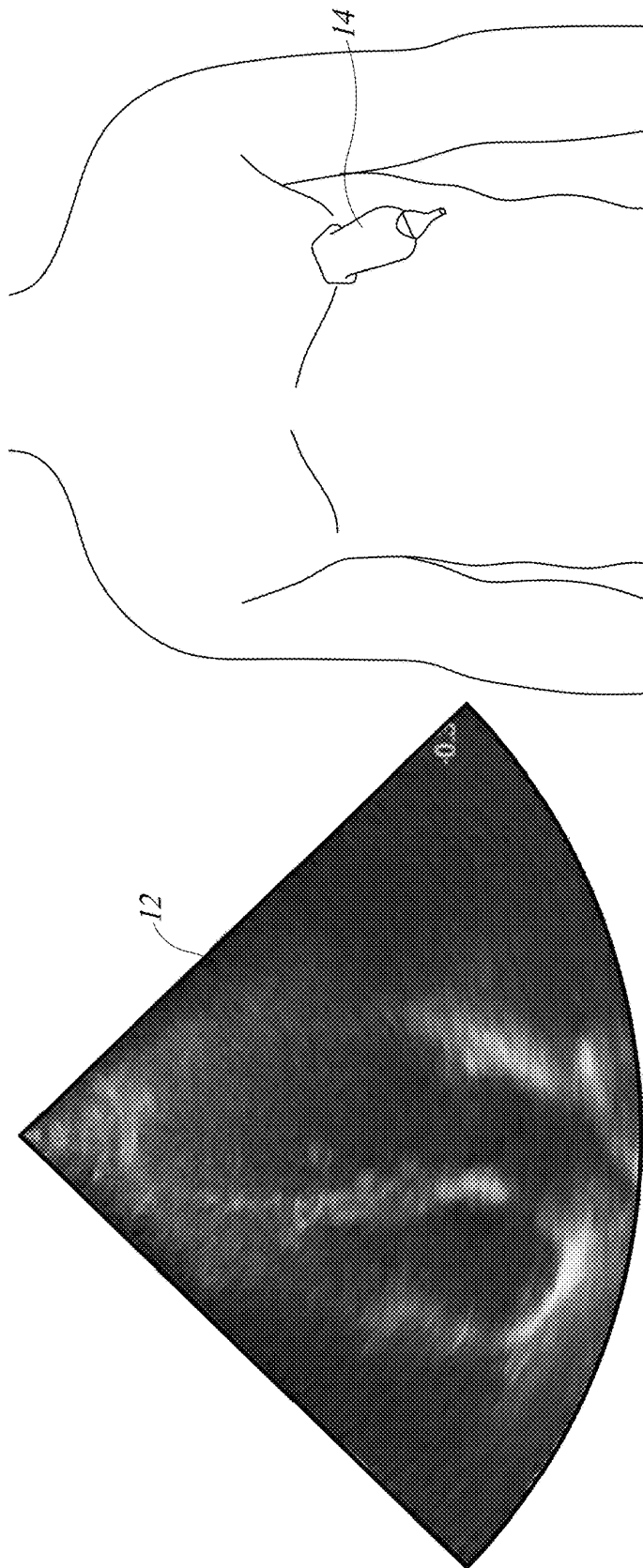


FIG. 1

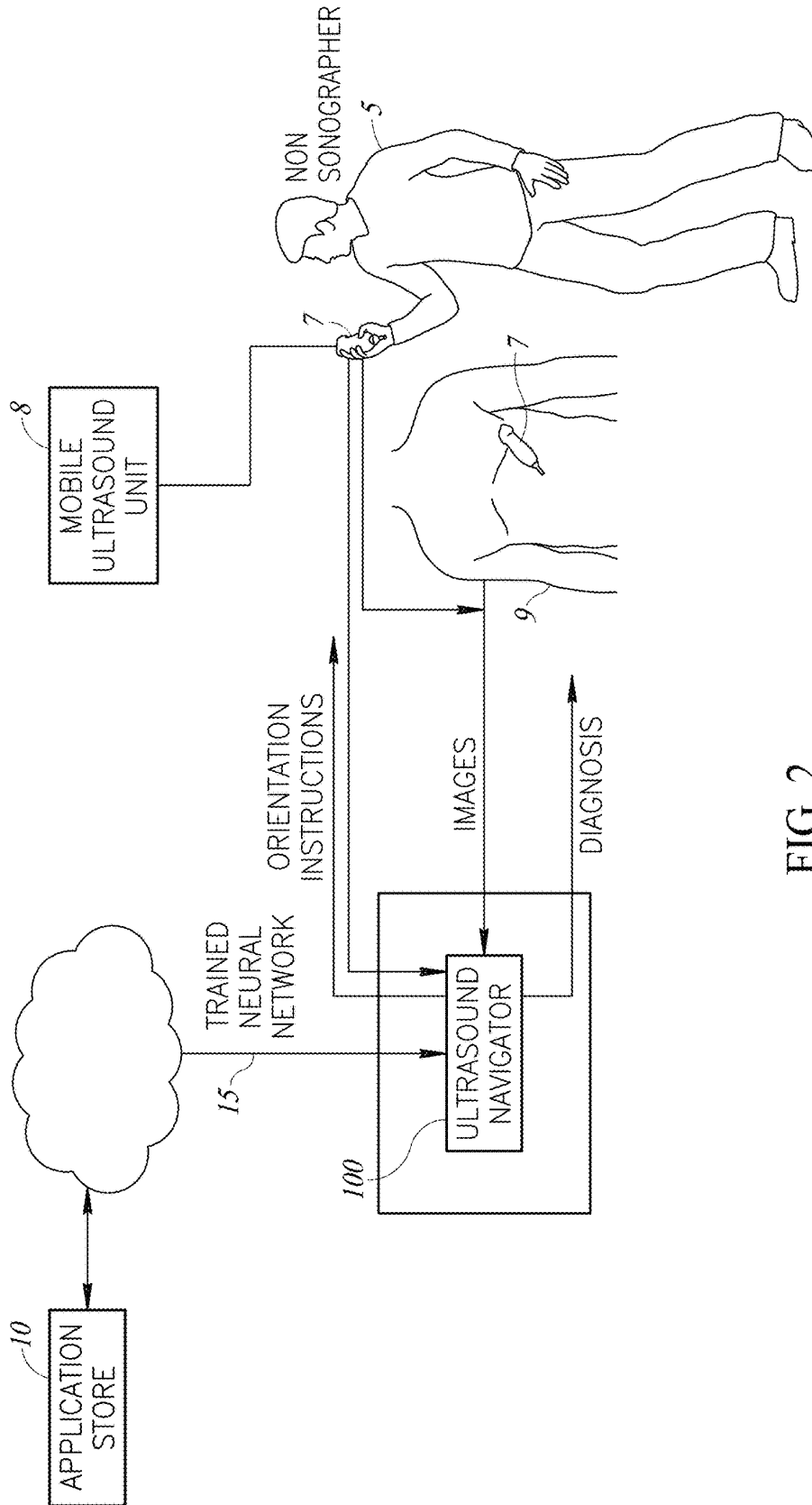


FIG. 2

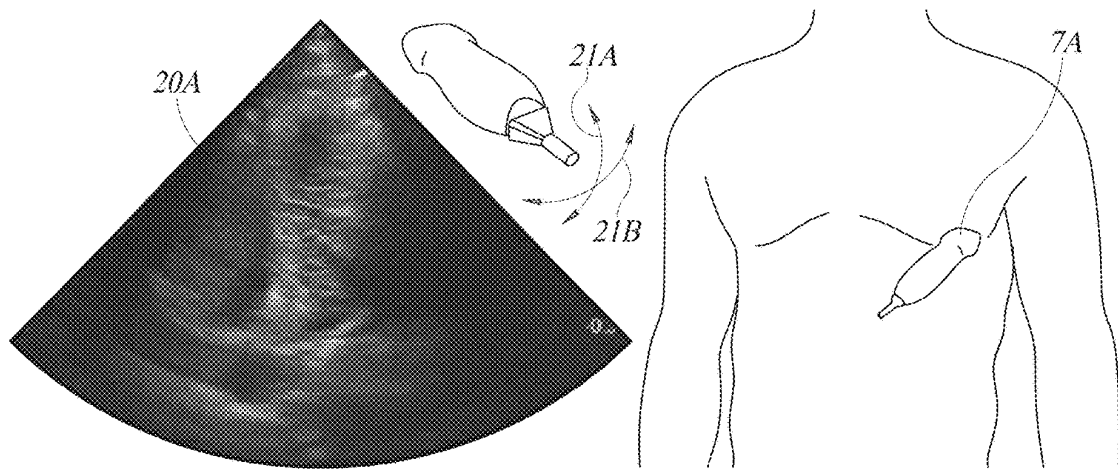


FIG. 3A

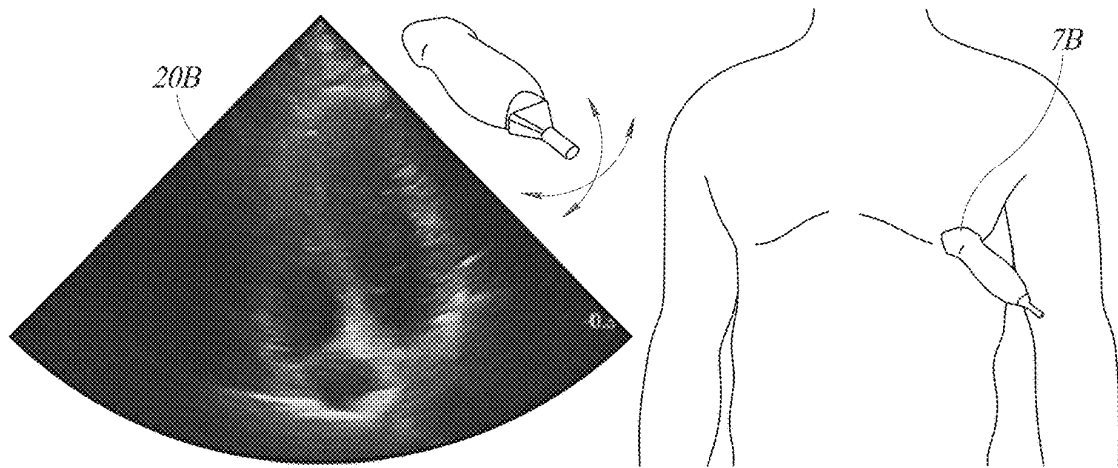


FIG. 3B

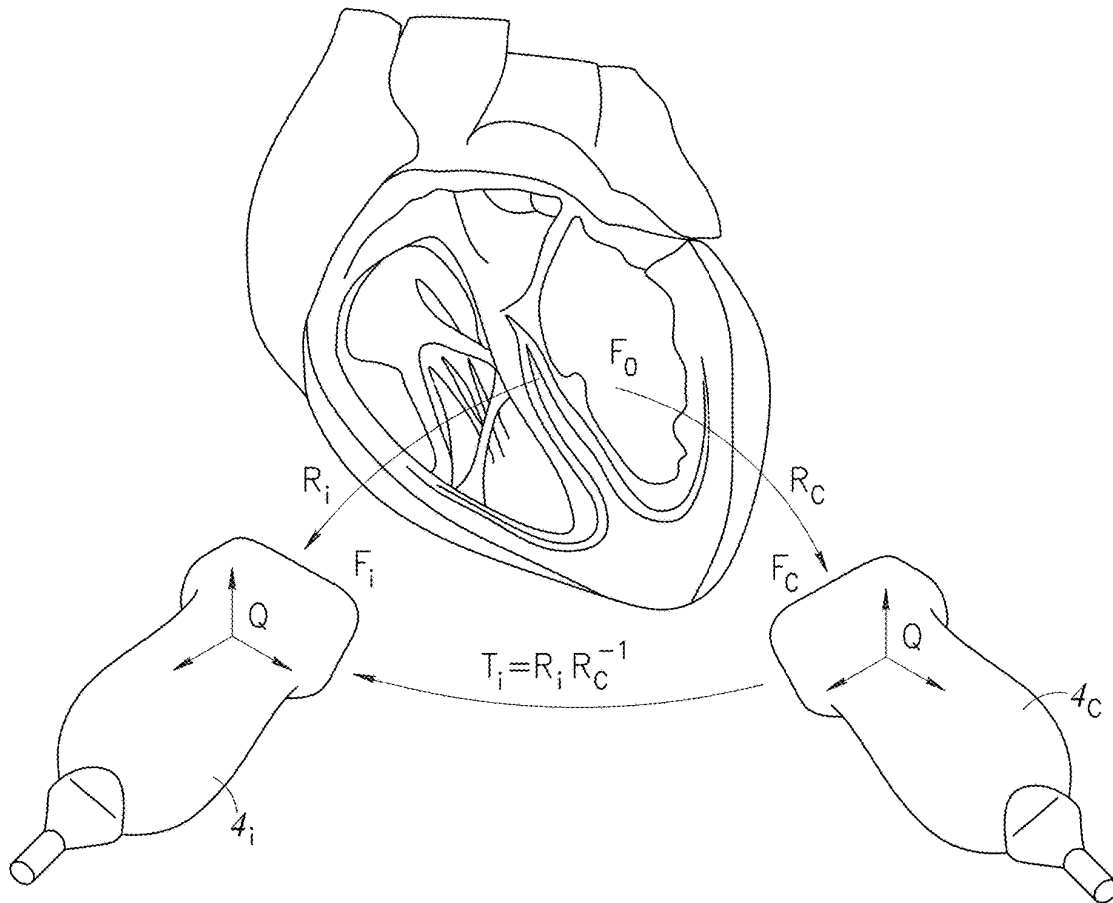


FIG. 4

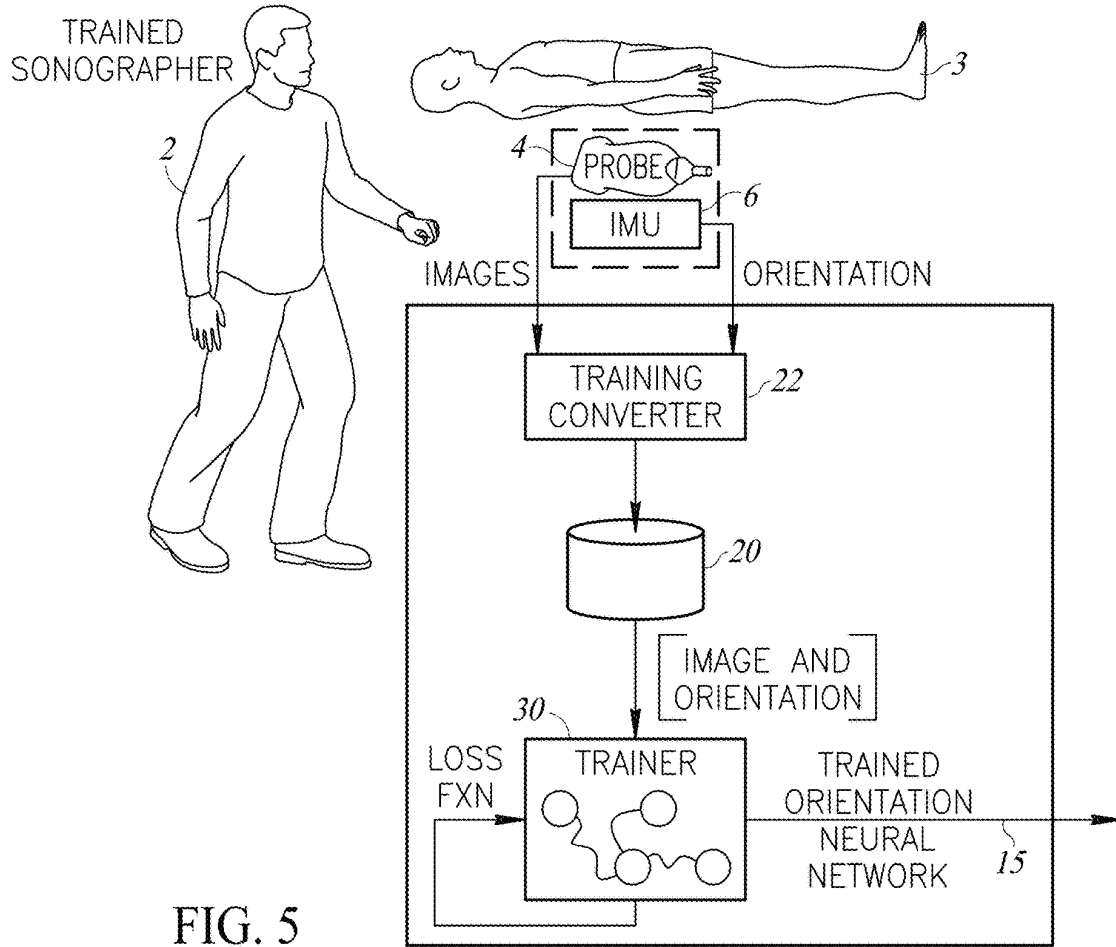


FIG. 5

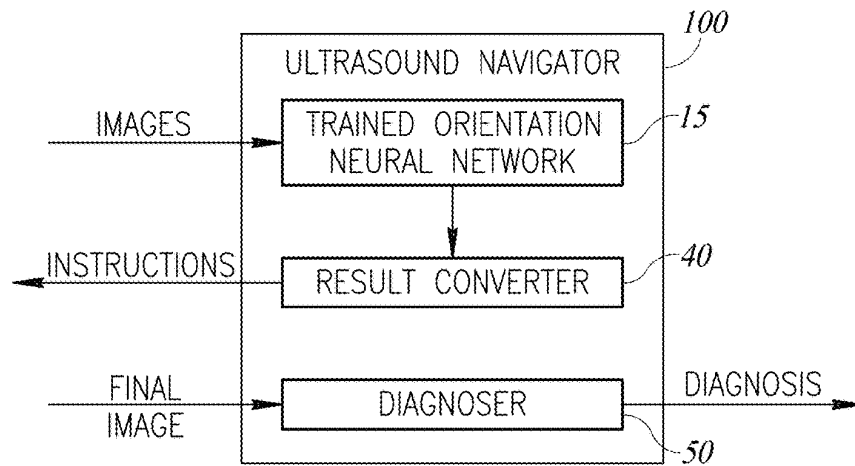


FIG. 6

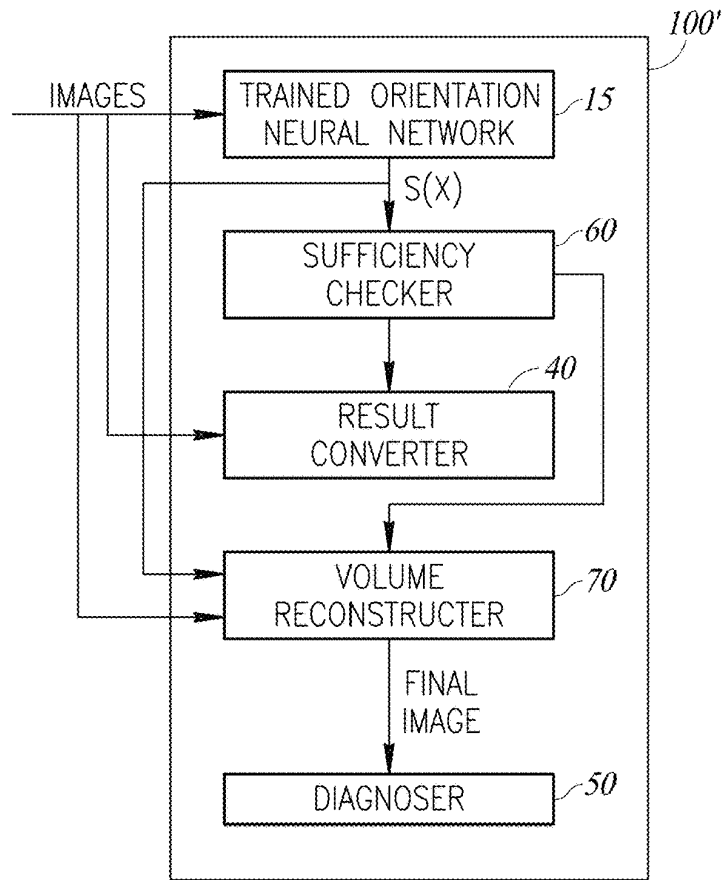


FIG. 7

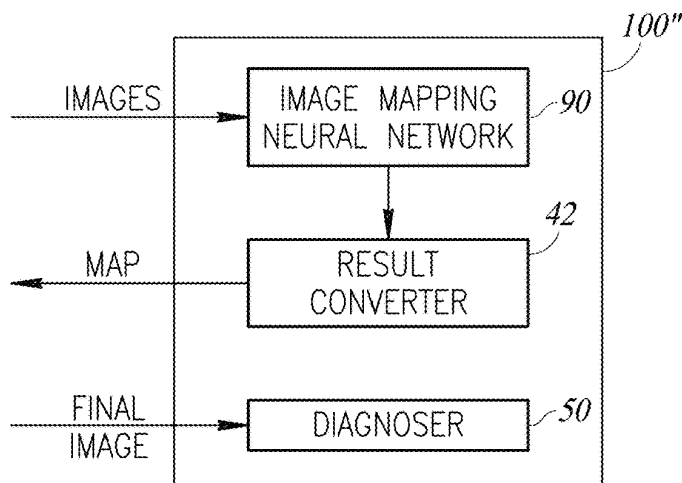


FIG. 8A

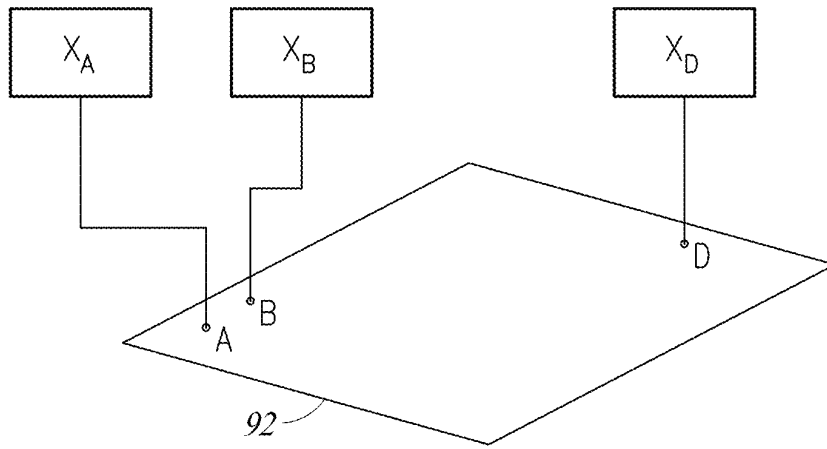


FIG. 8B

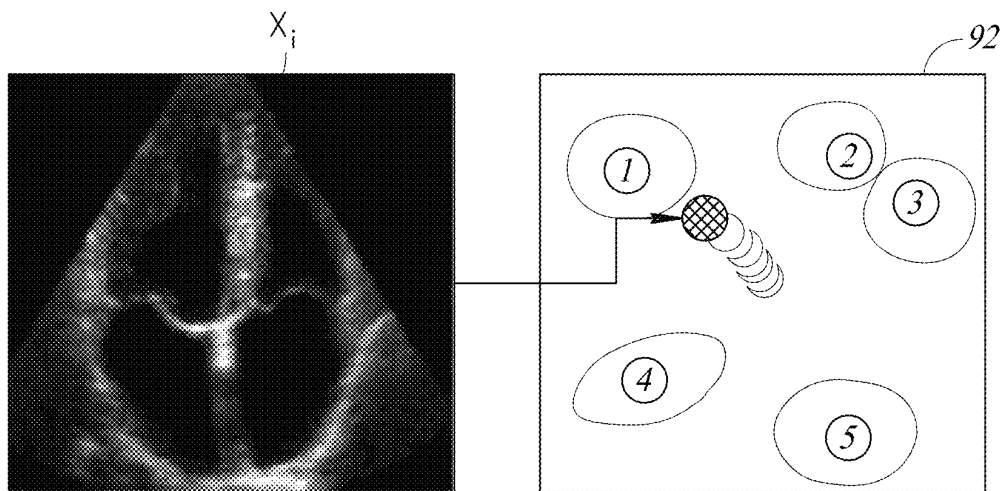


FIG. 8C

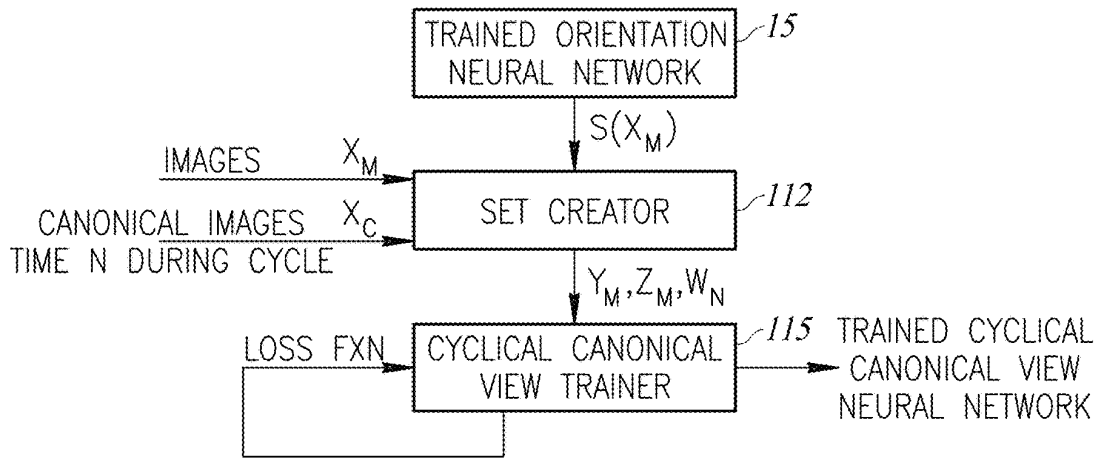


FIG. 9A

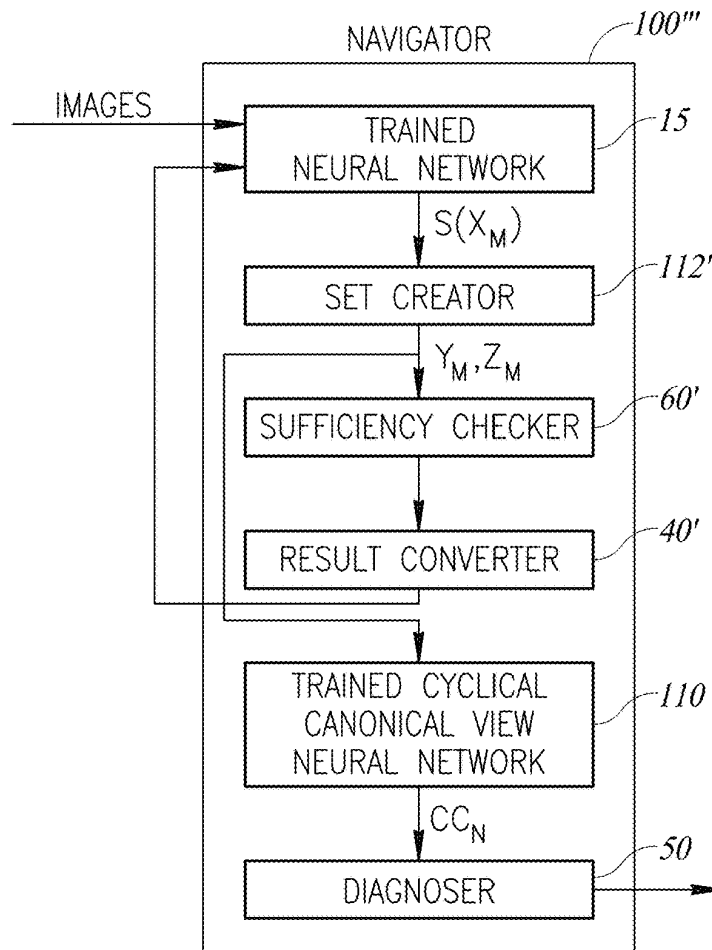


FIG. 9B

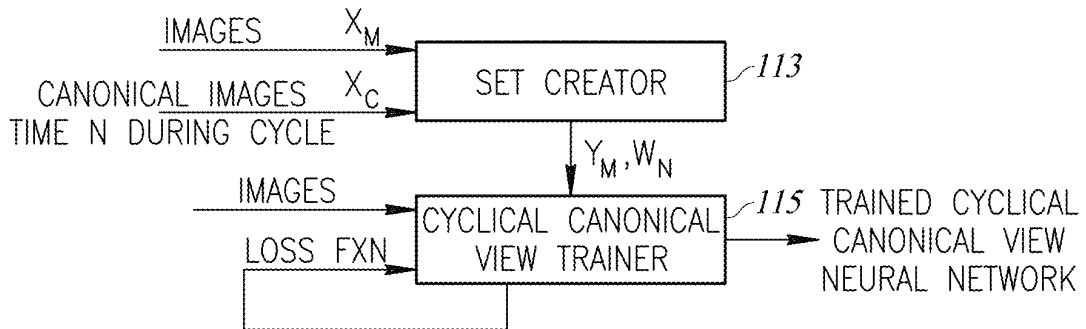


FIG. 10A

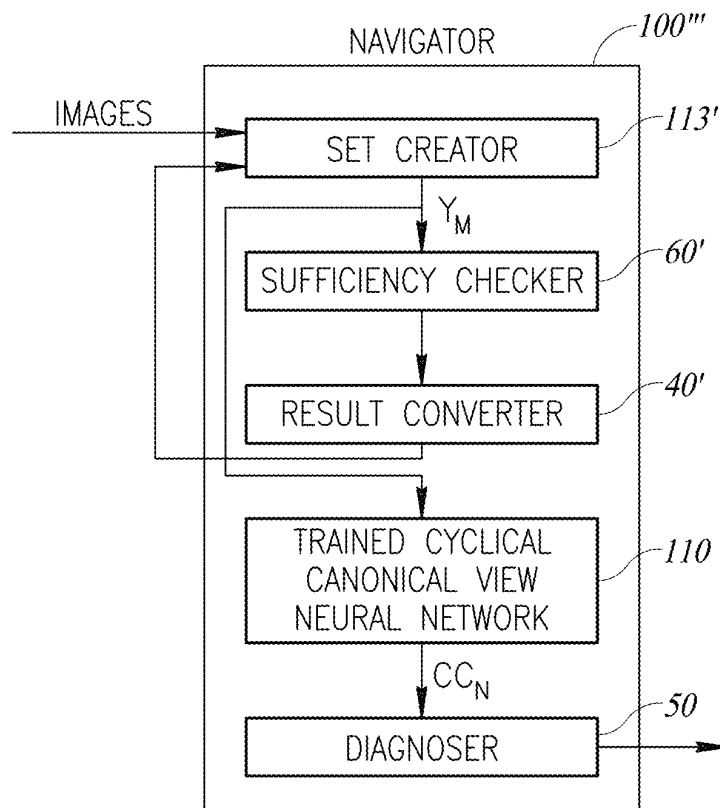


FIG. 10B

SYSTEM AND METHOD FOR ORIENTATING CAPTURE OF ULTRASOUND IMAGES

CROSS REFERENCE TO RELATED APPLICATIONS

This application claims priority from U.S. provisional patent application 62/671,692, filed May 15, 2018, which is incorporated herein by reference.

FIELD OF THE INVENTION

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

BACKGROUND OF THE INVENTION

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.

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.

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.

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.

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.

SUMMARY OF THE PRESENT INVENTION

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.

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.

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.

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 reduce a distance between a calculated transformation produced by the untrained orientation neural network and a ground truth transformation for each non-canonical image.

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

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

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.

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.

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.

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.

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

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

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 reconstructor 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.

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.

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

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.

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.

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.

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.

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.

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.

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.

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.

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.

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.

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

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.

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.

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.

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.

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

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

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 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.

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.

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.

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.

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 similar to the straight, constant speed trajectories.

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.

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.

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

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.

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

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.

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.

Prior art systems such as that described in US Patent Publication No. US2018/0153505 entitled "Guided Navigation of an Ultrasound Probe", published Jun. 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.

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.

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.

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 be integrated or used as an overlay with processing software of the pertinent mobile ultrasound machine

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.

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.

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.

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 F_i 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.

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 F_i , there may be a transformation R_i from the origin O, where the transformation R_c may be a transformation to the desired orientation, labeled F_o , for viewing the canonical image, as follows:

$$R_c = F_o F_o^{-1}$$

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

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

$$T_i = R_i R_c^{-1} = F_i F_o^{-1} (F_o F_o^{-1}) = F_i F_o^{-1} \quad (2)$$

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.

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_o . 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.

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.

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.

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 T_i to each non-canonical image. A loss function “Loss” may be calculated as:

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

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.

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**.

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).

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.

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, published 26 Jul. 2018, assigned to the common assignees of the present invention, and incorporated herein by reference.

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**.

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 $T_{c',i}$.

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

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

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:

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

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.

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

Volume reconstructor **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 X_i produced by probe **7**. In this embodiment, the images X_i may be considered as cross-sections of the body part of interest.

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.

Upon an indication from sufficiency checker **60**, volume reconstructor **70** may generate the 3D/4D volume, after which, reconstructor **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.

Volume reconstructor **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 volumetric 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 X_i from a fixed 2D imaging plane to the 3D orientation Q in space in which probe **4**, was positioned when it produced image X_i .

Volume reconstructor **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 CS_i of the body part. Volume reconstructor **70** may then use tomographic reconstruction to build the volume of the body part of interest from the images cross-sections $CS(X_i)$.

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 reconstructor **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_p , as follows:

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

Volume reconstructor **70** may provide the generated canonical image to diagnoser **50** which may then produce a diagnosis from it, as described hereinabove.

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**.

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**.

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.

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.

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 :

$$\text{Loss} = \text{loss}(M(X_i), M(X_c)) \quad (7)$$

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 j th desired canonical image c . The loss function may then be updated to be:

$$\text{Loss} = \text{loss}(M(X_i), \sum p_{i,j} M(X_c)) \quad (8)$$

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

$$\text{Loss} = \text{loss}(M(X_i), \sum p_{i,j} M(X_c)) + \text{loss}(\text{dist}(X_p, X_j), \|M(X_i) - M(X_j)\|_2) \quad (9)$$

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.

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 diastole and back to systole, for cardiac function analysis.

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 cyclus **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.

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**.

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.

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 $Y_m = \{X_1, X_2, \dots, X_g\}$ and Z_m may consist of the transformation information $S(X)$ of the images Y_m such that $Z_m = \{S(X_1), S(X_2), \dots, S(X_g)\}$. Typically, g may be 10-100 images.

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 .

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:

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

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

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.

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**.

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'**.

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.

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).

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 .

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.

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.

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.

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.

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.

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. It is, therefore, to be understood that the appended claims are intended to cover all such modifications and changes as fall within the true spirit of the invention.

What is claimed is:

1. A portable computing device for a mobile ultrasound unit having an ultrasound probe, the device comprising:
 - a trained orientation neural network to receive a non-canonical image of a body part from said mobile ultrasound unit 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 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.
2. The device according to claim **1** and comprising a trainer 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 device according to claim **2** and wherein said trainer comprises a training converter to receive inertia measurement unit (IMU) data during training sessions from an IMU mounted on a training probe, 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 device according to claim 2 and wherein said trainer 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 device 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 device according to claim 1 wherein said canonical image is one of a plurality of canonical images.

7. The device according to claim 1 and also comprising a diagnoser to make a diagnosis from a final image generated by said probe when viewing said canonical image.

8. The device according to claim 1 and wherein said device is implemented on one of: a smartphone, a tablet, a laptop, a personal computer, and a smart appliance.

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

- a set creator to receive a multiplicity of transformations from said trained orientation neural network in response to images from said 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 said body part during a body part cycle.

10. The navigator according to claim 9 and also comprising a cyclical canonical view trainer 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 cycle.

11. The navigator according to claim 9 wherein said body part cycle is a cardiac cycle.

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

13. A method for a mobile ultrasound unit having an ultrasound probe, implemented on a portable computing device, the method comprising:

- receiving a non-canonical image of a body part from said mobile ultrasound unit and generating, using a trained orientation neural network, 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 of said probe and providing and

displaying said orientation instructions to said user to change the position and rotation of said probe.

14. The method according to claim 13 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.

15. The method according to claim 14 and wherein said training comprises receiving inertia measurement unit (IMU) data during training sessions from an IMU mounted on a training probe, 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.

16. The method according to claim 14 and wherein said trained mapping neural network comprises a loss function to ensure that changes in the motion of said probe generate small motions on said 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.

17. The method according to claim 16 wherein said loss function additionally includes a probability to constrain said calculated transformation to one of a plurality of different canonical orientations.

18. The method according to claim 13 wherein said canonical image is one of a plurality of canonical images.

19. The method according to claim 13 and also comprising making a diagnosis from a final image generated by said probe when viewing said canonical image.

20. The method according to claim 13 and wherein said portable computing device is one of: a smartphone, a tablet, a laptop, a personal computer, and a smart appliance.

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

- receiving a multiplicity of transformations from said trained orientation neural network in response to images from said 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 said body part during a body part cycle.

22. The method according to claim 21 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 cycle.

23. The method according to claim 21 wherein said body part cycle is a cardiac cycle.

24. The method according to claim 21 wherein each set has a single element therein.

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