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(54) **ULTRASOUND IMAGING SYSTEM WITH A NEURAL NETWORK FOR IMAGE FORMATION AND TISSUE CHARACTERIZATION**

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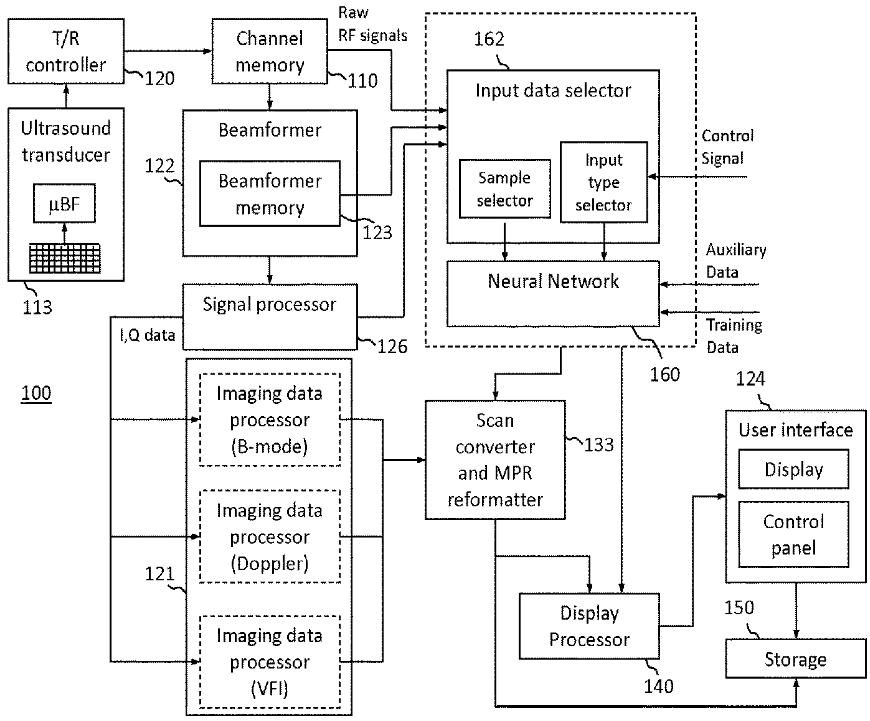
(57) **ABSTRACT**

An ultrasound imaging system according to the present disclosure may include or be operatively associated with an ultrasound transducer configured to acquire echo signals responsive to ultrasound pulses transmitted toward a medium. The system may include a channel memory configured to store the acquired echo signals, a neural network coupled to the channel memory and configured to receive one or more samples of the acquired echo signals, one or more samples of beamformed signals based on the acquired echo signals, or both, and to provide imaging data based on the one or more samples of the acquired echo signals, the one or more samples of beamformed signals, or both, and may further include a display processor configured to generate an ultrasound image using the imaging data provided by the neural network. The system may further include a user interface configured to display the ultrasound image produced by the display processor.



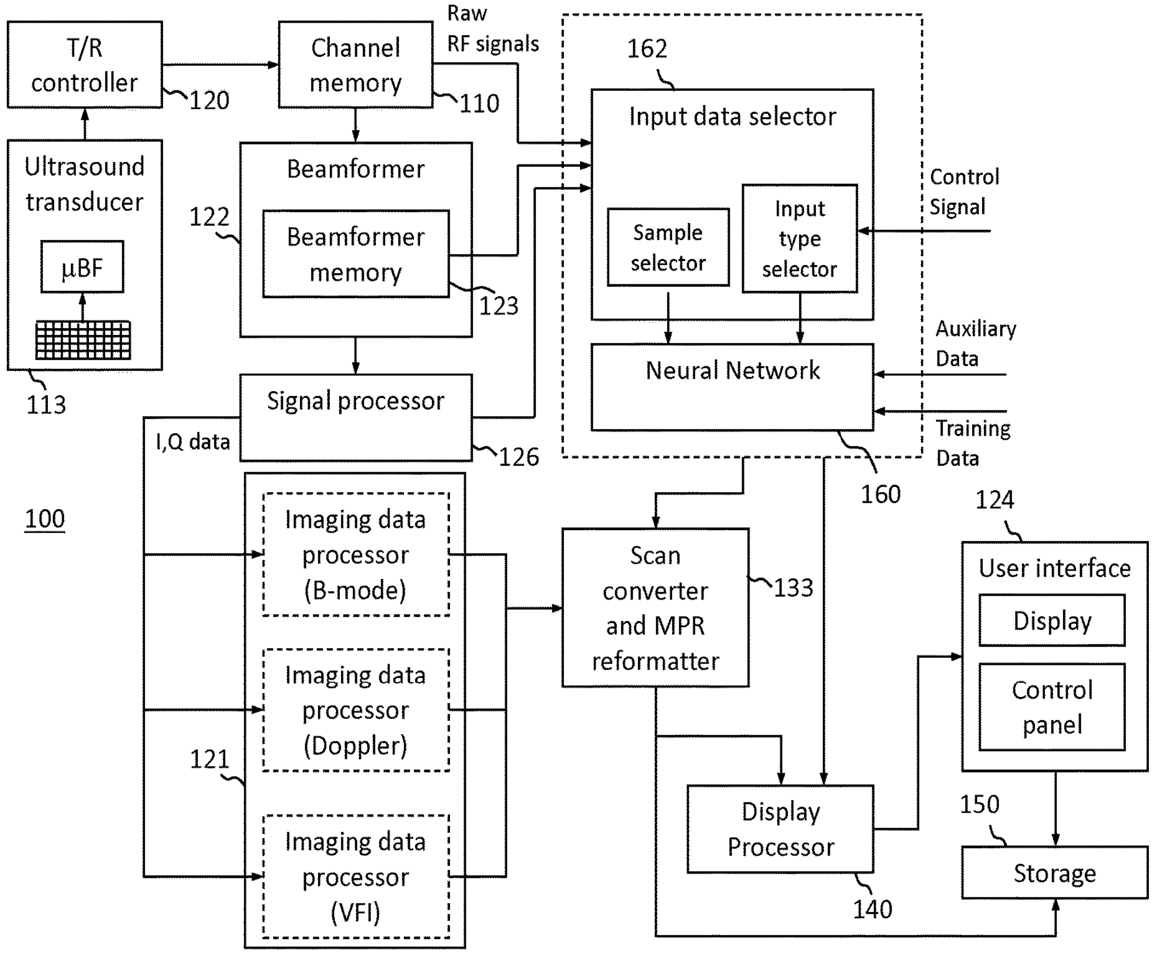

T/R controller
120
Channel memory
Raw RF signals
110
162
Input data selector
Ultrasound transducer
μBF
Beamformer
122
Beamformer memory
123
Sample selector
Input type selector
Control Signal
Auxiliary Data
Neural Network
113
Signal processor
I,Q data
126
Training Data
160
100
Imaging data processor (B-mode)
Scan converter and MPR reformatter
133
124
User interface
Display
Control panel
Imaging data processor (Doppler)
121
150
Imaging data processor (VFI)
Display Processor
Storage
140

FIG. 1

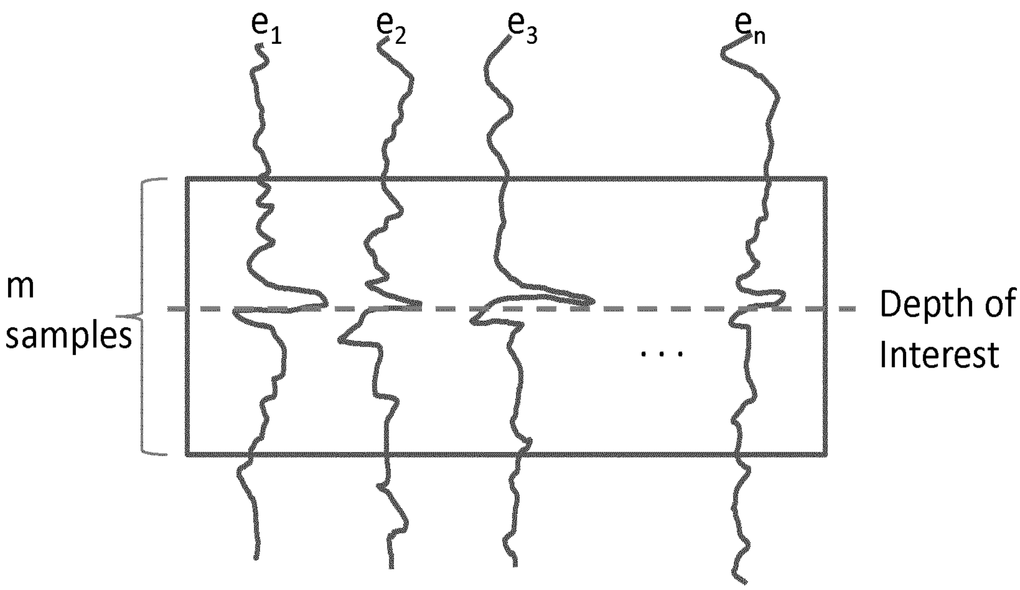


FIG. 2

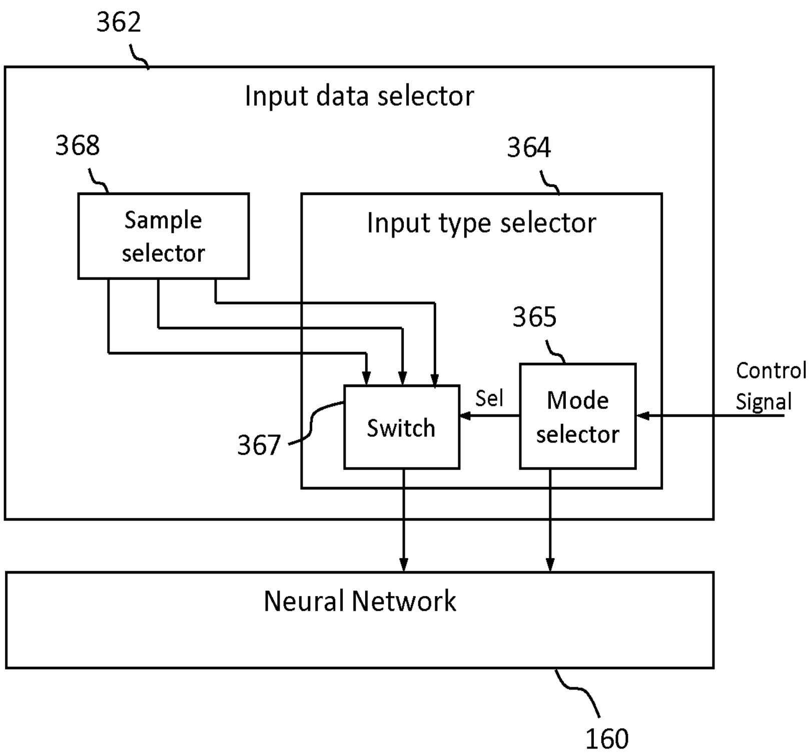

362
Input data selector
368
364
Sample selector
Input type selector
365
Sel
Mode selector
Control Signal
Switch
367
Neural Network
160

FIG. 3

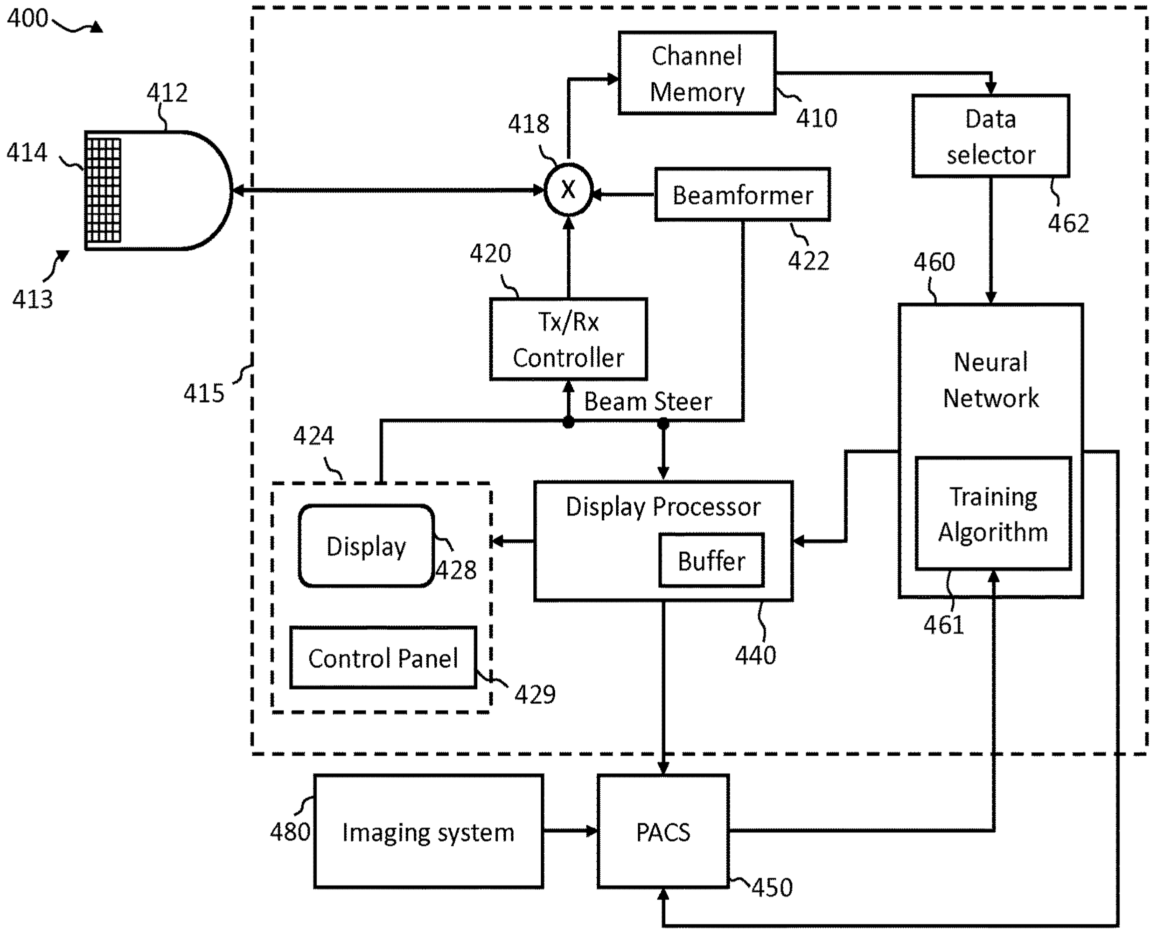

400
412
414
413
415
418
Channel Memory
410
Data selector
462
Beamformer
422
420
Tx/Rx Controller
Beam Steer
460
Neural Network
Training Algorithm
461
424
Display
428
Control Panel
429
Display Processor
Buffer
440
480
Imaging system
PACS
450

FIG. 4

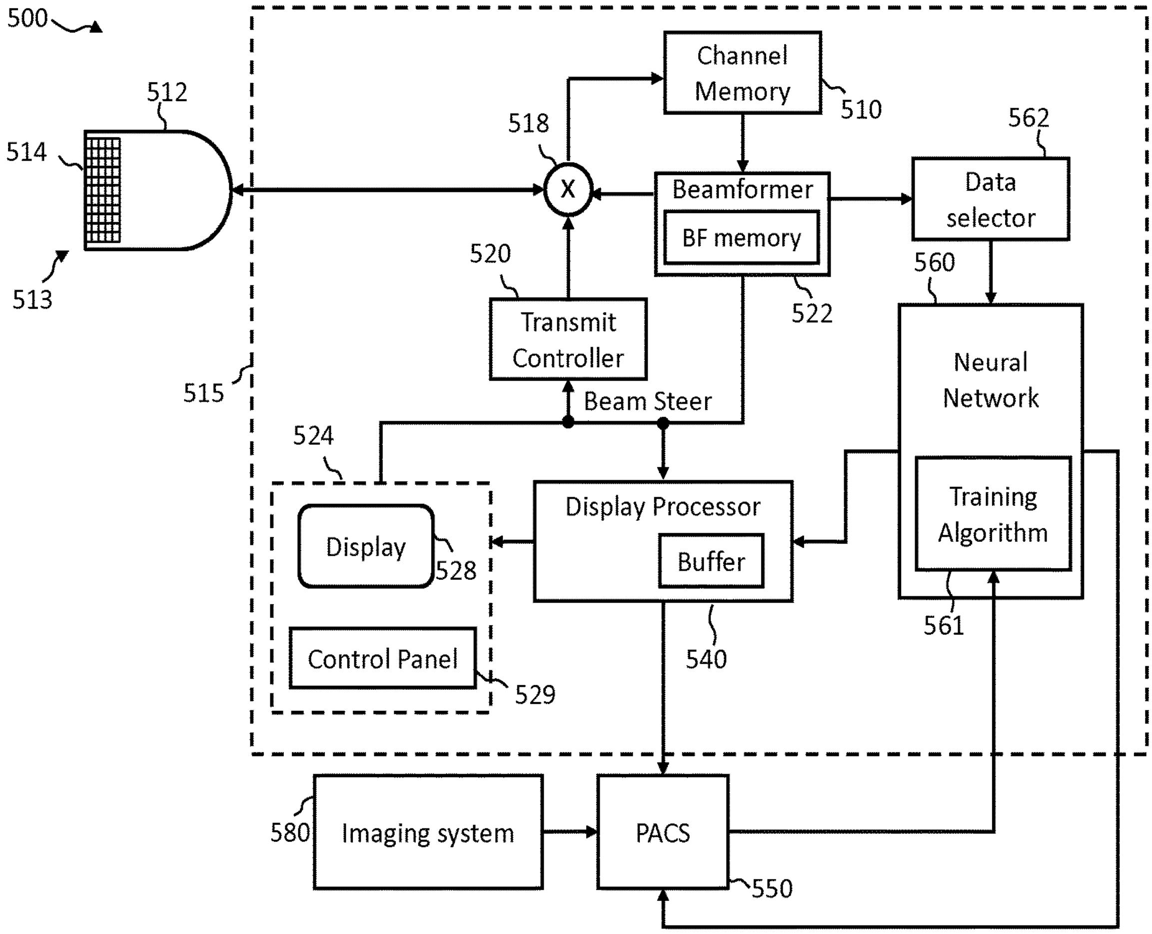

500
512
514
513
515
518
Channel Memory
510
Beamformer
BF memory
522
562
Data selector
560
520
Transmit Controller
Beam Steer
Neural Network
Training Algorithm
561
524
Display
528
Control Panel
529
Display Processor
Buffer
540
580
Imaging system
PACS
550

FIG. 5

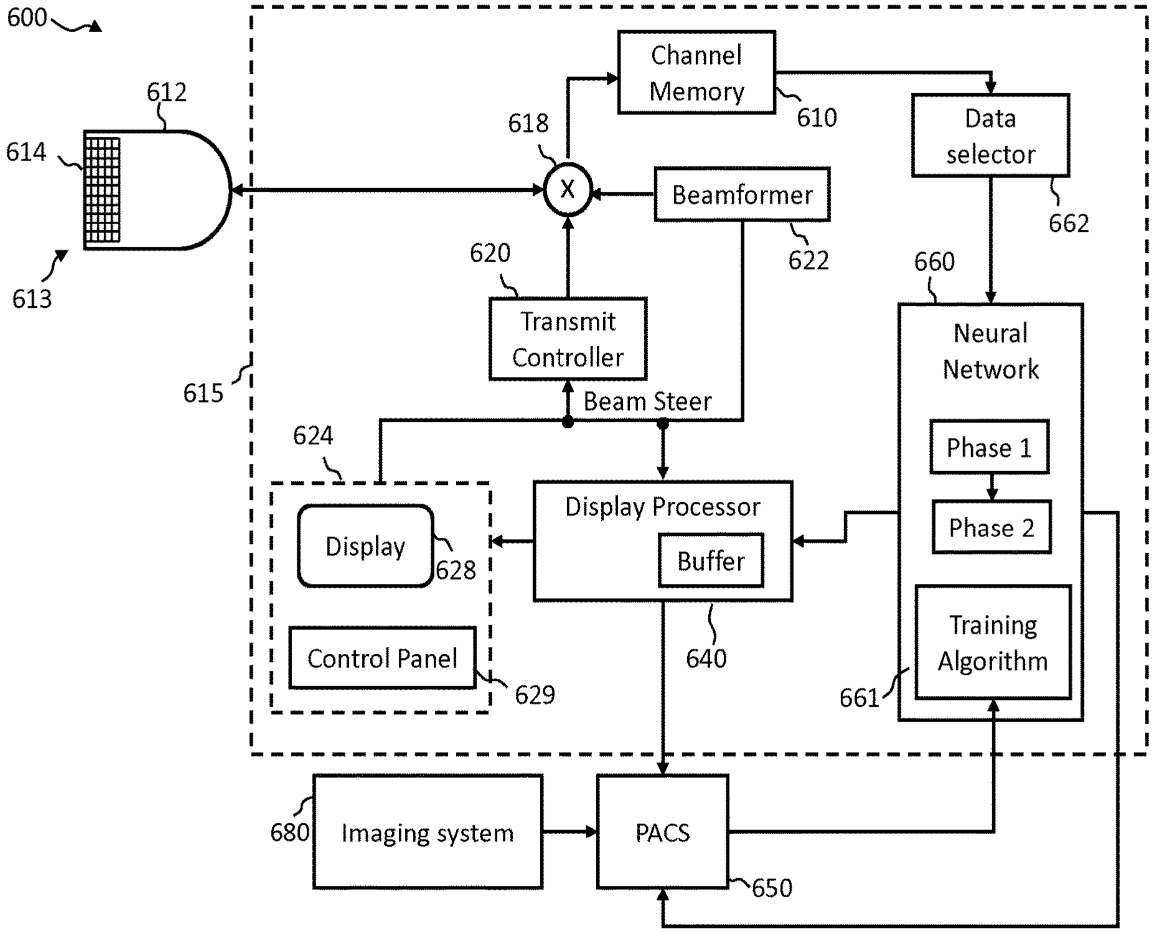

600
612
614
613
615
618
Channel Memory
610
Data selector
662
Beamformer
622
620
Transmit Controller
Beam Steer
660
Neural Network
Phase 1
Phase 2
Training Algorithm
661
624
Display
628
Control Panel
629
Display Processor
Buffer
640
680
Imaging system
PACS
650

FIG. 6

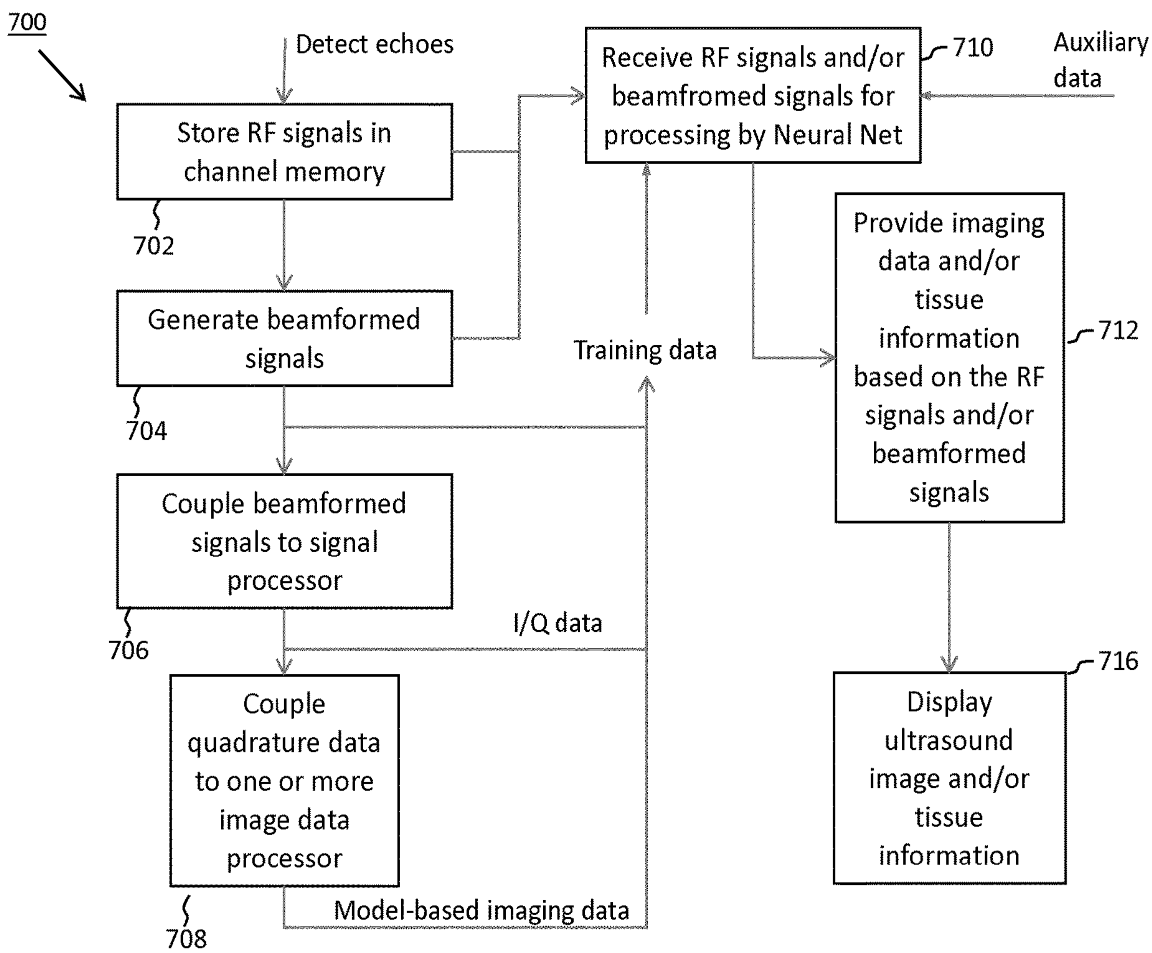

700
Detect echoes
Store RF signals in channel memory
702
Generate beamformed signals
704
Couple beamformed signals to signal processor
706
I/Q data
Couple quadrature data to one or more image data processor
708
Model-based imaging data
Training data
Receive RF signals and/or beamfromed signals for processing by Neural Net
710
Auxiliary data
Provide imaging data and/or tissue information based on the RF signals and/or beamformed signals
712
Display ultrasound image and/or tissue information
716

FIG. 7

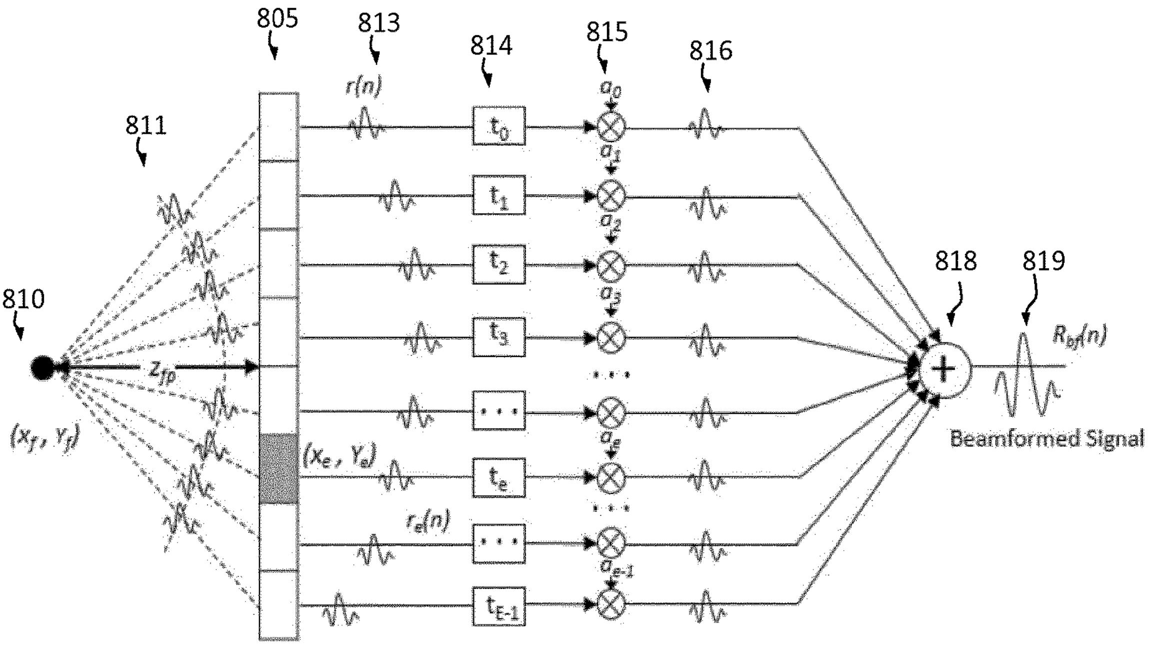

805
813
814
815
816
811
r(n)
t_0
a_0
a_1
t_1
a_2
t_2
a_3
t_3
818
819
810
z_{fp}
$R_{bf}(n)$
(x_f, y_f)
Beamformed Signal
(x_e, y_e)
a_e
t_e
$r_e(n)$
a_{e-1}
t_{E-1}

FIG. 8

ULTRASOUND IMAGING SYSTEM WITH A NEURAL NETWORK FOR IMAGE FORMATION AND TISSUE CHARACTERIZATION

TECHNICAL FIELD

[0001] The present disclosure pertains to ultrasound systems and methods for obtaining ultrasonic images and/or tissue information using a neural network.

BACKGROUND

[0002] Ultrasound is a widely used imaging modality in medical imaging as it can provide real-time non-invasive imaging of organs and tissue for diagnosis, pre-operative care and planning, and post-operative patient monitoring. In a conventional ultrasound imaging system, a transducer probe transmits ultrasound toward the tissue to be imaged and detects echoes responsive to the ultrasound. Acquired echo signals (also referred to as radio frequency or RF signals) are passed through a series of signal processing components, including for example a beamformer which combines raw channel data (e.g., RF signals from multiple transducer elements) or partially beam-formed signals of patches of transducer elements into fully beamformed signals, a demodulator which extracts quadrature signals from the beamformed signals, and one or more filters, to produce an image data (e.g., pixel information that may be used to produce a 2D or 3D ultrasound image). The various signal processing components of a conventional ultrasound system implement model-based algorithms in order to transform the input signal to a desirable output. That is, the signal processing components of a conventional ultrasound system have been pre-programmed to manipulate the input signals to produce an output based on our understanding of ultrasound physics.

[0003] For example, a conventional beamformer may perform delay and sum beamforming (see FIG. **8**). As shown in FIG. **8**, the beamformer receives the per-channel RF signals **813**, which correspond to echoes **811** of a reflector **810** as detected by elements **805** of the array. The raw RF signals **813** are then delayed by an appropriate amount of time **814**to temporally align them (as shown at **816**) and then combined (at **818**) into a beamformed signal **819**, which may also be referred to as beamformed RF signal or summed RF signal. In some cases, the temporally aligned signals may be multiplied by a factor (as shown at **815**) before they are summed In some cases, a microbeamformer may be included, for example in the transducer probe, which performs partial beamforming of signals received by patches of elements (e.g., a subset of the elements detecting echoes in any given transmit/receive cycle) and thereby reduces the number of channel inputs into the main beamformer. The beamformed signals are typically coupled to further downstream signal processing components to extract information about the signal properties, such as signal intensity or power or, in the case of Doppler imaging, for extracting frequency shift data from multiple temporal samples of RF data in order to obtain fluid velocity information, which information is then processed for generating images based on the signal properties.

[0004] Conventional ultrasound system, while providing a significant advancement in medical imaging, may still benefit from further improvements. For example, conventional signal processing components (e.g., beamformers and other signal and image processors) rely on and implement our understanding of ultrasound into hard-wired circuitry or pre-programmed general purpose processors. Thus, these conventional signal processing components are not particularly adaptive and may be limited by hardware limitations or the imperfections in the physical models implemented thereon. Therefore, improvements in this area may be desirable. Also, current ultrasound systems generally require the user to carefully watch the ultrasound system display, coordinate transducer movements and manipulate user controls to precisely record the desired anatomy or pathology of interest. After capturing the desired images the user will typically review the images and manually annotate specific anatomy or pathology. Techniques for simplifying operation of an ultrasound imaging system without sacrificing image and/or diagnostic information quality may thus also be desirable.

SUMMARY

[0005] The present disclosure describes a system which utilizes a machine-trained neural networks (e.g., a machine-trained algorithm) developed through one or more machine learning algorithms to output image data and/or a variety of tissue information. In some embodiments, the neural network may be a deep neural network capable of analyzing patterns using a with a multi-dimensional (2-or more dimensional) data set, which may also be thought of as localized data sets, and where the location of data within the data set and the data values may both contribute to the analyzed result.

[0006] An ultrasound imaging system according to the present disclosure may include or be operatively associated with an ultrasound transducer configured to acquire echo signals responsive to ultrasound pulses transmitted toward a medium. The system may include a channel memory configured to store the acquired echo signals, a neural network coupled to the channel memory and configured to receive one or more samples of the acquired echo signals, one or more samples of beamformed signals based on the acquired echo signals, or both, and to provide imaging data based on the one or more samples of the acquired echo signals, the one or more samples of beamformed signals, or both, and may further include a display processor configured to generate an ultrasound image using the imaging data provided by the neural network. The system may further include a user interface configured to display the ultrasound image produced by the display processor.

[0007] In some embodiments, the system may include a data selector configured to select a subset of echo signals from the acquired echo signals stored in the channel memory and provide the subset of echo signals to the neural network, wherein the echo signals in the subset are associated with adjacent points within a region of imaged tissue. In some such embodiments, the system may further include a beamformer configured to receive a set of the echo signals from the acquired echo signals and to combine the set of echo signals into a beamformed RF signal, wherein the neural network is further configured to receive the beamformed RF signal and to provide imaging data based, at least in part, on the beamformed RF signal. In some such embodiments, the data selector may be further configured to selectively couple the subset of echo signals or the beamformed RF signal to the neural network to as input data based on a control signal

received by the data selector. In some embodiments, the control signal may be generated responsive to user input. In other embodiments, the control signal may be based at least in part on the imaging mode during acquisition of the echo signals.

[0008] In some embodiments, the neural network may include a deep neural network (DNN), a convolutional neural network (CNN), or a combination thereof. In some embodiments, the imaging data provided by the neural network may include B-mode imaging data which may be used by the display processor to produce an anatomy ultrasound image (e.g., a grayscale also referred to as B-mode image), and/or it may include Doppler imaging data, which may be used to produce a flow image (e.g., a colorflow Doppler image, a spectral Doppler image, or a color power angio image). In yet further examples, the imaging data may include vector flow imaging data, which may be used to produce a flow image providing a graphical representation of transmit-beam-independent velocities of the tissue (e.g., blood flow) within the field of view. In yet further embodiments, the imaging data may include tissue strain imaging data, wall shear stress data associated with an anatomical structure containing a fluid therein, contrast-enhanced imaging data (e.g., imaging data identifying the presence of ultrasound contrast media, such as microbubbles or another ultrasound contrast medium, in the imaged regions), or any combinations thereof.

[0009] In some embodiments, the neural network may be further configured to receive auxiliary data as input, which may include ultrasound transducer configuration information, beamformer configuration information, information about the medium, or combinations thereof, and the imaging data provided by the neural network may be further based on the auxiliary data.

[0010] In some embodiments, the neural network may be operatively associated with a training algorithm configured to receive an array of training inputs and known outputs, wherein the training inputs include echo signals, beamformed signals, or combinations thereof associated with a region of imaged tissue and the known outputs include known properties of the imaged tissue. In some such embodiments, the known properties provided to the training algorithm may be obtained using an imaging modality other than ultrasound, for example magnetic resonance imaging (MRI), computed tomography (CT), or other currently known or later developed imaging modalities. In some embodiments, the neural network may be implemented in hardware, for example where each or at least some of the nodes of the network are represented by hard-wired electrical pathways in an integrated circuit (e.g., an application specific integrated circuit (ASIC). In some embodiments, the neural network may be implemented, at least in part, in a computer-readable medium comprising executable instructions which when executed by a processor coupled to the channel memory, the beamformer, or both, cause the processor to perform a machine-trained algorithm to produce the imaging data based on the one or more samples of the acquired echo signals, the one or more samples of beamformed signals, or both.

[0011] According to further embodiments, an ultrasound imaging system of the present disclosure may be operatively associated with an ultrasound transducer which is operable to acquire echo signals responsive to ultrasound pulses transmitted by the transducer toward a medium and the system may include channel memory which stores the acquired echo signals, a neural network configured to receive an input array comprising samples of the acquired echo signals corresponding to a location within a region of imaged tissue and trained to propagate the input through the neural network to estimate pixel data associated with the location within the region of imaged tissue, and a display processor configured to generate an ultrasound image including the location within the region of imaged tissue using the pixel data provided by the neural network.

[0012] In some embodiments, the neural network may be trained to output pixel data indicative of intensities of the echo signals in the samples provided to the neural network. In some embodiments, the neural network may be trained to output pixel data indicative of Doppler frequencies associated with the echo signals in the samples provided to the neural network. In yet further embodiments, the neural network may be trained to output pixel data indicative of tissue strain within the imaged region, wall shear stress of a bodily structure within the imaged region, multi-component velocity information about flow within the imaged region, or any combinations thereof. In some embodiments, the display processor may be configured to buffer multiple sets of pixel data, each associated with a sub region within a field of view of the ultrasound transducer and accompanied by spatial information indicative of the sub region within the field of view of the ultrasound transducer, and to construct the ultrasound image by arranging the sets of pixel data based on their spatial information. In some embodiments, the neural network may include a plurality of propagation pathways including a first pathway configured to output first pixel data indicative of intensities of the echo signals in the samples and a second pathway configured to output second pixel data indicative of Doppler frequencies associated with the echo signals in the samples, and the display processor may be configured to generate an ultrasound image comprising an overlay of image components including a first image component comprising an anatomy image generated using the first pixel data and a Doppler image generated using the second pixel data.

[0013] According to further embodiments, an ultrasound imaging system of the present disclosure may be operatively associated with an ultrasound transducer which is operable to acquire echo signals responsive to ultrasound pulses transmitted by the transducer toward a region of interest in a medium, and the system may include a channel memory configured to store the acquired echo signals, a beamformer configured to receive to sets of the acquired echo signals and generate beamformed RF signals corresponding to scan lines or scan regions within the medium, a neural network configured to receive an input array comprising samples of the beamformed RF signals and trained to propagate the input through the neural network to estimate pixel data associated with the plurality of scan lines or scan regions within the medium, and a display processor configured to generate an ultrasound image of the region of interest using the pixel data provided by the neural network. In some such embodiments, the beamformer may include a beamformer memory configured to store a plurality of beamformed RF signals generated over multiple transmit-receive cycles. In some such embodiments, the neural network may be trained to output first pixel data indicative of intensities of the sets of echo signals, second pixel data indicative of Doppler frequencies associated with the sets echo signals, or both, and the display processor may be configured to generate an ultrasound image including an anatomy image component generated using the first pixel data, a flow image component generated using the second pixel data, or an overlay image wherein the anatomy image is overlaid with a spatially-corresponding flow image component.

[0014] A method of ultrasound imaging according to the present disclosure may include generating echo signals responsive to ultrasound transmitted by a transducer operatively coupled to an ultrasound system, storing the echo signals in channel memory, beamforming a plurality of the echo signals from the channel memory to produce beamformed signals, coupling samples of the echo signals, the beamformed signals, or a combination thereof, to a neural network trained to output imaging data responsive to the samples the echo signals, the beamformed signals, or a combination thereof, and generating an ultrasound image based, at least in part, on the imaging data produced provided by the neural network. The imaging data output by the neural network may include B-mode imaging data, Doppler imaging data, vector flow imaging data, strain imaging data, wall shear stress of an anatomical structure containing a fluid therein, contrast-enhanced imaging data, or any combinations thereof. In some embodiments, the step of coupling samples of the echo signals, the beamformed signals, or a combination thereof, comprises coupling the samples to a deep neural network (DNN) or a convolutional neural network (CNN). In some embodiments, the step of coupling samples of the echo signals, the beamformed signals, or a combination thereof, comprises selectively coupling, responsive to user input, echo signals or beamformed signals as input data to the neural network, and selecting a corresponding operational mode of the neural network based on the selected input data. In some embodiments, the selecting of the operational mode may be based on user input or it may be automatic by the system, such as based on an imaging mode of the ultrasound system during acquisition of the echo signals. In some embodiments, the method may further include training the neural network using imaging data obtained from an imaging modality other than ultrasound. In some embodiments, the method may further include beamforming the echo signals, demodulating the beamformed signals to obtain quadrature data, generating sets of training ultrasound images based on the quadrature data, and using the acquired echo signals and corresponding training ultrasound images to further train the neural network.

[0015] Any of the methods described herein, or steps thereof, may be embodied in non-transitory computer-readable medium comprising executable instructions, which when executed may cause a processor of a medical imaging system to perform method or steps embodied therein.

BRIEF DESCRIPTION OF THE DRAWINGS

[0016] FIG. **1** is block diagram of an ultrasound system in accordance with principles of the present inventions.

[0017] FIG. **2** is an illustration of aspects of input data selection for a neural network in accordance with principles of the present inventions.

[0018] FIG. **3** is block diagram of an input data selector accordance with further principles of the present inventions.

[0019] FIG. **4** is block diagram of an ultrasound system in accordance with some examples of the present invention.

[0020] FIG. **5** is block diagram of another ultrasound system in accordance with further examples of the present inventions.

[0021] FIG. **6** is block diagram of yet another ultrasound system in accordance with the principles of the present inventions.

[0022] FIG. **7** is a flow diagram of a process of producing ultrasound images in accordance with the principles of the present inventions.

[0023] FIG. **8** is an illustration of conventional beamforming technique.

DESCRIPTION

[0024] The following description of certain exemplary embodiments is merely exemplary in nature and is in no way intended to limit the invention or its applications or uses. In the following detailed description of embodiments of the present systems and methods, reference is made to the accompanying drawings which form a part hereof, and in which are shown by way of illustration specific embodiments in which the described systems and methods may be practiced. These embodiments are described in sufficient detail to enable those skilled in the art to practice the presently disclosed systems and methods, and it is to be understood that other embodiments may be utilized and that structural and logical changes may be made without departing from the spirit and scope of the present system. Moreover, for the purpose of clarity, detailed descriptions of certain features will not be discussed when they would be apparent to those with skill in the art so as not to obscure the description of the present system. The following detailed description is therefore not to be taken in a limiting sense, and the scope of the present system is defined only by the appended claims.

[0025] An ultrasound system according to the present disclosure may utilize a neural network, for example a deep neural network (DNN), a convolutional neural network (CNN) or the like, to bypass certain processing steps in conventional ultrasound imaging. In some examples, the neural network may be trained using any of a variety of currently known or later developed machine learning techniques to obtain a neural network (e.g., a machine-trained algorithm or hardware-based system of nodes) that are able to derive or calculate the characteristics of an image for display from raw channel data (i.e., acquired radio frequency (RF) echo signals) or in some cases, from partially- or fully-beamformed signals. Neural networks may provide an advantage over traditional forms of computer programming algorithms in that they can be generalized and trained to recognize data set features by analyzing data set samples rather than by reliance of specialized computer code. By presenting appropriate input and output data to a neural network training algorithm, the neural network of an ultrasound system according to the present disclosure can be trained to produce images and/or tissue characterization and diagnostic information (e.g., flow information, tissue content or type, strain/stress data, etc.) without the need for a physically-derived model to guide system operation.

[0026] An ultrasound system in accordance with principles of the present invention may include or be operatively coupled to an ultrasound transducer configured to transmit ultrasound pulses toward a medium and generate echo signals responsive to the ultrasound pulses. The ultrasound system may include channel memory configured to store the acquired echo signals (raw RF signals), a beamformer which may perform transmit and/or receive beamforming and which may include a beamformer memory configured to store beamformed signals generated based on the echo signals, and a display for displaying ultrasound images generated by the ultrasound imaging system. The ultrasound imaging system may include a neural network, which may be implemented in hardware and/or software components, which is machine trained to output ultrasound images from a variety of inputs including the raw RF signals, beamformed signals, or combinations thereof. In some embodiments, the neural network may be trained to output ultrasound images from beamformed signals without utilizing conventional signal processing of the beamformed signals (e.g., for demodulating and extracting echo intensity or other type of signal information). In yet further examples, the neural network may be trained to output ultrasound images and/or a variety of tissue characterization or diagnostic information (collectively referred to herein as tissue information) from raw RF signals, beamformed signals, or combinations thereof.

[0027] The neural network according to the present disclosure may be hardware- (e.g., neurons are represented by physical components) or software-based (e.g., neurons and pathways implemented in a software application), and can use a variety of topologies and learning algorithms for training the neural network to produce the desired output. For example, a software-based neural network may be implemented using a processor (e.g., single or multi-core CPU, a single GPU or GPU cluster, or multiple processors arranged for parallel-processing) configured to execute instructions, which may be stored in computer-readable medium, and which when executed cause the processor to perform a machine-trained algorithm for producing ultrasound images and/or outputting tissue information from one or more of the above identified inputs. The ultrasound system may include a display or graphics processor, which is operable to arrange the ultrasound image and/or additional graphical information, which may include annotations, tissue information, which may also be output by the neural network, and other graphical components, in display window for display on the display of the ultrasound system. In some embodiments, the ultrasound images and tissue information may additionally be provided to a storage device, such as a picture archiving and communication system (PACS) or a local or network-connected storage device, for reporting purposes or future machine training (e.g., to continue to enhance the performance of the neural network). In yet further examples, imaging data obtained from a variety of different imaging modalities (e.g., magnetic resonance imaging (MRI), computed tomography (CT), or another), which may be stored, for example in PACS, may alternatively or additionally be used to train the neural network. As will be appreciated, systems according to the present disclosure may include a two-way communication link coupling the system, and more specifically the neural network to source(s) of training data (e.g., a storage device) and/or to other machine-trained systems for ongoing feedback and training.

[0028] FIG. **1** shows an example ultrasound system according to principles of the present disclosure. The ultrasound system **100** includes channel memory **110**, a neural network **160**, an optional display processor **140**, and a user interface **124**. The example in FIG. **1** also shows an ultrasound transducer **113**, a transmit/receive controller **120**, beamformer **122**, beamformer memory **123**, signal processor **126**, imaging data processor **121**, scan converter and multiplaner reformatter **133**, input data selector **162**, and a storage component **150**. The components and arrangement thereof shown in FIG. **1** is exemplary only, and modifications such as the addition, omission, or rearrangement of one or more of the illustrated components is contemplated without departing from the scope of the present disclosure.

[0029] As described, the ultrasound transducer **113** may acquire echo signals responsive to ultrasound signals transmitted toward a medium to be imaged (e.g., tissue). The ultrasound transducer **113** may include an array of elements capable, under control from a transmit/receive controller **120**, to transmit pulses of ultrasound toward the medium and detect echoes responsive to the transmit pulses. The transmit/receive controller **120** controls the transmission of ultrasound signals by the transducer **113** and the reception of ultrasound echo signals by individual elements or groups of elements (e.g., in the case of a transducer including a microbeamformer (AF)) of the array. The ultrasound transducer **113** is communicatively coupled to channel memory **110**, which receives and stores the echo signals acquired by the ultrasound transducer **113**. The channel memory **110** may be configured to store per-element or group (in the case of microbeamformed signals) echo signals (also referred to as raw RF signals or simply RF signals, or per-channel data). The pre-channel data may be accumulated in memory over multiple transmit/receive cycles.

[0030] The channel memory **110** may couple the RF signals to a neural network **160**, which is trained to produce imaging data, extract tissue information, or any combinations thereof, directly from the RF signals, e.g., without the need for conventional beamforming or downstream signal processing. In some embodiments, the RF signals from the channel memory **110** are coupled to the neural network **160** via an input data selector **162**. The input data selector **162** may be configured to select, for each point or region of interest (ROI) in an imaging field of view, a corresponding array of m echo signal samples from each or a subset of elements of the transducer array. In some examples, the input data selector **162** may be configured to select the samples such that the centers of the samples of echo signals correspond approximately to the round trip time delay and thus to the depth of interest (see e.g., FIG. **2**). As shown in FIG. **2**, m samples of echo signals e_i (i.e. per-channel data represented by e_1, e_2, e_3, . . . e_n) are shown to have been selected based on having their centers corresponding to the depth of interest. In some examples, as long as the data segment lengths are long enough to include the information from each echo surrounding the depth of interest, it may not be strictly necessary to center the depth of interest within the echo segments. In some embodiments, the data selector **162** may thus be configured to select a subset of echo signals from the acquired echo signals, which are associated with adjacent points within a region of imaged tissue. After selection of the appropriate input data set, imaging and other tissue data extraction would be performed implicitly by the neural network **160** without the reliance on conventional beamforming.

[0031] To train a neural network **160** according to the present disclosure, training sets which include multiple instances of input arrays and output classifications, {Xi,Yn}, may be presented to the training algorithm(s) of the neural network **160** (e.g., an AlexNet training algorithm, as described by Krizhevsky, A., Sutskever, I. and Hinton, G. E. "*ImageNet Classification with Deep Convolutional Neural Networks,*" NIPS 2012 or its descendants). In the training data set, the input data [Xi] may include per-channel echo signals, e.g., as illustrated in FIG. **2**, optionally together with auxiliary data, described further below, and the output data [Yi] may include any known properties of the tissue corresponding to the sample of echo signals (e.g., known velocities in the case of blood flow or other tissue motion imaging, known strain/stress values, or echo intensity data for producing anatomy imaging information, etc.). The input [Xi] and output [Yi] data of the training data sets may be acquired by an ultrasound imaging system which has components for conventional ultrasound imaging or an imaging system configured for another type of imaging modality (e.g., an MRI scanner, CT scanner, and others). In some embodiments the system **100** may also include conventional beamforming, signal and image processing components such that it may be used, when operated in a conventional mode, to acquire input and output data sets for use as training sets to the training algorithm. For example, different types of tissue may be scanned (e.g., ultrasonically scanned) using a transducer which is operatively associated with a spatial localization system (e.g., an EM or ultrasonically tracked probe), which can spatially correlate the point or region of interest of tissue being scanned to the output data (e.g., the imaging data and/or tissue characterization information to be used as the output in the training set). In further examples, the neural network **160** may be trained using a suitable ultrasound simulation such as the Field II program (as described by J. A. Jensen: *A Model for the Propagation and Scattering of Ultrasound in Tissue,* J. Acoust. Soc. Am. 89, pp. 182-191, 1991), which takes as input the spatial distribution of points representing scatterers in an image field together with data about the geometry of the ultrasound transducer and the transmitted pulse and outputs computed ultrasonic data representing the per-element echo signals (also referred to as simulated echoes). The system **100** may use this type of data for training purposes, e.g., by using the simulated echoes and auxiliary data about the transducer and transmitted pulses for one or more given points in space and present them to the neural network as input training data [Xi] with the corresponding output data [Yi] being the scatterer densities from the simulation. Other algorithms or techniques may additionally or alternatively be used for training the neural network **160**. Also, as noted, in some cases, the output data (e.g., imaging data and/or known properties of tissue) may be obtained using an imaging modality different from ultrasound, for example MRI, CT or others or any combinations thereof. The neural network **160** may thus be trained to produce imaging data, and in some case images of higher quality (e.g., higher resolution) than may otherwise be possible through conventional ultrasound image processing directly from the RF signals.

[0032] A neural network training algorithm associated may be presented with thousands or even millions training data sets in order to train the neural network **160** to directly estimate or output imaging data or other tissue properties based on the raw measurement data (i.e., raw acquired RF signals) without reliance on an explicit model of the input/output relationship (e.g., pre-programmed physics-based models typically implemented in conventional beamformers, signal processors or imaging data processors of existing ultrasound systems). That is, hundreds, thousands, or millions of training data sets may be presented to a machine learning algorithm to develop a network of artificial neurons or nodes arranged in accordance with any one of a variety of topographies or models. The neurons of the neural network are typically connected in layers and signals travel from the first (input) layer to the last (output) layer. With advancements in modern neural networks and training algorithms, a neural network comprising hundreds of thousands to millions of neurons or nodes and connections therebetween may be developed. The signals and state of the artificial neurons in a neural network **160** may typically be real numbers, typically between 0 and 1, and a threshold function or limiting function may be associated with each connection and/or node itself, such that the signal must equal or exceed the threshold/limit before propagating.

[0033] The output of the training process may be a set of weights (also referred to as connection or node weights) which may be used by the neural network **160** during operation (e.g., to adjust the threshold or limiting functions controlling propagation through the layers of the neural net). Once trained, the neural network **160** may be configured to operate on any input array, Xk, to produce one or more output values that can be interpreted loosely as a probability or confidence estimate that Xk is a member of the output set Yn (e.g. that the sample of echo signals correspond to a set of pixel image data). The output sets, Yn, can also represent numerical value ranges. In this manner, a set of RF signals may be provided as input to the neural network **160**, the set of RF signals corresponding to a subset of a given spatial locations (e.g., a region of interest in the imaged tissue) within the medium and the neural network may provide as output a set of corresponding pixel data for producing a portion of the image at the given spatial location. In some examples, by changing the weights of the neural network, this system can be dynamically reconfigured to produce images of a wide variety of different characteristics. In some embodiments, the neural network **160** may be a deep-learning or simply deep neural network (DNN) and/or an adaptive neural network. In some embodiments, a deep neural network (DNN), such as a deep convolutional neural networks (deep CNN) also referred to as fully convolutional network (FCN), may be used to localize objects within an image on a pixel by pixel basis. In examples, the input training arrays, Xi, may be formed from the image data surrounding each point in an image. Each training array may be classified into one or more output sets or values based on the set membership of the output point or pixel in question. As such, the ultrasound system **100** may be configured to output ultrasound images, for example, without performing any of the conventional steps of RF filtering, demodulations, compression, etc. Rather, the image data formation would be accomplished implicitly within the neural network.

[0034] The output of the neural network **160** may be coupled to a display processor **140**, which may arrange the subsets of pixel data based on their spatial attributes to construct an ultrasound image of the field of view. In some examples, the display processor **140** may temporarily buffer, if needed, the subsets of pixel data until pixel data for the entire image has been output by the neural network. In some examples, prior to passing the output data to the display processor **140**, the output of the neural network may be passed through a data conditioner (not shown), which may be configured to spatially and temporally process the output data to highlight certain spatial and/or temporal characteristics thereof. In some examples, the data conditioner may perform multi-resolution image processing. In further examples, the functionality of arranging the subsets of pixel data into a desired format for display (e.g., into a 2D or 3D image) may be performed by a scan converter and multiplanar reformatter **133**, following which the ultrasound image may be passed to the display processor **140** for additional image enhancement, annotations and/or combination with other imaging data (e.g., graphical representations of tissue, blood flow, and/or strain/stress information). The ultrasound imaging data (e.g., after formatting for display) may be processed in the same manner as image data on a conventional ultrasound system. For example, it may be displayed in real-time, e.g., on a display unit of the user interface **124**, buffered into a cineloop memory for displaying temporal sequences of images, and/or exported to a storage device **150** or a printing system. Stored ultrasound images (or pre-formatted/pre-annotated image data) may be retrieved for subsequent analysis and diagnosis, inclusion in a report and/or for use as training data. The ultrasound image data may be further processed using conventional techniques to extract additional quantitative and/or qualitative information about the anatomy or characteristics of the tissue being scanned.

[0035] In further examples, the channel memory **110** may additionally or alternatively couple the raw RF signals to a beamformer **122**, which may perform conventional beamforming, such as conventional delay and sum beamforming, dual apodization with cross-correlation, phase coherence imaging, capon beamforming and minimum variance beamforming, or Fourier beamforming, all operating on the per-channel data to combine the information from the echo signals and form an image line of the backscattered ultrasound energy from tissue. The beamformed signals obtained through conventional beamforming may then, alternatively or additionally, be coupled to the neural network **160**, which may be trained to produce ultrasound images and/or tissue characterization information from the conventionally beamformed signals rather than from raw RF data but again bypassing downstream signal and image processing (e.g., RF signal filtering, amplitude detection, compression, etc.) of existing ultrasound systems. For example, when using beamformed RF signals instead of per-channel signals, the e_i in FIG. **2** would represent beamformed RF signals corresponding to scanlines from the region of interest and as well as neighboring lines of sight, or they could may represent beamformed RF signals corresponding to scanlines generated from successive transmit events. An ultrasound image can then be produced by the neural network and/or tissue characterization performed directly from the beamformed RF signals.

[0036] In some cases, the neural network **160** may be trained to use both raw RF data and beamformed data for image production bypassing further downstream processing. Similar to the earlier examples, appropriate training data sets may be provided to the training algorithm of the neural network **160** in some cases optionally with auxiliary data. For example, sets of beamformed RF signals (over single or multiple transmit/receive cycles) may be stored in beamformer memory **123** and coupled to the neural network **160**, e.g., via the input data selector **162**. The input data selector **162** may be similarly configured to select the appropriate set of beamformed RF signals corresponding to the ROI and output an image or other information bypassing any subsequent signal or imaging data processing. In yet further examples, the beamformer **122** may be configured to perform partial beamforming, for example by delaying the individual ultrasonic echo signals by the appropriate amount and align the per-element echo data together corresponding to a specific depth along a scan line, but without performing the summation step. These partially beamformed signals may then be provided to an appropriately trained neural network to reconstruct the ultrasound image therefrom.

[0037] As with the prior example, the training data sets may be used optionally additionally with auxiliary data during the training process. The auxiliary data may include information about the programming of the beamformer **122**, properties of the transducer **113** (e.g., number, arrangement, and/or spacing of elements of the array, type of array, etc.), known information about the anatomy being imaged, and/or the spatial location of the point or region of interest (e.g., as may be obtained by a transducer tracking system). Other types of information, for example in the case of training sets from different imaging modalities, may also be provided as auxiliary information to the training algorithm. As illustrated in FIG. **1**, in yet further example, this concept may be extended further downstream of the signal processing path of a conventional ultrasound system, e.g., to utilize at least partially processed RF signals, e.g., demodulated quadrature data or I/Q data produced by a signal processor **126**, as input to the neural network **160** to obtain a ultrasound image without further subsequent image processing such as conventional amplitude detection, speckle reduction, reduction of flash or other artefacts, etc.) as may be performed by the one or more imaging data processors **121** (e.g., B-mode, Doppler, and/or vector flow imaging processors) of a current ultrasound system.

[0038] In some examples, the neural network **160** may be trained to operate in a plurality of modes based on the input data type (e.g., per-channel data, beamformed signals, quadrature data, or a combination thereof). In such examples, an input data selector **362** may include an input type selector **364**, which may selectively couple the type of data and activate the appropriate operational mode of the neural network **160**. The input type selection may be responsive to a control signal, which may be generated responsive to user input or which may be a pre-programmed default based on the imaging mode. As shown in FIG. **3**, the input type selector **364** may include a switch **367** and a mode selector **365**. The switch **367** may be configured to selectively couple a sample of the appropriate type of input data based to the neural network based on a select signal received from the mode selector **365**. The mode selector may also transmit a mode control signal to the neural network to active the appropriate operational mode based on the selected input data.

[0039] As previously described, the system **100** may include conventional beamforming, signal and image processing components such that it may produce ultrasound images in conventional manner, which images can be stored (e.g., in storage **150**) and used as training data for further enhancements of the neural network **160**. That is, the system **100** may be operable in a neural net mode during which ultrasound images may be produced in part based on outputs from the neural network **160**, and may also be operable in a conventional mode during which ultrasound images may be produced through conventional signal and image processing, the modes being user selectable.

[0040] For example, the system **100** may include a signal processor **126** which is configured to process the received echo signals in various ways, such as by bandpass filtering, decimation, I and Q component separation, and harmonic signal separation. The signal processor **126** may also perform additional signal enhancement such as speckle reduction, signal compounding, and noise elimination. The processed signals may be coupled to one or more imaging data processors, e.g., a B-mode processor, a Doppler processor, a Vector Flow Imaging (VFI) processor, etc. The B-mode processor can employ amplitude detection for the imaging of structures in the body. The Doppler processor may be configured to estimate the Doppler shift and generate Doppler image data. In some examples, the Doppler processor may include an auto-correlator, which estimates velocity (Doppler frequency) based on the argument of the lag-one autocorrelation function and which estimates Doppler power based on the magnitude of the lag-zero autocorrelation function. Motion can also be estimated by known phase-domain (for example, parametric frequency estimators such as MUSIC, ESPRIT, etc.) or time-domain (for example, cross-correlation) signal processing techniques. Other estimators related to the temporal or spatial distributions of velocity such as estimators of acceleration or temporal and/or spatial velocity derivatives can be used instead of or in addition to velocity estimators. In some examples, the velocity and power estimates may undergo threshold detection to reduce noise, as well as segmentation and post-processing such as filling and smoothing. The velocity and power estimates may then be mapped to a desired range of display colors in accordance with a color map. The VFI processor may be configured to estimate beam-angle-independent velocity vector data from the acquired echo signals, for example using the transverse oscillation method or synthetic aperture method (e.g., as described by Jensen et al., in "*Recent advances in blood flow vector velocity imaging,*" 2011 IEEE International Ultrasonics Symposium, pp. 262-271, the disclosure of which is incorporated herein by reference in its entirety for any purpose), or any other currently known or later developed vector flow imaging technique.

[0041] The signals produced by the B-mode processor, and or flow data (e.g., color data or VFI data produced by the Doppler processor and the VFI processor, respectively) may be coupled to the scan converter and multiplanar reformatter **133**, which may be configured to arrange the data in the spatial relationship from which they were received in a desired image format. For example, the scan converter and multiplanar reformatter **133** may arrange the echo signal into a two dimensional (2D) sector-shaped format, or a pyramidal or otherwise shaped three dimensional (3D) format. The scan converter and multiplanar reformatter **133** may also be configured to convert echoes which are received from points in a common plane in a volumetric region of the body into an ultrasonic image (e.g., a B-mode image) of that plane, for example as described in U.S. Pat. No. 6,443,896 (Detmer). The output of the scan converter and multiplanar reformatter may be coupled to the display processor **140**, which may perform additional image processing and/or add annotation. In some examples, the display processor **140** may be operable generate an image of the 3D dataset as viewed from a given reference point, e.g., as described in U.S. Pat. No. 6,530,885 (Entrekin et al.).

[0042] Image data obtained from the conventional mode of system **100** or another conventional ultrasound system may be used to train the neural network **160** of system **100** to essentially mimic conventional ultrasound imaging, or alternatively as described, the neural network **160** of system **100** may be trained to mimic the image quality of other types of imaging modalities, such as MRI, CT, etc. Further examples of ultrasound systems according to embodiments of the present disclosure will now be described with reference also to FIGS. **4-6**.

EXAMPLE 1

[0043] FIG. **4** shows a block diagram of an ultrasound system **400** in accordance with principles of the present invention. The system **400** includes channel memory **410** which is communicatively coupled to an ultrasound transducer **413**. The ultrasound transducer **413** may include an ultrasound transducer array **414**, which may be provided in a probe **412**, such as a handheld probe or a probe which is at least partially controlled or actuated by a machine. In other embodiments, the ultrasound transducer array **414** may be implemented using a plurality of patches, each comprising a sub-array of transducer elements and the array **414** may be configured to be conformably placed against the subject to be imaged. The ultrasound transducer **413** is operable to transmit ultrasound (e.g., ultrasound pulses) toward a region of interest (ROI) within a medium (e.g., tissue of a patient) and to receive echoes signals responsive to the ultrasound pulses, which signals can be used to produce images of the region of interest (ROI). A variety of transducer arrays may be used, such as linear arrays, curved arrays, or phased arrays. The array **414** may include, for example, a two dimensional array of transducer elements capable of scanning in both elevation and azimuth dimensions for 2D and/or 3D imaging. In some embodiments, the system **400** may include the ultrasound transducer **413**, which is typically removably coupled to an imaging base **415** (also referred to as ultrasound system base). The imaging base **415** may include electronic components, such as one or more signal and image processors, arranged to produce ultrasound images from echoes acquired by the transducer **413**, which electronic components are also collectively referred to as imaging device. The imaging device may be a portable imaging device (e.g., provided in a tablet or other handheld form factor) or it may be a traditional cart-based imaging device such as the SPARQ or EPIQ ultrasound imaging devices provided by Philips.

[0044] The ultrasound transducer **413** may be coupled to the channel memory **410** via a transmit/receive switch **418**. The channel memory **410** is configured to store the acquired echo signals acquired by the transducer **413**. In some embodiments, the channel memory **410** may be provided in the base **415** or it may be provided, at least partially, in the ultrasound transducer **413** or otherwise communicatively coupled between the transducer **413** and the base **415**. The ultrasound transducer **413** may also be coupled to a beamformer **422**, which may be configured to provide transmit beamforming, e.g., to control directionality of ultrasound pulses transmitted by the array **414**. In some embodiments, the array **414** may be coupled to a microbeamformer (not shown here), which may be located in the probe **412** (see μBF in FIG. **1**) or in the ultrasound system base **415**. The microbeamformer may be configured to perform transmit and/or receive beamforming on groups or patches of elements of the array, e.g., to enable a system with a reduced number of signal channels between the transducer **413** and the base **415**. The beamformer and/or microbeamformer may control, under the direction of transmit/receive controller **410**, the transmission and reception of signals by the ultrasound transducer **413**. As shown, the transducer **412** may be coupled to the ultrasound system base via a transmit/receive (T/R) switch **418** typically located in the base. The T/R switch **418** may be configured to switch between transmission and reception, e.g., to protect the main beamformer **422** from high energy transmit signals. In some embodiments, the functionality of the T/R switch **418** and other elements in the system may be incorporated within the probe, such as a probe operable to couple to a portable system, such as the LUMIFY system provided by PHILIPS. The probe **412** may be communicatively coupled to the base using a wired or wireless connection. In some embodiments, the transducer, the channel memory, and hardware storing the neural network, and/or a display processor can be located in the probe. A user interface for displaying images created by the neural network can be communicatively coupled to the probe. For example, the display can be coupled via a cable to the probe or via wireless communication, in which the probe can include a wireless transmitter to send the image data to the display. In certain embodiments, the system can include a graphics processing unit (GPU) to fully or partially train the neural network in the system. For example, a GPU can be located in a probe with the transducer, the channel memory and the hardware storing the neural network. Alternatively, the GPU can be located separately from the probe, such as being located in a tablet or other computing device, such as a smart phone.

[0045] The transmission of ultrasonic pulses from the array **414** may be directed by the transmit controller **420** coupled to the T/R switch **418** and the beamformer **422**. The transmit controller may receive input from the user's operation of a user interface **424**. The user interface **424** may include one or more input devices such as a control panel **429**, which may include one or more mechanical controls (e.g., buttons, encoders, etc.), touch sensitive controls (e.g., a trackpad, a touchscreen, or the like), and other known input devices. User input may be received via the control panel **429** or in some cases, such as in the cases a touch sensitive display. Another function which may be controlled by the transmit controller **420** is the direction in which beams are steered. Beams may be steered straight ahead from (orthogonal to) the transmission side of the array **414**, or at different angles for a wider field of view.

[0046] In accordance with some embodiments, the system **400** may also include a neural network **460**. The neural network **460** may be configured to receive, from channel memory **410**, an input array comprising samples of the acquired echo signals corresponding to a location within a region of imaged tissue. The neural network **460** may be trained to propagate the input through the neural network to estimate pixel data associated with the location within the region of imaged tissue. The neural network **460**, which may be implemented in hardware, software, or combinations thereof, may be trained for example as described herein to produce the pixel data directly from the input array, e.g., bypassing conventional signal processing steps such as beamforming, RF filtering, demodulation and I/Q data extraction, amplitude detection, etc. For example, the neural network **460** may be trained to output pixel data which is indicative of intensities (i.e., amplitude) of the echo signals. In some embodiments, the neural network **460** may be trained to additionally or alternatively output pixel data indicative of Doppler frequencies associated with the echo signals, tissue strain within the imaged region, wall shear stress of a bodily structure within the imaged region, multi-component velocity information about flow within the imaged region, or any combinations thereof. The output of the neural network **460** responsive to any input array may thus be pixel data associated with the same location in the field of view as the input array, the pixel data including, for example, grayscale or RGB values that may be used to reconstruct an ultrasound image. In some embodiments, the neural network **460** may include multiple propagation pathways, each of which is configured to receive an input array (e.g., samples of echo signals) and each of which produces different pixel data (e.g., predicts different aspects of the tissue associated with the location of the acquired echo signals). For example, one propagation pathway may be trained for outputting pixel data indicative of echo signal intensities (e.g., grayscale pixel values which may be arranged into a grayscale image of the anatomy). Another propagation pathway, which may analyze the input array concurrently, sequentially, or in a time-interleaved manner with the first pathway, may be trained for outputting pixel data indicative of Doppler information (e.g., RGB values at a set of adjacent locations in the imaged region), which may be used to reconstruct a flow image similar to a colorflow Doppler image, a color power angio image, and other types of Doppler images (e.g., spectral Doppler or M-mode images, etc.)

[0047] The output of the neural network **460** is coupled to a display processor **440**, which is operable to produce an ultrasound image including the location within the region of imaged tissue using the pixel data. In some embodiments, the pixel data associated with any given input array represents only a subset of the pixels needed to reconstruct a full image of the field of view. The display processor **440** may include a buffer to temporarily store sets of pixel data from different sub regions within the field of view and to construct the full image once sufficient pixel data has been output by the neural network **460**. The inputs to and outputs of the neural network may be localized (e.g., associated with spatial information) such as to enable the display processor **440** to spatially arrange the sets of pixel data. The ultrasound image produced by display processor **440** may then be coupled to the user interface **424**, e.g., for displaying it to the user on a display **428**, and/or may also be coupled to a storage device **450**, which may be a local storage device, a storage device of a picture archiving and communication system (PACS), or any suitable networked storage device.

[0048] In some embodiments, the display processor **440** may optionally and additionally generate graphic overlays for display with the ultrasound images. These graphic overlays may contain, e.g., standard identifying information such as patient name, date and time of the image, imaging parameters, and other annotations. For these purposes, the display processor **440** may be configured to receive input from the user interface **524**, such as a typed patient name.

[0049] The neural network **460** may be operatively associated with a training algorithm **461** which may be used to train the neural network **460**, for example to initially train the network and/or to continue to enhance the performance of the network after deployment. The training algorithm **461** may be operatively arranged to receive training data sets either from the system **400** or in some case from other imaging system(s) **480**, which may or may not use ultrasound as the modality for imaging. For example, the training algorithm **461** may receive along with training input array a corresponding known output array of the training data which includes known tissue parameters (e.g., pixel data) associated with the same location in the tissue as the input array but which was obtain using a modality different from ultrasound, for example MRI, CT, PET, PET-CT, etc.

EXAMPLE 2

[0050] FIG. **5** shows a block diagram of an ultrasound system **500** in accordance with further principles of the present invention. Similar to the prior example, system **500** includes channel memory **510** which is communicatively coupled to an ultrasound transducer **513**. The ultrasound transducer **513** may include an ultrasound transducer array **514**, which may be provided in a probe **512**, such as a handheld probe or a probe which is at least partially controlled or actuated by a machine. In other embodiments, the ultrasound transducer array **514** may be implemented using a plurality of patches, each comprising a sub-array of transducer elements and the array **514** may be configured to be conformably placed against the subject to be imaged. The ultrasound transducer **513** is operable to transmit ultrasound (e.g., ultrasound pulses) toward a region of interest (ROI) within a medium (e.g., tissue of a patient) and to receive echoes signals responsive to the ultrasound pulses, which signals can be used to produce images of the region of interest (ROI). A variety of transducer arrays may be used, such as linear arrays, curved arrays, or phased arrays. The array **514** may include, for example, a two dimensional array of transducer elements capable of scanning in both elevation and azimuth dimensions for 2D and/or 3D imaging. In some embodiments, the system **500** may include the ultrasound transducer **513**, which may be removably coupled to an imaging base **515**. The imaging base **515** may include electronic components, such as one or more signal and image processors, arranged to produce ultrasound images from echoes acquired by the transducer **513**, which electronic components are collectively referred to as imaging device. The imaging device may be a portable imaging device (e.g., provided in a tablet or other handheld form factor) or it may be a traditional cart-based imaging device such as the SPARQ or EPIQ ultrasound imaging devices provided by Philips. The ultrasound transducer **513** may be coupled to the channel memory **510** via a transmit/receive switch **518**. The channel memory **510** is configured to store the acquired echo signals acquired by the transducer **513**. In some embodiments, the channel memory **510** may be provided in the base **515** or it may be provided, at least partially, in the ultrasound transducer **513** or otherwise communicatively coupled between the transducer **513** and the base **515**.

[0051] The ultrasound transducer **513** may also be coupled to a beamformer **522**. In this example, the beamformer **522** may be configured to perform both transmit beamforming, e.g., to control directionality of ultrasound pulses transmitted by the array **514**, and receive beamforming, e.g., to combine sets of acquired echo signals (i.e., raw RF signals) into beamformed RF signals corresponding to scan lines or scan regions within the field of view of the array **514**. In some embodiments, the array **514** may also be coupled to a microbeamformer (see e.g., μBF in FIG. **1**) which may be located in the transducer **513**. The microbeamformer may be configured to perform transmit and/or receive beamforming on groups or patches of elements of the array. The beamformer and/or microbeamformer may control, under the direction of transmit/receive controller **510**, the transmission and reception of signals by the ultrasound transducer **513**. As shown, the transducer **512** may be coupled to the ultrasound system base via a transmit/receive (T/R) switch **518** typically located in the base. The T/R switch **518** may be configured to switch between transmission and reception, e.g., to protect the main beamformer **522** from high energy transmit signals. In some embodiments, the functionality of the T/R switch **518** and other elements in the system may be incorporated within the probe, such as a probe operable to couple to a portable system, such as the LUMIFY system provided by PHILIPS. The transducer **513** may be communicatively coupled to the base using a wired or wireless connection.

[0052] The transmission of ultrasonic pulses from the array **514** may be directed by the transmit controller **520** coupled to the T/R switch **518** and the beamformer **522**. The transmit controller may receive input from the user's operation of a user interface **524**, which may include a display **528** for displaying ultrasound images and a control panel **529** including one or more mechanical or software-based controls (also referred to as soft controls). In some examples, the display **528** may be a touch sensitive display and may provide at least some of the soft controls. Another function which may be controlled by the transmit controller **520** is the direction in which beams are steered. Beams may be steered straight ahead from (orthogonal to) the transmission side of the array **514**, or at different angles for a wider field of view. As described, the beamformer **522** may combine raw echo signals from individual elements or partially beamformed signals from groups of transducer elements or patches of the array into a fully beamformed signal (also referred to as beamformed RF signal). Beamformed RF signals from multiple transmit and receive cycles may be stored in a beamformer memory, as needed.

[0053] In accordance with some embodiments, the system **500** may also include a neural network **560**. The neural network **560** may be configured to receive, from the beamformer **522**, an input array comprising samples of the beamformed RF signals. The neural network **560** may be trained to propagate the input through the neural network to estimate pixel data associated with the plurality of scan lines or scan regions.

[0054] The neural network **560**, which may be implemented in hardware, software, or combinations thereof, may be trained for example as described herein to produce the pixel data directly from the input array, e.g., bypassing conventional signal processing steps such as demodulation and I/Q data extraction, filtering, amplitude detection, etc. For example, the neural network **560** may be trained to output pixel data which is indicative of intensities of the echo signals summed in a given beamformed signal (i.e., the amplitude of the echoes from a given scan line or from a given scan region). In some embodiments, the neural network **560** may be trained to additionally or alternatively output pixel data indicative of Doppler frequencies associated with the echo signals used to produce a given beamformed signal, tissue strain, wall shear stress of a bodily structure, or multi-component velocity information about flow associated with a given scan line or scan region, or any combinations thereof.

[0055] The output of the neural network **560** responsive to any input array may thus be pixel data associated with the same scan line or region in the field of view as the input array, the pixel data including, for example, grayscale or RGB values that may be used to reconstruct an ultrasound image. In some embodiments, the neural network **560** may include multiple propagation pathways, each of which is configured to receive an input array (e.g., samples of beamformed RF signals) and each of which produces different pixel data (e.g., predicts different aspects of the tissue associated with the scan lines or regions corresponding to the combined echo signals in the respective beamformed RF signals). For example, one propagation pathway may be trained to output pixel data for generating an anatomy image and another propagation pathway may be trained to output for generating a flow image, which may be processed concurrently, sequentially, or in a time-interleaved manner, and the resulting different types of pixel data may be used to generate different types of ultrasound image components which may be overlaid for display (e.g., similar to conventional duplex B-mode/Doppler imaging) or otherwise concurrently displayed.

[0056] The output of the neural network **560** may be coupled to a display processor **540**, which is operable to produce an ultrasound image including using the pixel data. In some embodiments, the pixel data that is output by the neural network **560** responsive to any given input array may represent only a single or a few of hundreds of scan lines or scan display processor **540** may include temporarily buffer sets of pixel data from different scan lines or regions within the field of view and construct a frame of the full image once sufficient pixel data has been received from the neural network **560**. In some cases, the buffering function may be performed by the neural network which may supply to the display processor the necessary pixel data as may be needed to reconstruct a full image frame. The ultrasound image produced by display processor **440** responsive to outputs of the neural network may be provided on a display of the system **500**, and/or stored for subsequent use(s) such as additional training of the neural network, further analysis and diagnosis, including in reports, etc.

[0057] Similar to system **400**, in some embodiments, the display processor **540** may optionally and additionally generate graphic overlays for display with the ultrasound images. These graphic overlays may contain, e.g., standard identifying information such as patient name, date and time of the image, imaging parameters, and other annotations. For these purposes, the display processor **540** may be configured to receive input from the user interface **524**, such as a typed patient name. As described, the neural network **560** may be operatively associated with a training algorithm **561** which may be used to train the neural network **560**, for example prior to deployment and/or subsequently in the field to further improve the performance of the network. The training algorithm **561** may be operatively arranged to receive training data sets either from the system **500** or in some case from other imaging system(s) **580**, which may utilize different imaging modalities than system **500**.

EXAMPLE 3

[0058] FIG. **6** shows a block diagram of an ultrasound system **600** in accordance with further principles of the present invention. System **600** has a similar arrangement of components as system **400**, however in this example the system is configured to propagate the inputs through the neural network in phases. System **600** includes many components similar those in system **400**, and the similar components are numbered using similar reference numbers. For example, the system **600** include includes channel memory **610** which is communicatively coupled to an ultrasound transducer **613**. The ultrasound transducer **613** includes an ultrasound transducer array **614**, which may be located in probe **612**, and which may be a one dimensional array or a two dimensional array of transducer elements capable of scanning in both elevation and azimuth dimensions for 2D and/or 3D imaging. A variety of transducer arrays may be used, such as linear arrays, curved arrays, or phased arrays. The transducer **613** is thus operable to transmit ultrasound (e.g., ultrasound pulses) toward a region of interest (ROI) within a medium (e.g., tissue of a patient) and to receive echoes signals responsive to the ultrasound pulses.

[0059] The ultrasound transducer **613** may be coupled to the channel memory **610** via a transmit/receive switch **618**. The channel memory **610** is configured to store the acquired echo signals. In some embodiments, the channel memory **610** may be provided in the ultrasound imaging base **615** or it may be provided, at least partially, in the ultrasound transducer **613** or otherwise communicatively coupled between the transducer **613** and the base **615**. The ultrasound transducer **613** may also be coupled to a beamformer **622**, which may be configured to provide transmit beamforming, such as to control direction of the ultrasound pulses transmitted by the array **614**. In some embodiments, the array **614** may be coupled to a microbeamformer. The microbeamformer may be configured to perform transmit and/or receive beamforming on groups or patches of elements of the array, e.g., to enable a system with a reduced number of signal channels between the transducer **613** and the ultrasound imaging base **615**. The beamformer and/or microbeamformer may control, under the direction of transmit/receive controller **610**, the transmission and reception of signals by the ultrasound transducer **613**. As shown, the transducer **612** may be coupled to the ultrasound system base via a transmit/receive (T/R) switch **618** typically located in the base. The T/R switch **618** may be configured to switch between transmission and reception. In some embodiments, the functionality of the T/R switch **618** and other elements in the system may be incorporated within the probe, such as a probe operable to couple to a portable system, such as the LUMIFY system provided by PHILIPS. The transducer **613** may be communicatively coupled to the base using a wired or wireless connection.

[0060] The transmit controller **620** coupled to the T/R switch **618** and the beamformer **422** may control the transmission and reception of ultrasonic pulses from the array **614**, and may in some cases receive input from the user's operation of a user interface **624**. The user interface may include a display **628** for displaying ultrasound images and a control panel **629** including one or more mechanical or software-based controls (also referred to as soft controls). In some examples, the display **628** may be a touch sensitive display and may provide at least some of the soft controls. Another function which may be controlled by the transmit controller **620** is the direction in which beams are steered. Beams may be steered straight ahead from (orthogonal to) the transmission side of the array **614**, or at different angles for a wider field of view.

[0061] The system **600** may also include a neural network **660** configured to receive, from channel memory **610**, an input array comprising samples of the acquired echo signals corresponding to a location within a region of imaged tissue. The neural network **660** may be trained to propagate the input through the neural network to estimate pixel data associated with the location within the region of imaged tissue and/or obtain other tissue information associated with the imaged region. In this embodiment the neural network **460**, which may be implemented in hardware, software, or combinations thereof, may be configured to propagate the inputs in phases, which may mimic the beamforming, signal processing and/or image processing steps of conventional ultrasound imaging. That is, the neural network may be configured to propagate the input of echo signals in a first phase to obtain a predicted set of beamformed signals corresponding to the input echo signals as an output of the first phase and then propagate the predicted set of beamformed signals as an input to a second phase and obtain a set of predicted values associated with the locations in the tissue represented by the beamformed signals. The predicted values output from phase two may be quadrature components, which may then be passed through another one or more phases to obtain pixel data for generating ultrasound images. In some embodiments, the second phase may be configured to directly output the pixel data needed for generating the ultrasound image. The input/output pairs of each phase may be varied in other examples, e.g., the first phase in another example may predict quadrature data directly from the raw echo signals, and a second phase may output pixel data corresponding to the quadrature data output from first phase. The phases may thus be tailored as desired by providing the appropriate training data sets to a training algorithm **661** associated with neural network **660**. Additionally and optionally, the neural network **660** may further include different propagation pathways, each of which may be configured to receive a same set of input data but provide a different type of ultrasound imaging data. These different pathways may be defined in one or each of the plurality of phases of the neural network **660**.

[0062] The output of the neural network **660** (e.g., the output of the last phase thereof) may be coupled to a display processor **640**, which is operable to produce an ultrasound image including the imaged region or quantitative information about tissue properties within the region of interest. Images and/or quantitative information may be output to the user, e.g., via user interface **624** and/or to a storage device **650**. In some examples, the training algorithm **661** may be communicatively coupled with the storage device **650** and may receive training data from the storage device, which may include outputs of the system **600** from prior imaging sessions and/or imaging data from other imaging system(s) **680**, which may utilize ultrasonic or other imaging modalities.

[0063] In some embodiments, any of the systems **400**, **500**, and **600** may also include conventional signal and image processing components, which may be implemented in software and hardware components including one or more CPUs, GPUs, and/or ASICs, and which may also receive signals based on the acquired echo signal and which may process the received signals in accordance with conventional phsysics-based pre-programmed models to derive imaging data for producing ultrasound images. These images may be coupled to a training algorithm associated with the neural networks of the respective system **400**, **500**, and **600** for further training of the system.

[0064] FIG. **7** shows a flow diagram of a process in accordance with some examples of the present disclosure. The process **700** may begin by storing the acquired echo signals or RF signals in channel memory, as shown in block **702**. The RF signals stored in channel memory correspond to the echoes detected from the tissue being image response to ultrasound transmitted by a transducer (e.g., transducer **113**) operatively coupled to an ultrasound system (e.g., system **100**). In some embodiments, the method may also include generating beamformed RF signals from the echo signals, as shown in block **704**, and which signals may be stored in beamformer memory. Samples of the per-channel RF signals may be coupled to a neural network (e.g., neural net **160**), as shown in **710**, and may then propagate through the nodes of the network to output produce imaging data and/or tissue information directly from the raw RF signals or beamformed RF signals, as shown in block **712**. In some examples, the neural network may be deep neural network (DNN) or a convolutional neural network (CNN), which may be implemented in hardware (e.g., nodes corresponding to hardware components) or software (e.g., where nodes are represented using computer code). In some embodiments, the coupling of samples of raw or beamformed RF signals may be selective, e.g., responsive to user input or automatically controlled by the system based on the imaging mode or clinical application. The neural network may be trained to operate in a plurality of different modes each associated with a type of input data (e.g., raw channel data or beamformed data), and thus a corresponding operational mode of the neural network may be selected (automatically or responsive to user inputs) based on the type of input data to the neural network. The imaging data and/or tissue information output by the neural network may include B-mode imaging data, Doppler imaging data, vector flow imaging data, strain imaging data, wall shear stress of an anatomical structure containing a fluid therein, or any combinations thereof. Ultrasound images may be produced and displayed using the imaging data and/or tissue information provided by the neural network, e.g., as shown in block **716**.

[0065] In yet further examples, the acquired echo signals may be processed according to conventional techniques, e.g., by beamforming the echo signals (as in block **704**), demodulating the beamformed signals by a signal processor (e.g., as shown in block **706**) for example to obtain quadrature data, and coupling the quadrature data to a conventional image processor (e.g., as shown in block **708**) to produce one or more model-based ultrasound images (also referred to as training ultrasound images). As shown in FIG. **7**, any of the conventionally obtained outputs (e.g., the I/Q data and/or the model based imaging data) may be coupled, as training data, to the training algorithm of the neural network as known outputs along with the acquired echo signals as known inputs, to further train the neural network. In some embodiments, the method may also include steps for training the neural network using imaging data or tissue information obtained from an imaging modality other than ultrasound.

FURTHER EXAMPLES

[0066] In some embodiments, the neural network of an ultrasound system according to the present disclosure may be configured to perform ultrasonic tissue characterization, for example to characterize fat content, plaque, or for ultrasonic contrast imagining, e.g., by presenting the neural network during a training phase with appropriate training data sets of inputs and known outputs, for example obtained through conventional ultrasound imaging or through imaging using a different modality.

[0067] For example, in ultrasonic liver imaging, ultrasonic attenuation and back-scattering (i.e., tissue echogenicity) increases in proportion to fat content while speed of ultrasound correspondingly reduces. By quantifying the ultrasound attenuation, echogenicity and/or speed from the beamformed RF echoes and correlating this attenuation with fat content, estimates of the fat content of the liver (or other tissue or organs, in other applications) may be performed with ultrasound. The customer-facing output of such a system may be quantitative (e.g., a single value representing the fat fraction within the imaged tissue), which may be displayed onto an image of the anatomy (e.g., for a specific point or region of interest) or it may be graphically represented, with each quantitative value being color-coded and overlaid on a 2D image or a 3D volume rendering of the liver (or other organ or tissue) similar to conventional overlays of blood flow or elastography information. As described, a neural network

[0068] To train a neural network to extract tissue information pertaining to tissue content (e.g., fat content), the neural network may be presented with training data sets including localized raw RF signals and/or beamformed RF signals as inputs and the corresponding quantified tissue parameter (e.g., fat content or other type of tissue content), which may be obtained via the ultrasound quantification method above or through other imaging or non-imaging process capable of determining the tissue content of the tissue being imaged, as the known output. Once appropriately trained, the neural network may be operable to implicitly extract this information directly from the raw RF signals and/or beamformed RF signals without reliance on the ultrasound quantification method used to initially obtain the training data.

[0069] In another example, plaque characterization may be enhanced by a neural network appropriately trained to replace existing vessel hemodynamics models that are preprogrammed in conventional ultrasound systems, such as may be used by intravascular ultrasound (IVUS) catheters to provide colorized tissue map of plaque composition with lumen and vessel measurements. For example, the VH algorithm provided by Philips Volcano can be said to generally utilize beamformed ultrasound RF signals from an IVUS catheter and analyze the short-time windowed RF spectral properties of these echo signals to classify the tissue into one of several different categories such as fibrous tissue, necrotic core, dense calcium and fibro-fatty tissue. An image may then be provided showing the distribution of these tissue types within a vessel wall. Thus, to train the neural network of a system according to the present disclosure to provide relevant vessel hemodynamic information, training data sets including IVUS-obtained RF signals may be provided as input with corresponding known tissue classifications (e.g., fibrous, necrotic core, dense calcium, etc.) as known outputs during a training phase of the neural network. Generally, raw RF signals and/or beamformed RF signals and corresponding vascular pathology data obtained using an existing IVUS system may be used to train an ultrasonic imaging system with a neural network to estimate vascular tissue composition directly from the detected echoes and/or beamformed signals, without the need for Fourier transforms and heuristic techniques that may currently be employed by conventional IVUS systems.

[0070] In yet further examples, the neural network may be trained to characterize tissue with respect to the presence of ultrasonic contrast agents. In ultrasonic contrast imaging, per-channel data from multi-pulse sequences (e.g. power modulation) are typically beamformed and then combined to form an image representing the volume density of microbubble contrast agents across the imaging field of view. The same may be implicitly (without beamforming and/or explicitly calculating the volume density) be achieved by a neural network which is trained with input training data in the form of per-channel data and/or at least partially beamformed data and corresponding known volume density of microbubble contrast agents.

[0071] In further examples, human hearts from multiple test subjects could be scanned using 1D or 2D array transducers and the resulting images and/or 3D volumes could be segmented (manually or automatically) into regions that are either a) within a cardiac chamber; or b) comprising myocardial tissue. These images may be used to train the neural network **160** to perform cardiac chamber recognition. In examples, the input data, [xi], may be per-channel data and optionally auxiliary data as described above, while the output data would be a classification (i.e., either a) or b). In examples, the neural network may include an appropriately trained semantic classifier to perform this type of classification. The so trained neural network may then be used to segment and identify cardiac chambers directly from the raw or beamformed data without having to first reconstruct an image of the anatomy and without reliance on image processing techniques. This segmentation information could be used to suppress imaging artifacts, or it could be fed directly into algorithms to quantify ejection fraction or other clinical parameters. The system may be similarly trained to identify other types of tissue or anatomical structures (e.g., walls of vessels, lung/pleura interface) and quantify relevant clinical parameters associated therewith (e.g., obtain a nuchal translucency measurement).

[0072] In various embodiments where components, systems and/or methods are implemented using a programmable device, such as a computer-based system or programmable logic, it should be appreciated that the above-described systems and methods can be implemented using any of various known or later developed programming languages, such as “C”, “C++”, “FORTRAN”, “Pascal”, “VHDL” and the like. Accordingly, various storage media, such as magnetic computer disks, optical disks, electronic memories and the like, can be prepared that can contain information that can direct a device, such as a computer, to implement the above-described systems and/or methods. Once an appropriate device has access to the information and programs contained on the storage media, the storage media can provide the information and programs to the device, thus enabling the device to perform functions of the systems and/or methods described herein. For example, if a computer disk containing appropriate materials, such as a source file, an object file, an executable file or the like, were provided to a computer, the computer could receive the information, appropriately configure itself and perform the functions of the various systems and methods outlined in the diagrams and flowcharts above to implement the various functions. That is, the computer could receive various portions of information from the disk relating to different elements of the above-described systems and/or methods, implement the individual systems and/or methods and coordinate the functions of the individual systems and/or methods described above.

[0073] In view of this disclosure it is noted that the various methods and devices described herein can be implemented in hardware, software and firmware. Further, the various methods and parameters are included by way of example only and not in any limiting sense. In view of this disclosure, those of ordinary skill in the art can implement the present teachings in determining their own techniques and needed equipment to affect these techniques, while remaining within the scope of the invention. The functionality of one or more of the processors described herein may be incorporated into a fewer number or a single processing unit (e.g., a CPU) and may be implemented using application specific integrated circuits (ASICs) or general purpose processing circuits which are programmed responsive to executable instruction to perform the functions described herein.

[0074] Although the present system may have been described with particular reference to an ultrasound imaging system, it is also envisioned that the present system can be extended to other medical imaging systems where one or more images are obtained in a systematic manner. Accordingly, the present system may be used to obtain and/or record image information related to, but not limited to renal, testicular, breast, ovarian, uterine, thyroid, hepatic, lung, musculoskeletal, splenic, cardiac, arterial and vascular systems, as well as other imaging applications related to ultrasound-guided interventions. Further, the present system may also include one or more programs which may be used with conventional imaging systems so that they may provide features and advantages of the present system. Certain additional advantages and features of this disclosure may be apparent to those skilled in the art upon studying the disclosure, or may be experienced by persons employing the novel system and method of the present disclosure. Another advantage of the present systems and method may be that conventional medical image systems can be easily upgraded to incorporate the features and advantages of the present systems, devices, and methods.

[0075] Of course, it is to be appreciated that any one of the examples, embodiments or processes described herein may be combined with one or more other examples, embodiments and/or processes or be separated and/or performed amongst separate devices or device portions in accordance with the present systems, devices and methods.

[0076] Finally, the above-discussion is intended to be merely illustrative of the present system and should not be construed as limiting the appended claims to any particular embodiment or group of embodiments. Thus, while the present system has been described in particular detail with reference to exemplary embodiments, it should also be appreciated that numerous modifications and alternative embodiments may be devised by those having ordinary skill in the art without departing from the broader and intended spirit and scope of the present system as set forth in the claims that follow. Accordingly, the specification and drawings are to be regarded in an illustrative manner and are not intended to limit the scope of the appended claims.

1. An ultrasound imaging system comprising:

an ultrasound transducer configured to acquire echo signals responsive to ultrasound pulses transmitted toward a medium;

a channel memory configured to store the acquired echo signals;

a neural network coupled to the channel memory and configured to receive one or more samples of the acquired echo signals, one or more samples of beamformed signals based on the acquired echo signals, or both, and to provide imaging data based on the one or more samples of the acquired echo signals, the one or more samples of beamformed signals, or both.

2. The ultrasound imaging system of claim **1**, further comprising a data selector configured to select a subset of echo signals from the acquired echo signals stored in the channel memory and provide the subset of echo signals to the neural network, wherein the echo signals in the subset are associated with adjacent points within a region of imaged tissue.

3. The ultrasound imaging system of claim **2**, further comprising a beamformer configured to receive a set of the echo signals from the acquired echo signals and to combine the set of echo signals into a beamformed RF signal, wherein the neural network is further configured to receive the beamformed RF signal and to provide imaging data based, at least in part, on the beamformed RF signal.

4. The ultrasound imaging system of claim **3**, wherein the data selector is further configured to selectively couple the subset of echo signals or the beamformed RF signal to the neural network to as input data based on a control signal received by the data selector.

5. The ultrasound imaging system of claim **1**, further comprising a display processor configured to generate an ultrasound image using the imaging data provided by the neural network; and a user interface configured to display the ultrasound image responsive to the display processor.

6. The ultrasound imaging system of claim **1**, wherein the neural network comprises a deep neural network (DNN) or a convolutional neural network (CNN).

7. The ultrasound imaging system of claim **1**, wherein the imaging data provided by the neural network includes B-mode imaging data, Doppler imaging data, vector flow imaging data, tissue strain imaging data, wall shear stress of an anatomical structure containing a fluid therein, contrast-enhanced imaging data, tissue content imaging data, or combinations thereof.

8. The ultrasound imaging system of claim **1**, wherein the neural network is further configured to receive auxiliary data as input, the auxiliary data including ultrasound transducer configuration information, beamformer configuration information, information about the medium, or combinations thereof, and wherein the imaging data provided by the neural network is further based on the auxiliary data.

9. The ultrasound imaging system of claim **1**, wherein the neural network is operatively associated with a training algorithm configured to receive an array of training inputs and known outputs, wherein the training inputs comprise echo signals, beamformed signals, or combinations thereof associated with a region of imaged tissue and the known outputs comprise known properties of the imaged tissue.

10. The ultrasound imaging system of claim **9**, wherein the known properties are obtained using an imaging modality other than ultrasound.

11. The ultrasound imaging system of claim **9**, wherein the training algorithm is communicatively coupled to a storage device selected from PACS, a networked storage device or a local storage device for receiving the training inputs, the known outputs, or both.

12. The ultrasound imaging system of claim **1**, wherein the neural network is implemented, at least in part, in a computer-readable medium comprising executable instructions, which when executed by a processor coupled to the channel memory, the beamformer, or both, cause the processor to perform a machine-trained algorithm to produce the imaging data based on the one or more samples of the acquired echo signals, the one or more samples of beamformed signals, or both.

13. The ultrasound imaging system of claim **1**, wherein the neural network is configured to receive one or more samples of the acquired echo signals and to provide imaging data based on the one or more samples of the acquired echo signals.

14. The ultrasound imaging system of claim **5**, further comprising a probe comprising the transducer, the channel memory, the neural network and the display processor.

15. The ultrasound imaging system of claim **14**, wherein the user interface is electrically or wirelessly coupled to the ultrasound system.

* * * * *

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摘要(译)

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