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(54) **AI-DRIVEN MOTION CORRECTION OF PET DATA**

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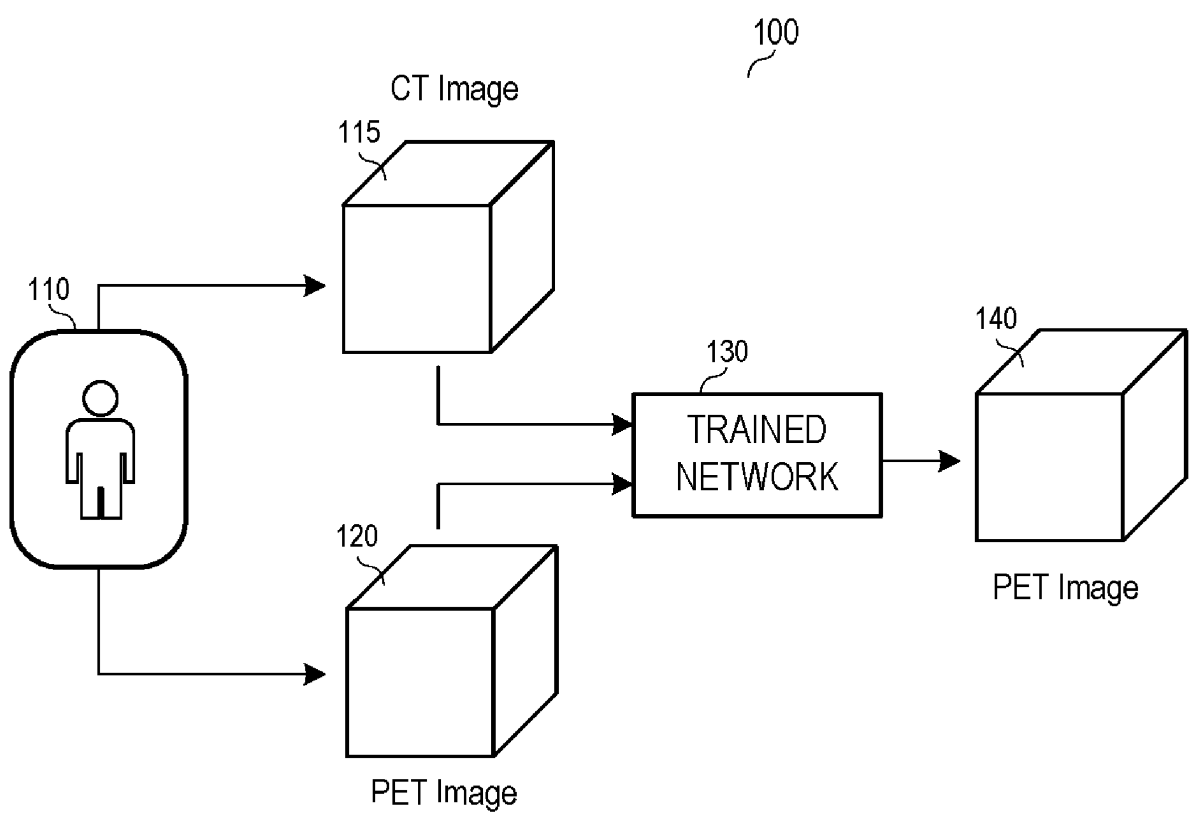
(57) **ABSTRACT**

Systems and methods include acquisition of an anatomical image of an object, acquisition of molecular imaging data of the object at the plurality of photon detectors, reconstruction of a functional image based on the molecular imaging data, input of the anatomical image and the functional image to a trained neural network to generate a second functional image, and presentation of the second functional image.



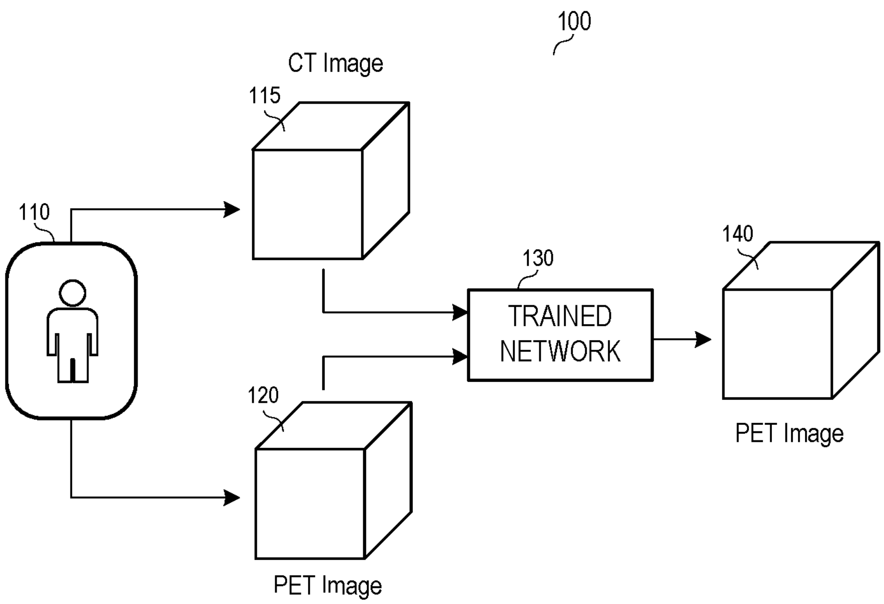

100
CT Image
115
110
130
TRAINED NETWORK
140
120
PET Image
PET Image

FIG. 1

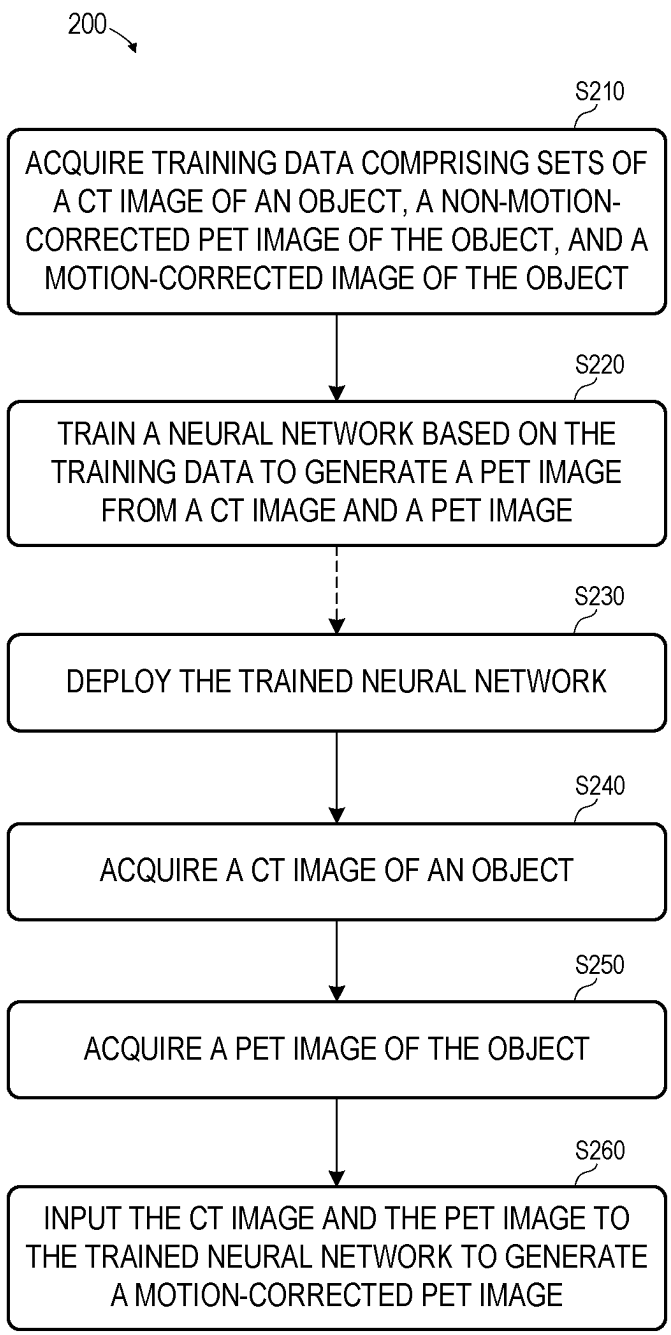

200
S210
ACQUIRE TRAINING DATA COMPRISING SETS OF A CT IMAGE OF AN OBJECT, A NON-MOTION-CORRECTED PET IMAGE OF THE OBJECT, AND A MOTION-CORRECTED IMAGE OF THE OBJECT
S220
TRAIN A NEURAL NETWORK BASED ON THE TRAINING DATA TO GENERATE A PET IMAGE FROM A CT IMAGE AND A PET IMAGE
S230
DEPLOY THE TRAINED NEURAL NETWORK
S240
ACQUIRE A CT IMAGE OF AN OBJECT
S250
ACQUIRE A PET IMAGE OF THE OBJECT
S260
INPUT THE CT IMAGE AND THE PET IMAGE TO THE TRAINED NEURAL NETWORK TO GENERATE A MOTION-CORRECTED PET IMAGE

FIG. 2

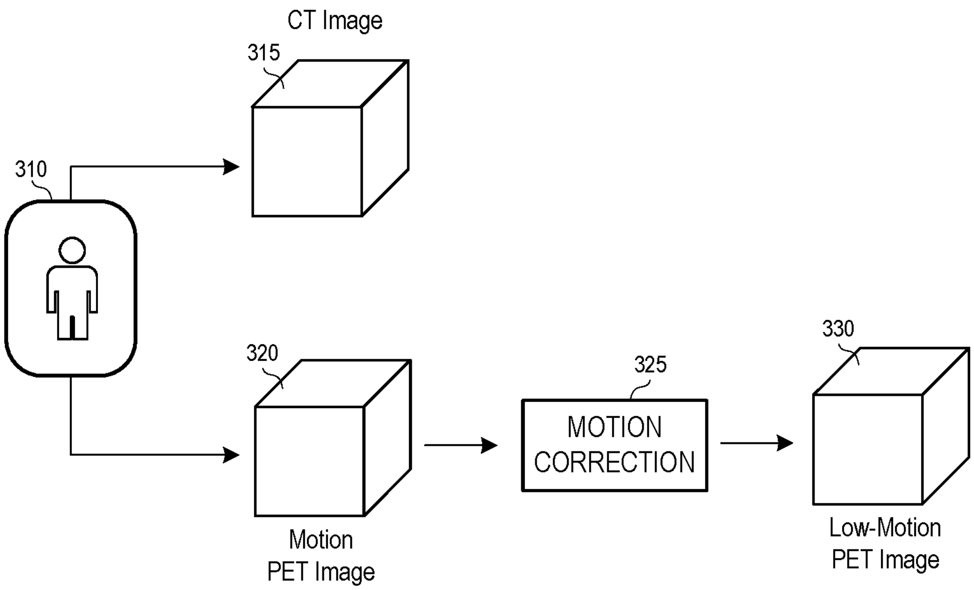

CT Image
315
310
320
Motion
PET Image
325
MOTION
CORRECTION
330
Low-Motion
PET Image

FIG. 3

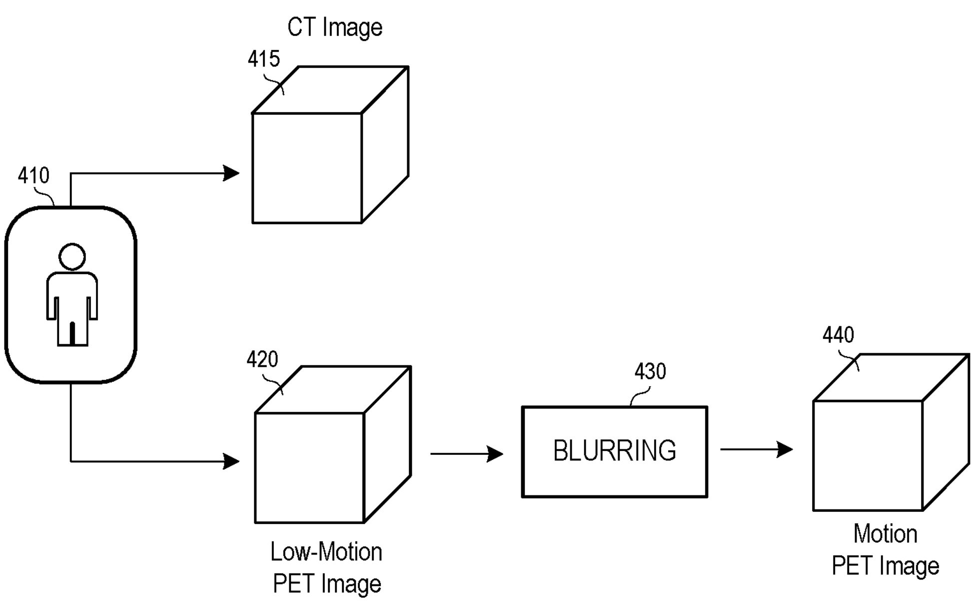

CT Image
415
410
420
Low-Motion
PET Image
430
BLURRING
440
Motion
PET Image

FIG. 4

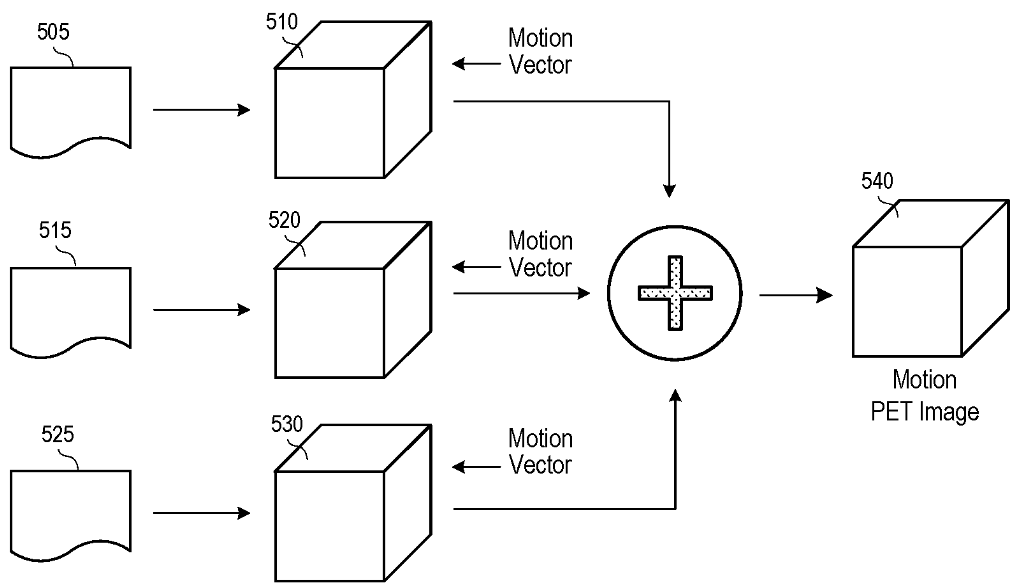

505
510
Motion
Vector
515
520
Motion
Vector
525
530
Motion
Vector
540
Motion
PET Image

FIG. 5

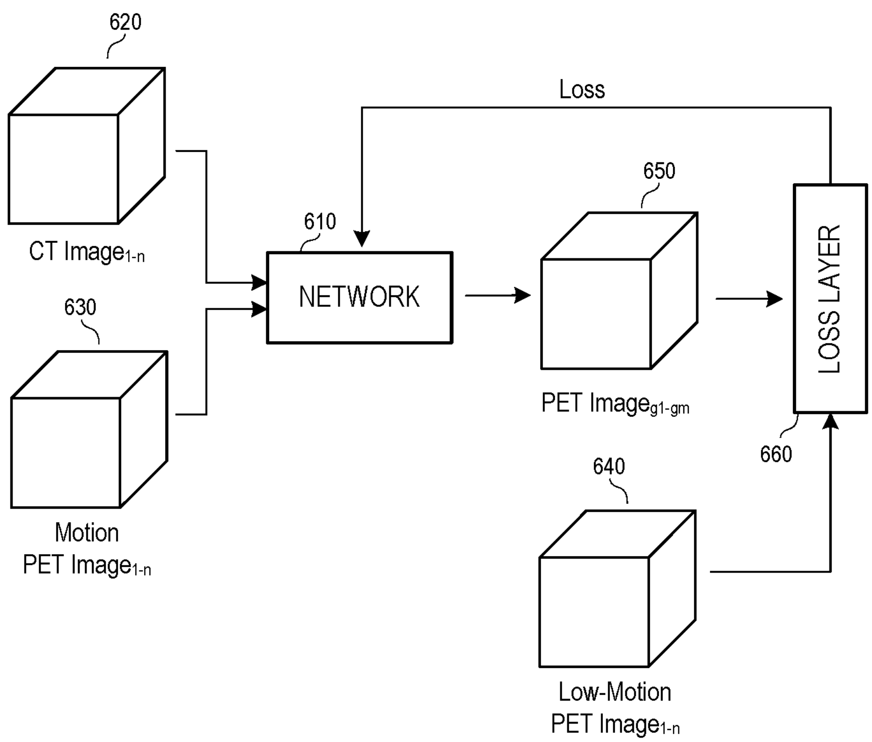

620
CT Image1-n
630
Motion
PET Image1-n
610
NETWORK
Loss
650
PET Imageg1-gm
LOSS LAYER
660
640
Low-Motion
PET Image1-n

FIG. 6

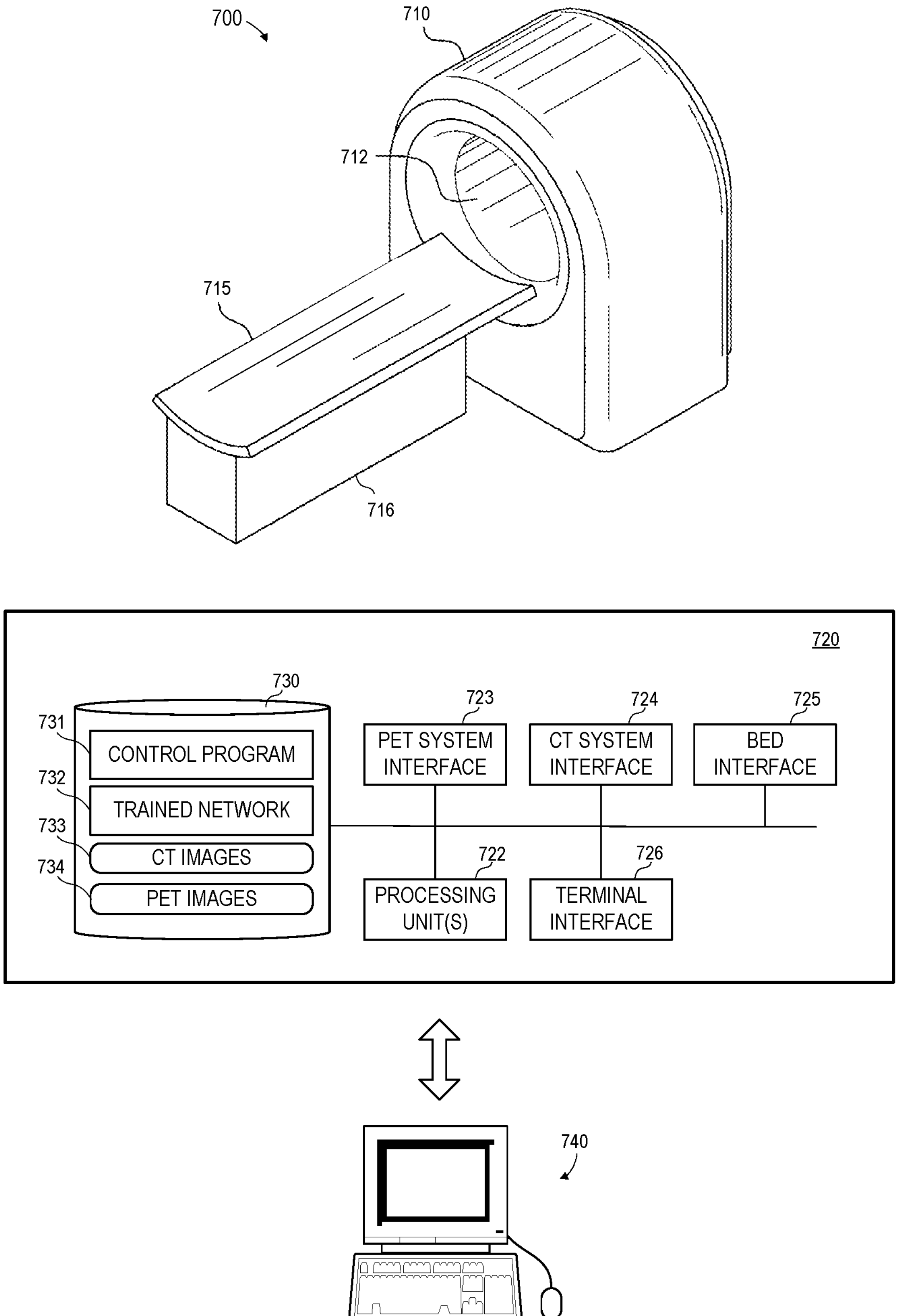

700
710
712
715
716
720
730
731
CONTROL PROGRAM
732
TRAINED NETWORK
733
CT IMAGES
734
PET IMAGES
723
PET SYSTEM INTERFACE
724
CT SYSTEM INTERFACE
725
BED INTERFACE
722
PROCESSING UNIT(S)
726
TERMINAL INTERFACE
740

FIG. 7

AI-DRIVEN MOTION CORRECTION OF PET DATA

BACKGROUND

[0001] Molecular Imaging (MI) generates functional images which represent biological processes (e.g., glucose metabolism, receptor affinity) occurring within a patient. According to MI techniques, a radiotracer is administered to a patient and radiation (e.g., gamma rays) is emitted from within the patient and captured by detectors. The detectors may capture a plurality of sets of emission data, each of which may be considered a "frame" and is associated with a respective time period. The time period of two frames may overlap in some scenarios.

[0002] A patient may exhibit respiratory and/or other motion while the sets of emission data are being captured. This motion adversely affects the diagnostic quality of images generated from the emission data. For instance, motion patterns caused by breathing can lead to significant organ displacement and subsequent blurring of clinically-relevant features in a resulting image.

[0003] To address this problem, motion patterns are monitored using external devices or by identifying movement in the raw data domain. The patterns are characterized into phases, and the emission data is segmented into one motion-frozen frame for each phase. In some approaches, an image is reconstructed from the emission data of each motion-frozen frame, the reconstructed images are registered to a target image, and the registered images are averaged to generate a final image. According to another approach, a single image is reconstructed from all available emission data while incorporating the characterized motion patterns into the reconstruction process. Each of these approaches is computationally-intensive and requires accurate characterization of motion phases corresponding to correction factors such as attenuation.

[0004] Systems are desired to generate diagnostically-suitable motion-corrected images from MI data in a computationally-efficient manner.

BRIEF DESCRIPTION OF THE DRAWINGS

[0005] FIG. **1** is a block diagram of a system to generate a motion-corrected MI image according to some embodiments.

[0006] FIG. **2** is a flow diagram of a process to train a network to generate a motion-corrected MI image and use the network to motion-correct an MI image according to some embodiments.

[0007] FIG. **3** illustrates generation of neural network training data according to some embodiments.

[0008] FIG. **4** illustrates generation of neural network training data according to some embodiments.

[0009] FIG. **5** illustrates generation of neural network training data according to some embodiments.

[0010] FIG. **6** illustrates training of a neural network to generate a motion-corrected MI image based on a Computed Tomography image and a Positron Emission Tomography image according to some embodiments.

[0011] FIG. **7** is a block diagram of an imaging system according to some embodiments.

DETAILED DESCRIPTION

[0012] The following description is provided to enable any person in the art to make and use the described embodiments. Various modifications, however, will remain apparent to those in the art.

[0013] Embodiments utilize a network to "deblur" MI images using a corresponding anatomical image. Such a network may be trained based on a plurality of sets of images consisting of an anatomical image, a corresponding MI image including motion artifacts, and a corresponding MI image including no or fewer motion artifacts (e.g., a motion-corrected MI image). Embodiments may require fewer resources than the above-described motion correction methods, due at least in part to eliminating the need to identify motion and compute motion vectors therefrom.

[0014] FIG. **1** is a block diagram of system **100** to generate a motion-corrected MI image according to some embodiments. The illustrated components of system **100** may be implemented in computer hardware, in program code and/or in one or more computing systems executing such program code as is known in the art. Such a computing system may include one or more processing units which execute program code stored in a memory system. More than one functional component may be implemented by a single computing system in some embodiments. One or more of the computing systems may comprise a virtual machine, and one- or more computing systems may comprise a cloud-based compute resource providing on-demand scalability and failure recovery.

[0015] Scanner **110** may be capable of acquiring Computed Tomography (CT) data and reconstructing CT images therefrom, and also of acquiring Positron Emission Tomography (PET) data and reconstructing PET images therefrom. Embodiments are not limited to these two imaging modalities. For example, embodiments may be implemented using other MI modalities including Single Photon Computed Tomography (SPECT) imaging and other anatomical imaging modalities such as Magnetic Resonance (MR) imaging.

[0016] Scanner **110** generates three-dimensional CT image **115** of a patient using any suitable CT imaging protocol. Scanner **110** may generate PET data substantially contemporaneously with the acquisition of CT image **115**. For example, a CT imaging system of scanner **110** may be operated to acquire CT image **115** while a patient lies in a given position on a bed of scanner **110**, and a PET imaging system of scanner **110** may be operated shortly thereafter to acquire PET data while the patient remains on the bed in the given position. Since the geometric transformation (if any) between coordinates of the CT imaging system and the PET imaging system is known, resulting images may be easily registered with one another.

[0017] Scanner **110** generates PET data using any suitable PET imaging protocol. For example, a radiopharmaceutical tracer is introduced into a patient body via arterial injection. Radioactive decay of the tracer generates positrons which eventually encounter electrons and are annihilated thereby. The annihilation produces two 511 keV photons which travel in approximately opposite directions. A ring of detectors surrounding the body detects 511 keV photons and identifies "coincidences" based thereon.

[0018] A coincidence is identified when two detector crystals disposed on opposite sides of the body detect the arrival of two photons within a short time window indicating that the two photons arose from the same positron annihilation. Because the two "coincident" photons travel in approximately opposite directions, the locations of the two detector crystals determine a Line-of-Response (LOR) along which an annihilation may have occurred. Time-of-flight (TOF) PET additionally measures the difference between the detection times of the two photons arising from the annihilation. This difference may be used to estimate a particular position along the LOR at which the annihilation occurred.

[0019] The acquired PET data may consist of raw (i.e., list-mode) data and/or sinograms. List-mode data may represent each detected annihilation as an LOR between two detector crystals, the time at which each photon of the annihilation reached each detector crystal and (in a TOF system) the difference between the arrival times of the two photons. A sinogram is a data array of the angle versus the displacement of each LOR. A sinogram includes one row containing the LOR for a particular azimuthal angle. Each of these rows corresponds to a one-dimensional parallel projection of the tracer distribution at a different coordinate. A sinogram stores the location of the LOR of each coincidence such that all the LORs passing through a single point in the volume trace a sinusoid curve in the sinogram.

[0020] PET image **120** is reconstructed from the acquired PET data using any suitable reconstruction operation that is or becomes known. Reconstruction may include subtraction of random coincidences and scatter coincidences from the PET data, application of attenuation correction based on a linear attenuation coefficient map ("mu-map") derived from CT image **115**, and any other suitable reconstruction steps. The reconstruction steps may be similar to reconstruction steps which were used to generate training PET images for use in training network **130**.

[0021] According to some embodiments, motion-correction is not performed on the PET data, either on the raw data or during image reconstruction. Accordingly, PET image **120** may be blurred (i.e., may exhibit motion artifacts) due to motion of the patient during acquisition of the PET data.

[0022] Network **130** may comprise hardware and software specifically-intended for executing algorithms based on a specified network architecture and trained parameters. Network **130** has been trained as will be described below to generate a PET image based on an input CT image and an input PET image. Accordingly, CT image **115** and PET image **120** are input to trained neural network **130**, which generates PET image **140** based thereon. PET image **140** output by network **130** is intended to represent a motion-corrected version of PET image **120**. In other words, trained network **130** (with the assistance of CT image **115**) acts as a substitute for prior motion-correction procedures.

[0023] FIG. **2** is a flow diagram of process **200** to train a network to generate a motion-corrected MI image and use the trained network to motion-correct an MI image according to some embodiments. Process **200** may be performed by any combination of hardware and software that is or becomes known. Program code embodying processes described herein may be stored by any non-transitory tangible medium, including a fixed disk, a volatile or non-volatile random-access memory, a DVD, a Flash drive, and a magnetic tape, and executed by any suitable processing unit, including but not limited to one or more microprocessors, microcontrollers, processor cores, and processor threads. Embodiments are not limited to the examples described below.

[0024] A plurality of sets of training data are acquired at **S210**. Each set of training data comprises a CT image of an object, a non-motion-corrected PET image of the object, and a corresponding motion-corrected image of the object. The non-motion-corrected PET image includes more motion artifacts than the motion-corrected image of the object.

[0025] FIG. **3** illustrates generation of a set of neural network training data according to some embodiments. Scanner **310** may comprise a PET/CT scanner which generates CT image **315** and corresponding motion PET image **320**, contemporaneously and of the same patient. Motion PET image **320** may exhibit motion artifacts due to movement of the patient during acquisition of the PET data from which motion PET image **320** was reconstructed.

[0026] Motion correction component **325** applies one or more motion correction algorithms to motion PET image **320** to generate low-motion PET image **330**. The one or more motion correction algorithms may comprise any motion correction algorithm that is or becomes known. Images **320** and **330** are denoted as motion and low-motion images, respectively, to indicate that low-motion image **330** exhibits fewer motion artifacts than motion PET image **320**. Image **330** may exhibit no motion artifacts in some embodiments.

[0027] CT image **315**, motion PET image **320** and low-motion PET image **330** comprise a set of training data. Many other sets of training data may be generated as shown in FIG. **3**, using different combinations of patients, patient motion, PET/CT scanners, and/or motion correction algorithms.

[0028] FIG. **4** illustrates generation of a set of neural network training data according to some embodiments. Scanner **410** contemporaneously generates CT image **415** and corresponding low-motion PET image **420**. PET image **420** is denoted as low-motion to indicate that that the imaged region of the patient was stationary (or substantially stationary) during acquisition of the PET data from which low-motion PET image **420** was reconstructed. Determination of whether the patient was stationary (or substantially stationary) during the acquisition may be based on external monitoring systems, an analysis of the raw PET data, and/or an examination of PET image **420** for motion artifacts.

[0029] Blurring component **430** applies one or more motion-simulating algorithms to low-motion PET image **420** to generate motion PET image **330**. The one or more motion-simulating algorithms applied by blurring component **430** may comprise any motion-simulating algorithm that is or becomes known. The motion-simulating algorithms may be applied to list-mode data or sinogram data from which image **420** was reconstructed, to PET image **420** itself, or in any other manner.

[0030] CT image **415**, motion PET image **440** and low-motion PET image **420** comprise a set of training data. Again, many other sets of training data may be generated as shown in FIG. **4**, using different combinations of patients, PET/CT scanners, and/or blurring algorithms.

[0031] FIG. **5** illustrates generation of a motion PET image of FIG. **4** according to some embodiments. It will be assumed that scanner **410** acquires list-mode data of low-motion PET image **420** over a period of time. As is known in the art, blurring component **430** may divide the list-mode data into frames **505**, **515** and **525**. Each of frames **505**, **515** and **525** includes list-mode data acquired over a respective time period. For example, frame **505** includes list-mode data acquired from t_0-t_1, frame **515** includes list-mode data acquired from t_1-t_2, and frame **525** includes list-mode data acquired from t_2-t_3.

[0032] A respective PET image is reconstructed from each frame of list-mode data using known techniques. As shown in FIG. **5**, image **510** is reconstructed from frame **505**, image **520** is reconstructed from frame **515**, and image **530** is reconstructed from frame **525**. Since image **420** is a low-motion image, images **510-530** should be similar to one another.

[0033] A motion vector is determined which represents a natural movement which might occur during time period to-t_1, and the motion vector is applied to image **510**. Next, a motion vector is determined which represents a natural movement which might occur during time period t_1-t_2 and is applied to image **520**. The time-period specific motion vectors may be determined from a previously-determined function of motion over time which represents a natural patient motion. Motion vectors are also determined and applied to all subsequent images. The resulting images are then summed to generate motion PET image **540**.

[0034] In other embodiments, the period-specific motion vectors are applied directly to corresponding list-mode data frames **505**, **515** and **525**. The resulting frames are summed to create a single list-mode frame and a motion PET image is reconstructed from the list-mode data frame.

[0035] Returning to process **200**, a neural network is trained at S**220** to generate a PET image from a CT image and a PET image based on the acquired training data. FIG. **6** illustrates training of neural network **610** according to some embodiments. Network **610** may comprise, for example, a generator of a Generative Adversarial Network (GAN) having trainable parameters as is known in the art. Network **610** may comprise any type of supervised or unsupervised learning-compatible network, algorithm, decision tree, etc. to receive image data and to output image data that is or becomes known, including but not limited to convolutional neural networks, cycle-GAN networks and U-Net networks.

[0036] Network **610** may comprise a plurality of layers of neurons which receive input, change internal state according to that input, and produce output depending on the input and internal state. The output of certain neurons is connected to the input of other neurons to form a directed and weighted graph. The weights as well as the functions that compute the internal states are iteratively modified during training s. Thusly-trained network **610** may be implemented by a set of linear equations, executable program code, a set of hyperparameters defining a model structure and a set of corresponding weights, or any other representation of the mapping of input to output which was learned as a result of the training.

[0037] The training data of FIG. **6** consists of N CT images **620**, N motion PET images **630** and N low-motion PET images **640**. A plurality of sets of corresponding images **620**, **630** and **640** may have been generated as described with respect to FIGS. **3** and **4**. In the case of FIG. **3**, the low-motion image **640** of a set is generated from the motion PET image **630** and, in the case of FIG. **4**, the motion image **630** of the set is generated from the low-motion image **640**.

[0038] During training, a batch of M CT images **620** and M corresponding motion PET images **630** is input to network **610**, which generates a PET image **650** for each input image of the batch. Loss layer **660** calculates a loss based on differences between each of generated M PET images **650** and its corresponding ground truth low-motion PET image **640**. The loss is back-propagated to network **610**, which is modified with the aim of minimizing the loss as is known in the art. Training continues in this manner until satisfaction of a given performance target or a timeout situation.

[0039] Training may include any components suitable to train network **610** in view of the type of network **610**. For example, if network **610** is a GAN, network **610** may comprise a generator trained using a discriminator, a random input generator, and a loss layer to determine generative loss and discrimination loss.

[0040] After training, network **610** may be deployed at S**230** as shown in FIG. **1**. The dashed arrow between S**220** and S**230** of process **200** indicates that S**220** and S**230** may occur at any temporal and/or geographical distance from one another. The trained network may be deployed in or in conjunction with many different scanners.

[0041] A CT image of an object is acquired at S**240** using any suitable CT imaging protocol. For example, a CT imaging protocol is executed to acquire projection images of a patient and to reconstruct a CT image from the projection images. Next, a PET image of the object is acquired at S**250**. The PET image may be acquired by a same scanner as used to acquire the CT image at S**240** and may be acquired closely before or after in time.

[0042] The CT image and the PET image are input to trained neural network at S**260**. Per its training, the trained neural network generates a motion-corrected PET image based on the input images. The motion-corrected PET image preferably exhibits less motion artifacts than the input PET image.

[0043] FIG. **7** illustrates PET/CT scanner **700** to execute one or more of the processes described herein. Embodiments are not limited to scanner **700** or to a multi-modality imaging system.

[0044] Scanner **700** includes gantry **710** defining bore **712**. As is known in the art, gantry **710** houses PET imaging components for acquiring PET image data and CT imaging components for acquiring CT image data. The CT imaging components may include one or more x-ray tubes and one or more corresponding x-ray detectors as is known in the art. The PET imaging components may include any number or type of detectors including background radiation-emitting crystals and disposed in any configuration as is known in the art.

[0045] Bed **715** and base **716** are operable to move a patient lying on bed **715** into and out of bore **712** before, during and after imaging. In some embodiments, bed **715** is configured to translate over base **716** and, in other embodiments, base **716** is movable along with or alternatively from bed **715**.

[0046] Movement of a patient into and out of bore **712** may allow scanning of the patient using the CT imaging elements and the PET imaging elements of gantry **710**. Bed **715** and base **716** may provide continuous bed motion and/or step-and-shoot motion during such scanning according to some embodiments.

[0047] Control system **720** may comprise any general-purpose or dedicated computing system. Accordingly, control system **720** includes one or more processing units **722** configured to execute executable program code to cause system **720** to acquire image data and generate images therefrom, and storage device **730** for storing the program code. Storage device **730** may comprise one or more fixed disks, solid-state random-access memory, and/or removable media (e.g., a thumb drive) mounted in a corresponding interface (e.g., a Universal Serial Bus port).

[0048] Storage device **730** stores program code of control program **731**. One or more processing units **722** may execute control program **731** to control CT imaging elements of scanner **700** using CT system interface **724** and bed interface **725** to acquire CT data and to reconstruct CT images **733** therefrom. One or more processing units **722** may execute control program **731** to, in conjunction with PET system interface **723** and bed interface **725**, detect photons emitted from the patient based on pulses generated by the PET detectors. The detected photons may be recorded in storage **730** as PET data, which may comprise raw (i.e., list-mode) data and/or sinograms. Control program **731** may also be executed to reconstruct PET images **734** based on PET data using any suitable reconstruction algorithm that is or becomes known. According to some embodiments, PET images **734** may be reconstructed based at least in part on CT images **733** (e.g., using a linear attenuation coefficient map determined from a CT image **733**).

[0049] Trained network **732** may comprise code executable to perform an input data-to-output data mapping specified by trained network parameters. A CT image **733** and a PET image **734** may be input to trained network **732** to generate a motion-corrected PET image as described above. Such a motion-corrected PET image may also be stored in PET images **734**.

[0050] PET images **734** and CT images **733** may be transmitted to terminal **740** via terminal interface **726**. Terminal **740** may comprise a display device and an input device coupled to system **720**. Terminal **740** may display the received PET images **734** and CT images **733**. Terminal **740** may receive user input for controlling display of the data, operation of scanner **700**, and/or the processing described herein. In some embodiments, terminal **740** is a separate computing device such as, but not limited to, a desktop computer, a laptop computer, a tablet computer, and a smartphone.

[0051] Each component of scanner **700** may include other elements which are necessary for the operation thereof, as well as additional elements for providing functions other than those described herein. Each functional component described herein may be implemented in computer hardware, in program code and/or in one or more computing systems executing such program code as is known in the art. Such a computing system may include one or more processing units which execute processor-executable program code stored in a memory system.

[0052] Those in the art will appreciate that various adaptations and modifications of the above-described embodiments can be configured without departing from the claims. Therefore, it is to be understood that the claims may be practiced other than as specifically described herein.

What is claimed is:

1. A molecular imaging scanner comprising:

a plurality of photon detectors; and

a processing unit to:

determine an anatomical image of an object;

acquire molecular imaging data of the object at the plurality of photon detectors;

reconstruct a functional image based on the molecular imaging data; and

input the anatomical image and the functional image to a trained neural network to generate a second functional image; and

a display to present the second functional image.

2. A scanner according to claim **1**, the processing unit to:

determine a linear attenuation correction map based on the anatomical image,

wherein reconstruction of the functional image is based on the linear attenuation correction map and the molecular imaging data.

3. A scanner according to claim **1**, wherein the neural network is trained based on a plurality of sets of training data, each of the plurality of sets of training data comprising:

a training anatomical image;

a training functional image exhibiting motion artifacts; and

a ground truth functional image exhibiting less motion artifacts than the training functional image.

4. A scanner according to claim **3**, wherein a first set of the plurality of sets of training data is generated by:

acquiring a first training anatomical image and a first training functional image; and

applying motion correction to the first training functional image to generate a first ground truth functional image.

5. A scanner according to claim **4**, wherein a second set of the plurality of sets of training data is generated by:

acquiring a second training anatomical image and a second ground truth functional image; and

applying motion vectors to the second ground truth functional image to generate a second training functional image.

6. A scanner according to claim **1**, wherein a first set of the plurality of sets of training data is generated by:

acquiring a first training anatomical image and a first ground truth functional image; and

applying motion vectors to the first ground truth functional image to generate a first training functional image.

7. A method comprising:

acquiring a computed tomography image of an object;

acquiring positron emission tomography data of the object;

reconstructing a positron emission tomography image based on the positron emission tomography data;

inputting the computed tomography image and the positron emission tomography image to a trained neural network to generate a second positron emission tomography image; and

presenting the second positron emission tomography image.

8. A method according to claim **7**, further comprising:

determining a linear attenuation correction map based on the computed tomography image,

wherein reconstructing the positron emission tomography image is based on the linear attenuation correction map and the positron emission tomography data.

9. A method according to claim **7**, wherein the neural network is trained based on a plurality of sets of training data, each of the plurality of sets of training data comprising:

a training computed tomography image;

a training positron emission tomography image exhibiting motion artifacts; and a ground truth positron emission tomography image exhibiting less motion artifacts than the training positron emission tomography image.

10. A method according to claim **9**, wherein a first set of the plurality of sets of training data is generated by:

acquiring a first training computed tomography image and a first training positron emission tomography image; and

applying motion correction to the first training positron emission tomography image to generate a first ground truth positron emission tomography image.

11. A method according to claim **10**, wherein a second set of the plurality of sets of training data is generated by:

acquiring a second training computed tomography image and a second ground truth positron emission tomography image; and

applying motion vectors to the second ground truth positron emission tomography image to generate a second training positron emission tomography image.

12. A method according to claim **7**, wherein a first set of the plurality of sets of training data is generated by:

acquiring a first training computed tomography image and a first ground truth positron emission tomography image; and

applying motion vectors to the first ground truth positron emission tomography image to generate a first training positron emission tomography image.

13. A non-transitory medium storing program code, the program code executable by at least one processing unit to cause a computing system to:

acquire an anatomical image of an object;

acquire molecular imaging data of the object at the plurality of photon detectors;

reconstruct a functional image based on the molecular imaging data;

input the anatomical image and the functional image to a trained neural network to generate a second functional image; and

present the second functional image.

14. A medium according to claim **13**, the program code executable by at least one processing unit to cause a computing system to:

determine a linear attenuation correction map based on the anatomical image,

wherein reconstruction of the functional image is based on the linear attenuation correction map and the molecular imaging data.

15. A medium according to claim **13**, wherein the neural network is trained based on a plurality of sets of training data, each of the plurality of sets of training data comprising:

a training anatomical image;

a training functional image exhibiting motion artifacts; and

a ground truth functional image exhibiting less motion artifacts than the training functional image.

16. A medium according to claim **15**, wherein a first set of the plurality of sets of training data is generated by:

acquiring a first training anatomical image and a first training functional image; and

applying motion correction to the first training functional image to generate a first ground truth functional image.

17. A medium according to claim **16**, wherein a second set of the plurality of sets of training data is generated by:

acquiring a second training anatomical image and a second ground truth functional image; and

applying motion vectors to the second ground truth functional image to generate a second training functional image.

18. A medium according to claim **13**, wherein a first set of the plurality of sets of training data is generated by:

acquiring a first training anatomical image and a first ground truth functional image; and

applying motion vectors to the first ground truth functional image to generate a first training functional image.

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