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METHOD FOR MONITORING AND/OR CONTROLLING A MEDICAL IMAGING PROCEDURE AND METHODS FOR PROVIDING TRAINED MACHINE LEARNING MODELS

Abstract

A computer-implemented method for monitoring and/or controlling a medical imaging procedure on a patient includes receiving breathing information concerning a breathing pattern of the patient and selecting a compliance class from at least two possible compliance classes based on the breathing information, wherein at least one of the possible compliance classes corresponds to a compliance of the acquired breathing information with a given desired breathing and/or breath-holding pattern. The method further includes (1) controlling the medical imaging procedure depending on the selected compliance class and/or (2) outputting non-compliance information to a user and/or storing the non-compliance information with an acquired medical image data when the selected compliance class does not indicate a compliance of the acquired breathing information with the given desired breathing and/or breath-holding pattern.

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Background/Summary

[0001] The present patent document claims the benefit of European Patent Application Ser. No. 24/158,895, filed Feb. 21, 2024, which is hereby incorporated by reference in its entirety.
TECHNICAL FIELD
[0002] The disclosure relates to a computer-implemented method for monitoring and/or controlling a medical imaging procedure on a patient, methods for providing trained machine learning models, a data processing system, a computer program, and a computer-readable medium.
BACKGROUND
[0003] For certain medical imaging protocols, in particular for many magnetic resonance imaging techniques, acquisitions require the patient to follow a particular breathing and/or breath-holding pattern. The compliance of the patient to a target breathing pattern is important for reducing motion artifacts and providing a good image quality, since the corresponding sequences may be designed with this assumption.
[0004] In certain medical imaging protocols, medical personnel overseeing medical imaging needs to recognize, whether the patient is following a desired breathing and/or breath-holding pattern, e.g., given instructions, while the imaging protocol is running. A sufficiently close monitoring may be challenging, e.g., in many x-ray and magnetic resonance imaging protocols.
[0005] In certain cases, motion artifacts or other issues caused by a patient not following the desired breathing and/or breath-holding pattern will only be detected when analyzing the final image data. This may lead to an extended time requirement for such imaging protocols to allow sufficient time for a repeat of the imaging sequence when it may be necessary and therefore to a lower utilization of the used imaging device or it might even require the patient to come back to an imaging facility for a further imaging after he has already left the facility.
SUMMARY AND DESCRIPTION
[0006] The scope of the present disclosure is defined solely by the appended claims and is not affected to any degree by the statements within this summary. The present embodiments may obviate one or more of the drawbacks or limitations in the related art.
[0007] The disclosure is based on the problem of providing an improved way of monitoring and/or controlling a medical imaging procedure with respect to the compliance of the patient to a desired breathing and/or breath-holding pattern.
[0008] The problem is solved by a computer-implemented method for monitoring and/or controlling a medical imaging procedure on a patient. The method includes: receiving a breathing information concerning a breathing pattern of the patient; selecting a compliance class from at least two possible compliance classes based on the breathing information, wherein at least one of the possible compliance classes corresponds to a compliance of the acquired breathing information with a given desired breathing and/or breath-holding pattern; and controlling the medical imaging procedure depending on the selected compliance class; and/or outputting a non-compliance information to a user and/or storing a non-compliance information with an acquired medical image data when the selected compliance class does not indicate a compliance of the acquired breathing information with the given desired breathing and/or breath-holding pattern.
[0009] As discussed in more detail below, various ways to detect a breathing state of the patient are

already known and, e.g., used for gating purposes, e.g., to only take measurement data from a specific phase of the breathing cycle into account. While a medical expert may manually evaluate such a breathing information to determine, whether the patient complies to the given desired breathing and/or breath-holding pattern, this approach would be quite time-consuming and therefore would only allow for a determination, whether the desired breathing and/or breath-holding pattern was matched, after the imaging procedure is already finished and potentially after the patient has already left the imaging facility.

[0010] By the proposed automatic selection of a compliance class based on the breathing information, it is possible to determine whether the desired breathing and/or breath-holding pattern was matched sufficiently closely to likely provide a satisfactory imaging quality while the imaging sequence is still running or even before the imaging sequence has started. This may allow for an adjustment of the parametrization of the imaging sequence on the fly, before it is even started or even while it is running, and/or for a quick abortion and restart of the imaging sequence, when it is already running. Overall, the required time and burden on the patient may be noticeably reduced by using the computer implemented method.

[0011] The desired breathing and/or breath-holding pattern may be specified by instructions that may be provided to the patient by medical personnel or automatically by the medical imaging device.

[0012] In one example, only two possible compliance classes may be used, wherein one of these compliance classes indicates a sufficient compliance of the patient, such that the medical imaging procedure may be performed without changes, and the other compliance class indicates, that the compliance is insufficient. When the compliance is insufficient, this may indicate that a planned imaging sequence may not be started and/or may be modified and/or that an imaging sequence that is already running or finished may be repeated.

[0013] It is also possible to allow the selection between more than two possible compliance classes. This may allow for multiple levels of compliance that may be classified, wherein the compliance may be classified on a scale from 1 to 5. This may be useful when at least some of the compliance classes still allow for the imaging to proceed but may require a modification of the imaging sequence and/or the postprocessing. It may therefore be advantageous, when the medical imaging procedure is controlled depending on the selected compliance class, even when the selected compliance class does indicate a sufficient compliance of the acquired breathing information with the given desired breathing and/or breath-holding pattern to allow for an imaging.

[0014] The breathing information may be based on the breathing of the patient during the medical imaging procedure and/or during a preparatory time interval before the imaging has started and/or during a further time interval after the imaging procedure has already ended. The acquisition of the breathing information may be performed before the beginning of the claimed computer-implemented method or it may be acquired as part of the act of the receiving of the breathing information.

[0015] The breathing information may be based on sensor data of at least one dedicated sensor. The dedicated sensor may be a chest band measuring an extension of the chest due to breathing, a nasal airflow sensor, an optical camera that may detect optical fiducial markers, and/or a laser range sensor. Additionally, or alternatively, the breathing information may be based on measurement data acquired by the medical imaging device used during the medical imaging procedure. It is, e.g., possible, that the medical imaging procedure includes a magnetic resonance imaging. In this case, a so-called pilot tone may be used to acquire measurement data concerning the movement of the diaphragm of the patient that corresponds to the breathing motion of the patient and may therefore be used as the breathing information.

[0016] The breathing information may describe a chronological sequence of multiple measurements concerning a respective breathing status, wherein the selection of the selected compliance class depends on the chronological sequence. It is possible to locally expand and/or compress this chronological sequence. This may allow the use of a common classifier function to select the compliance class for different sets of breathing information that may match different breathing and/or breath-holding patterns, e.g., having a different breath-holding time.

[0017] In certain examples, the compliance class may be determined by first determining a single value from the breathing information and then comparing this single value to a threshold. It is, e.g., possible to determine the variation of the measurements of the chronological sequence during at breath holding interval with the threshold. However, the robustness of the classification may be improved when multiple breathing pattern parameters that are determined from the chronological sequence are taken into account.

[0018] When the breathing information describes a chronological sequence of multiple measurements concerning a respective breathing status, a mapping function may be used to map these measurements to a number of breathing pattern parameters, wherein the number of breathing pattern parameters is smaller than the number of measurements in the chronological sequence. In other words, the mapping function maps the chronological sequence to an, in particular approximate, representation of a lower dimensionality. The number of breathing pattern parameter may be less than 50 or less than 20. The number of measurements in the chronological sequence may be a larger than 100 or larger than 1000. In particular, the number of breathing pattern parameters may be larger than 3 or larger than 10. The given intervals for this number allow for a robust classification, while keeping the complexity of the algorithms relatively low. The discussed mapping may include the local expansion and/or compression of the time sequence discussed above and/or a resampling of the chronological sequence as a preparatory act before the actual mapping to the breathing pattern parameters is performed.

[0019] A classifier used to select the compliance class may therefore operate on a lower number of input parameters, namely the breathing pattern parameters, therefore reducing the complexity of the classifier. This may especially be advantageous, when the classifier is formed by a model that is trained by machine learning, as discussed in more detail later. In this case, lowering of the dimensionality of the input data may lower the number of free parameters of the model, which need to be determined during the training of the model, e.g., by reducing the number of nodes in the input layer of a neural network and therefore, e.g., also in the following layers. This will, in turn, reduce the amount of training data required to train the model and also lower the resources required for the training of the model and for the use of the trained model.

[0020] The mapping function may include a first trained machine learning model that is based on multiple training data sets including a respective reference sequence of measurements concerning a respective breathing status of a respective patient.

[0021] The mapping function may be configured in such a way that a good approximation of the chronological sequence may be reconstructed from the breathing pattern parameters, even when a low number of breathing pattern parameters, e.g., less than 50 or less than 20, e.g., 16 breathing pattern parameters are used, while the chronological sequence may include hundreds or thousands of measurements.

[0022] To allow for such a strong reduction in dimensionality while keeping the loss of information low, it is advantageous to use prior knowledge about which kinds of chronological sequences may be expected. One way to take such prior knowledge into account is the use of a model that is based on training data concerning previously measured chronological sequences that may be used as reference sequences.

[0023] The training of the first trained machine learning model may be performed outside of the claimed method. In other words, the computer implemented method may use a first trained machine learning model based on the discussed training. The method may therefore, in particular, not include the training itself.

[0024] A trained machine learning model may mimic cognitive functions that humans associate with other human minds. In particular, by a training based on training data the machine learning model is able to adapt to new circumstances and to detect and extrapolate patterns. Another term for “trained machine learning model” is “trained function.”

[0025] Parameters of a machine learning model may be adapted by training. In particular, supervised training, semi-supervised training, unsupervised training, reinforcement learning, and/or active learning may be used. Furthermore, representation learning (an alternative term is “feature learning”) may be used. In particular, the parameters of machine learning models may be adapted iteratively by several acts of training. In particular, within the training a certain cost function may be minimized. In particular, within the training of a neural network the backpropagation algorithm may be used.

[0026] In particular, a machine learning model may include a neural network, a support vector machine, a decision tree, and/or a Bayesian network, and/or the machine learning model may be based on k-means clustering, Q-learning, genetic algorithms, and/or association rules. In particular, a neural network may be a deep neural network, a convolutional neural network, or a convolutional deep neural network. Furthermore, a neural network may be an adversarial network, a deep adversarial network, and/or a generative adversarial network.

[0027] The first trained machine learning model may be based on manifold learning. Manifold learning is an approach to non-linear dimensionality reduction and therefore particularly suited for the task of reducing the dimensionality of the chronological sequence. Algorithms for manifold learning are based on the idea, that the dimensionality of many data sets is only artificially high, e.g., in the example of the breathing information due to noise and very minor variations in the breathing patterns that are not really relevant for the medical imaging.

[0028] The first trained machine learning model may be based on a training of an autoencoder. Shallow learning and therefore, e.g., at neural network with a low number of layers may be used, since a relatively low amount of input data is processed and the amount of output data is also small, especially compared to an image processing task. Therefore, it is, e.g., possible to train the model using a relatively simple backpropagation of error approach, e.g. by using a gradient descent.

[0029] An autoencoder is a type of artificial neural network used to learn an efficient encoding of unlabeled data. An autoencoder includes two partial models, namely an encoder that transforms the input data to a sparse representation, namely the breathing pattern parameters, and a decoder that aims to recreate the input data, namely the chronological sequence, from the encoded representation. The autoencoder may be trained to minimize an error between the output sequence regenerated by the decoder and the original input, namely the chronological sequence.

[0030] Once the training of the autoencoder is finished, the partial model of the autoencoder forming the encoder may then be used as the first trained machine learning model in the mapping function.

[0031] In an advantageous embodiment, the first trained machine learning model may additionally be based on a respective reference class that is assigned to the respective reference sequence, and a cost function depending on a measure of the distance between on the one hand, the breathing pattern parameters for different reference sequences having the same assigned reference class, and/or on the other hand, the breathing pattern parameters for different reference sequences having a mutually different assigned reference class.

[0032] As discussed above, the cost function may additionally depend on the error between the respective reference sequence and the output sequence reconstructed by the trained autoencoder that includes the first trained machine learning model as the encoder. Therefore, the method may be implemented by extending the cost function used while training the auto encoder by additional terms that take the output of the encoder into account. Therefore, a minimization of the cost function may minimize the measure of the distance between points in the breathing pattern parameter space to which reference sequences with the same assigned reference class are mapped and/or maximize the measure of the distance between points in the breathing pattern parameter space to which reference sequences with mutually different assigned reference classes are mapped.

To take both of these measures into account, the additional terms may describe a triplet loss.

[0033] When the respective reference class may be considered to match or at least have a defined relationship with the compliance class that would be assigned to the associated reference sequence, the inclusion of the discussed measures of distance in the cost function may lead to a first trained machine learning model and therefore a mapping function that maps chronological sequences, for which the same compliance class may be selected, into close proximity to each other in the breathing pattern parameter space and/or that maps chronological sequences, for which different compliance classes may be selected into separate areas of the breathing pattern parameter space.

[0034] In certain examples, the breathing pattern parameter space, which corresponds to a geometrical space spanned by the breathing pattern parameters, may then be segmented into distinct areas, wherein each area is assigned a different compliance class. It is, e.g., possible to use a mapping function that maps all or essentially all chronological sequences that match a desired breathing and/or breath-holding pattern to an area delimited by a sphere or a polyhedron. The compliance class may then be determined by checking, whether the breathing pattern parameters for the respective chronological sequence lie within that area.

[0035] However, the accuracy of the determination may be even further improved when a classifier trained by machine learning is used to determine the compliance class from the breathing pattern parameters (discussed in greater detail below). The robustness of such a trained classifier may be improved by using the mapping function discussed above to determine the breathing pattern parameters.

[0036] In certain examples, the reference class may be contained in the respective training dataset and may be based on a manual classification by a medical expert that may either be purely based on the respective reference sequence itself or that may, additionally or alternatively, take the image quality of a medical image acquisition into account, during and/or before which the reference sequence was acquired.

[0037] The reference class assigned to the respective reference sequence may be based on a measure for an image quality of a medical image dataset acquired during a reference imaging procedure, for which the respective reference sequence was acquired, and/or on a clustering, in particular on a k-means clustering, of the reference sequences. Both approaches allow for an automatic determination of the respective reference class, in particular without requiring input from a medical expert.

[0038] By performing a clustering on the reference sequences, similar reference sequences may be grouped into two or more clusters. In certain examples, one of these clusters may indicate a sufficient compliance of the patient during the acquisition of the respective reference sequence and the other cluster may indicate an insufficient compliance.

[0039] It is also possible to use more than two clusters, e.g., to allow for different types of non-compliance and/or to distinguish between a degree, to which the patient follows instructions, and therefore, e.g., the accuracy of the timing of a breath hold, and the quality of the breath hold itself. Multiple clusters may also allow for a separation between multiple quality classes and allow, e.g., to distinguish between a good, a sufficient and an insufficient quality of the breath hold, of the accuracy with which the patient follows instructions and/or of the overall quality of the reference sequence.

[0040] Each of the reference sequences may be acquired during a previous medical imaging procedure, in particular during the same type or at least a comparable type of medical imaging procedure to the medical imaging procedure that is to be monitored and/or controlled. In this case, the reference class may additionally or alternatively be based on a determined measure for the image quality of the medical image dataset acquired during the respective imaging procedure. It may therefore be determined, if the actual breathing and/or breath-holding pattern represented by the reference sequence is well suited to provide a sufficient image quality.

[0041] The proposed clustering and/or image quality analysis may reduce the effort necessary to

provide the first trained machine learning model, since a manual classification of the potentially large number of reference sequences may be avoided.
[0042] A cluster information concerning multiple clusters in the parameter space spanned by the breathing pattern parameters may be received or determined, wherein the cluster information is based on a cluster analysis, in particular based on a k-means clustering, of multiple sets of breathing pattern parameters, wherein the respective set of the breathing pattern parameters is determined by a mapping of a respective sample sequence of measurements concerning a respective breathing status of a respective patient to this parameter space using the mapping function, wherein each of the clusters corresponds to one of the possible compliance classes, wherein the compliance class for the chronological sequence is determined, based on the cluster information, by determining to which one of the multiple clusters the set of breathing pattern parameters, to which the chronological sequence is mapped by the mapping function, belongs.
[0043] As discussed above, the mapping function may be designed or parametrized in such a way that chronological sequences, (e.g., which correspond to the same degree of compliance, e.g., to the same breath hold quality and/or the same degree to which the patient follows given instructions), are mapped closer to each other into the parameter space of the breathing pattern parameters than chronological sequences corresponding to different degrees of compliance. The described cluster analysis therefore provides a classification via geometrical segmentation of the parameter space, that was already discussed. Compared to other approaches for such a geometrical segmentation, cluster analysis may allow for a more robust classification.
[0044] In principle, it is possible to perform the full cluster analysis for each new chronological sequence, for which a compliance class is to be selected. To achieve this, the clusters may be provided by performing the cluster analysis on a group of sequences that includes the chronological sequence to be analyzed and the sample sequences.
[0045] When a sufficient number of sample sequences is used, the influence of the addition of the chronological sequence to the sample sequences will only influence the position and size of the various clusters to a negligible degree. It is therefore possible to provide a cluster information that describes fixed clusters as part of a classification algorithm that is used to select the classification based on the breathing pattern parameters determined for the respective chronological sequence. It is, e.g., possible to use the coordinates of the centers of the determined clusters as the cluster information and only use the distance of the coordinates determined by the application of the mapping function to the chronological sequence to the centers of the different clusters to assign the chronological sequence to the closest cluster and therefore to the compliance class assigned to this cluster.
[0046] The determination of the clusters and therefore the cluster information and therefore the training of the classification algorithm may be performed outside of the claimed method. In other words, the computer implemented method may use a classification algorithm based on the discussed cluster analysis. It may therefore, in particular, not include this cluster analysis.
[0047] The sample sequences of measurements concerning a respective breathing status of a respective patient may be identical or at least partially include the reference sequences. It may be advantageous to provide the sample sequences or at least some of the sample sequences as additional training data beyond the training data used to train at the first trained machine learning model, to provide a complete or at least a partial independence between the training of the first trained machine learning model and therefore the parametrization of the mapping function and the cluster analysis.
[0048] The discussed cluster analysis may also be used when the mapping function is not parametrized by machine learning and/or trained without the use of training data.
[0049] The clustering of the reference sequences, discussed above, may depend on a dynamic time warping distance between the different reference sequences or between partial sequences of the different reference sequences as a distance measure. Additionally, or alternatively, the cluster

analysis of the multiple sets of breathing pattern parameters may depend on a dynamic time warping distance between different reconstructed sequences, which are reconstructed from the respective set of breathing pattern parameters using a decoder, or between partial sequences of the different reconstructed sequences as a distance measure.

[0050] Dynamic time warping (DTW) is a well-known algorithm for measuring the similarity between two temporal sequences, which may vary in speed. Such a distance measure may be determined for two temporal sequences by distorting one of the temporal sequences in time, using a warping path, to minimize the sum of the local distances between the sequences. The sum of the remaining local distances, which results for an optimum warping path, may then be used as the time warping distance.

[0051] The use of such distance measure may be advantageous, since, even in the case of an optimum compliance of the patient to, e.g., breathing instructions, parts of the resulting breathing pattern may vary in speed. It is, e.g., possible, that different patients require different amounts of time to breathe in and/or out. Such differences may be compensated by using a distance measure based on dynamic time warping for the full respective sequence or for parts of the sequence, for which such a variance is expected and/or will likely not or hardly influence the medical imaging procedure.

[0052] The compliance class may be selected by using a classifier that processes the breathing pattern parameters as input data, wherein the classifier includes a second trained machine learning model. As discussed above, the use of the second trained machine learning model to select the compliance class may improve the accuracy of the classification, e.g., over a classification based on a geometrical segmentation of the breathing pattern parameter space that was discussed above. Due to the improvement of this classification, the accuracy of the monitoring and/or of the control of the medical imaging procedure is also improved.

[0053] The identification of this trained machine learning model as the second trained machine learning model is only chosen to distinguish the second trained machine learning model and features discussed with respect to this model from the first machine learning model and its features. The designation as the second trained machine learning model does not require the previously discussed first trained machine learning model to be used. It is therefore possible that the method uses only the first trained machine learning model, only the second trained machine learning model, or both of these trained machine learning models.

[0054] The discussion of features and possible implementations of a trained machine learning model that was given in the context of discussing the first trained machine learning model also applies for the second trained machine learning model.

[0055] The second trained machine learning model may be based on a relatively simple neural network, since a relatively small amount of input data, e.g., less than 20 breathing pattern parameters, are processed. It is, e.g., possible to only use a single hidden layer or a few, e.g., less than 3 or less than 5, hidden layers. In certain examples, at least some of the layers are fully connected layers.

[0056] The second trained machine learning model may be based on a supervised training using multiple training datasets, wherein each training dataset may include a set of breathing pattern parameters and the reference compliance class that may be selected as the compliance class for this set of breathing pattern parameters. The training may be performed using a backpropagation of error, e.g., by a gradient descent approach. The breathing pattern parameters may be directly given or they may be determined on the fly from a respective reference sequence using the mapping discussed above.

[0057] The reference compliance class may be manually determined by a medical expert by reviewing the breathing pattern parameters and/or a reference sequence from which the respective breathing pattern parameters are determined and/or image data that was acquired in the context of such a reference sequence and/or a reconstructed reference sequence that may be generated by processing the breathing pattern parameters using the decoder of the trained Autoencoder discussed above.

[0058] In certain embodiments, the selection of the reference compliance class for the respective training dataset is at least partially automated. It is, e.g., possible to perform a clustering, in particular a k-means clustering, of the reference sequences used to provide the reference breathing pattern parameters to allow the medical expert to review and classify such clusters. This may reduce the workload required for generating the training data.

[0059] Training data that is used to train the first and/or second trained machine learning model and/or a classifier based on cluster analysis may be selected and/or curated and/or labeled by medical experts.

[0060] The medical imaging procedure may be controlled by starting and/or stopping and/or continuing and/or restarting an imaging sequence and/or issuing a breathing command to the patient, when a respective trigger condition, that depends on the selected compliance class, is fulfilled, and/or by adjusting at least one parameter of the imaging sequence based on the selected compliance class.

[0061] The compliance class may be determined at different times during the imaging sequence and/or before the start of the imaging sequence. It is, in particular, possible to evaluate the compliance class multiple times during the medical imaging procedure.

[0062] In an example, the patient may be instructed to breathe out, then completely breath in and then hold his or her breath, until the measurement sequence is finished. These instructions also define the desired breathing and breath-holding pattern. In this example, the actual imaging sequence may only be started when the compliance class indicates that the patient complied with the first part of the desired breathing and breath-holding pattern, up until the initial breath-holding, sufficiently well.

[0063] When the compliance a class indicates an insufficient compliance, the imaging sequence may be paused or stopped and the instructions to the patient may be repeated. If the compliance class, e.g., indicates, that the compliance of the patient seems to be a very poor, optionally the parametrization the imaging sequence may be changed to, e.g., switch to an acquisition that requires less compliance of the patient and/or that require no breath-hold or a shorter breath-hold.

[0064] During the imaging sequence, e.g., during the acquisition of magnetic resonance data, the compliance class may be repeatedly determined using a respective updated breathing information. When the compliance class indicates an insufficient compliance of the patient, e.g., an insufficient breath-hold, the imaging sequence may be directly aborted. The breathing instructions may then be repeated and the measurement sequence may be restarted once the patient has followed these breathing instructions sufficiently well according to the newly determined compliance class.

[0065] Optionally, at least one parameter of the imaging sequence may be modified before the imaging sequence is started or restarted, e.g., to require a shorter breath-hold time than the original imaging sequence. The decision, if such a modification may be performed, may depend on the compliance class that was determined, while the previous iteration of the imaging sequence was running. This compliance class may allow for a distinction between an inability of the patient to perform a sufficiently long breath-hold and a breathing pattern that seems to indicate, that the patient simply did not comply with the instructions.

[0066] The imaging sequence may include the sequence of acts that are performed during the medical imaging procedure. During a respective act, one or more components of the medical imaging device used in the medical imaging procedure may be controlled. In a first example, the medical imaging procedure may include magnetic resonance imaging and the imaging sequence may include the generation of one or more excitation pulses, changes to gradient fields and/or the reception of signals, e.g., of a spin echo, from the patient. In a second example, in the case of a computed tomography, the imaging sequence may include the acquisition of several x-ray images for different projection directions.

[0067] The selection of the compliance class may additionally depend on at least one additional parameter, e.g., a timing of instructions concerning the desired breathing and/or breath-holding pattern given to the patient and/or on an imaging sequence used to control at least one medical imaging device during the medical imaging procedure and/or on a size and/or a weight of the patient and/or on a diagnostic information concerning the patient. The diagnostic information may be a diagnostic code, e.g., an ICD-or SCD code.
[0068] The given additional parameters may directly influence the desired breathing and/or breath-holding pattern or indirectly influence the desired pattern by modifying the imaging sequence. To take this influence into account, it is possible to pre-process the breathing information, e.g., to perform a local time scaling of the acquired chronological sequence.
[0069] Additionally, or alternatively, various functions used during the determination of the compliance class may be adjusted based on the at least one additional parameter. It is, e.g., possible to use a different mapping function and/or a different classifier and/or a different clustering for the cluster analysis depending on the value of the at least one additional parameter.
[0070] Additionally, or alternatively, the at least one additional parameter may form an additional input parameter for at least one of the functions used for selecting the compliance class. It is, in particular, possible to take these additional input parameters into account, when training the first and/or the second trained machine learning model.
[0071] The disclosure also relates to a method for providing the first trained machine learning model for the computer-implemented method for monitoring and/or controlling a medical imaging procedure discussed above. The method includes: receiving multiple training data sets including a respective reference sequence of measurements concerning a respective breathing status of a respective patient as input training data; training a machine learning model based on the input training data to determine the first trained machine learning model; and providing the first trained machine learning model.
[0072] Various details and advantageous embodiments of the training of the first machine learning model were already discussed above and these details and the features of the various embodiments discussed above may also be used in the computer-implemented method for providing the first trained machine learning model with the advantages given above and vice versa.
[0073] The first machine learning model may be trained as the encoder of an Autoencoder and that it is therefore possible to use unsupervised training to train the Autoencoder and therefore the first trained machine learning model.
[0074] As discussed above, it may however be advantageous to provide a respective reference class as additional training data and to train the machine learning model in additional dependence on this additional training data. The respective reference class may be determined on the fly during the training or be provided as part of the respective training dataset. Both of these approaches were already discussed above.
[0075] Additionally, the disclosure relates to a computer-implemented method for providing the second trained machine learning model for the computer-implemented method for monitoring and/or controlling a medical imaging procedure discussed above. The method includes: receiving multiple sets of breathing pattern parameters as input training data; receiving a respective associated reference compliance class for each one of the sets of breathing pattern parameters as output training data; training a machine learning model based on the input training data and the output training data to determine the second trained machine learning model; and providing the second trained machine learning model.
[0076] Various details and advantageous embodiments of the training of the second machine learning model were already discussed above and these details and the features of the various embodiments discussed above may also be used in the computer implemented method for providing the second trained machine learning model with the advantages given above and vice versa.

[0077] As discussed above, the second trained machine learning model may be trained using a supervised training using multiple training datasets, each including a set of breathing pattern parameters and the reference compliance class that may be determined for this set of breathing pattern parameters. The training may be performed using a backpropagation of error, in particular, by a gradient descent approach.
[0078] Additionally, the disclosure relates to a data processing system configured to carry out at least one of the previously discussed computer-implemented methods. The data processing system may be a desktop computer, a server or be implemented as a cloud solution. Additionally, or alternatively, the data processing system may be integrated into a medical imaging device. The data processing system may have hardware and/or software interfaces for receiving the various inputs discussed above.
[0079] The disclosure also relates to a computer program that includes instructions to carry out at least one of the previously discussed computer-implemented methods when the program is executed on a data processing system.
[0080] Additionally, the disclosure also relates to a computer-readable medium including the computer program.
[0081] Other objects and features of the present disclosure become apparent from the following detailed description considered in conjunction with the accompanying drawings. The drawings, however, are only sketches designed solely for the purpose of illustration and do not limit the disclosure.

Description

BRIEF DESCRIPTION OF THE DRAWINGS
[0082] FIG. **1** depicts a flowchart of an embodiment of the computer-implemented method for monitoring and/or controlling a medical imaging procedure on a patient.
[0083] FIG. **2** depicts examples of data structures that may be used in the method according to FIG. **1**.
[0084] FIG. **3** depicts an embodiment of the data processing system.
[0085] FIG. **4** depicts an example of a machine learning model.
[0086] FIG. **5** depicts a flowchart of an embodiment of the computer-implemented method for providing the second trained machine learning model.
[0087] FIG. **6** depicts a flowchart of an embodiment of the computer-implemented method for providing the first trained machine learning model.
[0088] FIG. **7** depicts a flow chart of a further embodiment of the selection of the compliance class in the computer-implemented method for monitoring and/or controlling a medical imaging procedure on a patient.
DETAILED DESCRIPTION
[0089] FIG. **1** shows a flowchart of a computer-implemented method for monitoring and/or controlling a medical imaging procedure on a patient. This method is described in conjunction with FIG. **2**, which shows some of the data structures that may be used in this method, and with FIG. **3** that shows an example of a usage situation for the method and the data processing system **55** used to implement this method.
[0090] In the example shown in FIG. **3**, the medical imaging is performed by a medical imaging device at **23**, e.g., a magnetic resonance tomograph, on a patient **22**. The method is implemented by the data processing system **55** that includes a programmable processor **58** and the memory **57** storing a program **56** that implements the method. In the example, the data processing system **55** is networked to a remote storage **30** to store the acquired medical image data **29** and to a desktop computer **28** that allows a user to control and monitor the medical imaging procedure.

[0091] The medical imaging procedure requires the patient **22** to closely follow a desired breathing and/or breath-holding pattern **26**, that may be communicated to the patient **22** using internal loudspeakers (not shown) of the medical imaging device **23** in act S**1**. The provision of these instructions may be fully automatic and a part of the imaging sequence used to acquire in medical image data **29**.

[0092] As discussed above, an insufficient compliance of the patient **22** with these instructions may lead to medical image data **29** that is potentially unusable and may therefore require a new image acquisition at a later point in time. To allow for an earlier detection of such non-compliance, the discussed method automatically monitors the compliance of the patient **22**.

[0093] In act S**2**, a breathing information **24** concerning a breathing pattern of the patient **22** is received by the data processing system **55**. In the example, the breathing information **24** is acquired using the medical imaging device **23** itself, namely using a pilot tone to determine the movement of the diaphragm of the patient **22**. Alternatively, the breathing information may be acquired using a dedicated sensor, such as those sensors already described herein.

[0094] The breathing information **24** describes a chronological sequence **31** of multiple measurements **32** concerning a respective breathing status, e.g. the position of the diaphragm or the extension of a chest belt over time. A graphical representation of an exemplary chronological sequence **31** is shown in FIG. **2**. The time and therefore in the number of the number of the sample is plotted on the x-axis and the y-axis corresponds to the breathing motion of the patient **22**.

[0095] The rising flanks **59** correspond to an inhaling by the patient **22** and the falling flanks **60** corresponds to an exhaling. The section **61** may be flat and correspond to a breath hold. The actual image acquisition is performed between the times **62** and **63** and therefore during the breath hold in the example. The example shown in FIG. **2** is therefore an example for a good compliance of the patient **22** with the desired breathing and/or breath-holding pattern **26**. A bad compliance might, e.g., be detected when large changes of the curve are present between the times **62** and **63** and/or by when there is no full breathing cycle before the time **62**.

[0096] Since the example shown in FIG. **1** includes several advantageous but optional features, the following gives a brief overview over the remaining acts of the method, before the individual acts are discussed in detail.

[0097] In acts S**3** to S**5**, a compliance class **25** is selected from multiple possible compliance classes based on the breathing information **24**. At least one of the possible compliance classes corresponds to a compliance of the acquired breathing information **24** with the desired breathing and/or breath-holding pattern **26**.

[0098] In acts S**6** to S**8**, the medical imaging procedure is controlled depending on the selected compliance class **25**. Additionally, a non-compliance information **27** may be given to the user, e.g., via the desktop computer **28**, and/or stored with the medical image data **29**, when the selected compliance class **25** does not indicate a compliance of the acquired breathing information **24** with the given desired breathing and/or breath-holding pattern **26**.

[0099] Continuing with the detailed discussion of the individual acts of the example, in act S**3**, a mapping function **33** is used to map the measurements **32** to a set **34** of breathing pattern parameters **35**. The mapping function **33** is chosen to output to a lower number of breathing pattern parameters **35** than the number of measurements **32** in the chronological sequence **31**. Therefore, the mapping function **33** reduces the dimensionality of the breathing information **24**.

[0100] The mapping function **33** may map the measurements **32** into a 16-dimensional breathing pattern parameters space **43**. An exemplary breathing pattern parameter space **43** is shown in FIG. **2**, wherein a two-dimensional breathing pattern parameter space **43** is used to simplify the illustration. The position defined by the breathing pattern parameters **34** is marked in FIG. **2**.

[0101] In the example, the mapping function **33** is implemented by a first trained machine learning model **36**. Further details concerning the first trained machine learning model **36** are described below with reference to FIG. **6** that concerns the training of this model.

[0102] The mapping function **33** may be designed and parametrized in such a way in the example, that sets **62** of breathing pattern parameters **35**, which correspond to chronological sequences having a first compliance class that indicates a good compliance and that are marked by a cross in FIG. **2** are grouped closely together, while sets **63** of breathing pattern parameters **35** corresponding to a second compliance class that indicates a bad compliance and that are marked by a circle in FIG. **2** are separated from the sets **60** due to the mapping.
[0103] In act S**4**, additional parameters **52** may optionally be provided, that may influence, which one of multiple possible classifiers **48** is used in act S**5**. The additional parameters may concern diagnostic information concerning the patient **22**. Other potentially relevant additional parameters include those already mentioned above.
[0104] Such additional parameters may influence, what degree of compliance is tolerated and/or influence the imaging sequence and therefore, e.g., the required breath-holding time. Alternatively, or additionally, it would also be possible to perform the mapping in act S**3** in dependence on these additional parameters **52**.
[0105] In act S**5**, the compliance classifier **25** is selected from multiple options based on the previously determined breathing pattern parameters **35**. In the example, the compliance class **25** is selected by using a classifier **48** that processes the breathing pattern parameters **35** as input data, wherein the classifier **48** is implemented by a second trained machine learning model **49**. Further details concerning the second trained machine learning model **49** are described below with reference to FIG. **5** that concerns the training of this model.
[0106] In act S**6**, a trigger condition 50 that depends on the selected compliance class **25** is evaluated. In the example, the trigger condition 50 is fulfilled when the selected compliance class **25** does not indicate a compliance of the acquired breathing information **24** with the given desired breathing and/or breath-holding pattern **26**.
[0107] When the trigger condition 50 is fulfilled in act S**6**, multiple actions may be triggered in act S**7** to handle the non-compliance of the patient **22** with the breathing and/or breath-holding pattern **26**. As described above, different actions may be used depending on whether the compliance class is selected before the imaging sequence has started, during the imaging sequence or after the imaging sequence is finished.
[0108] In all cases, a non-compliance information **27** may be output to a user, e.g., via the desktop computer **28**. When the image acquisition is already finished, the non-compliance information **27** may also be stored with the acquired medical image data **29**, to inform users of this data that the medical image data **29** is potentially compromised.
[0109] Additionally, or alternatively, an imaging sequence that is already running may be stopped and therefore aborted in act S**7** to allow for a faster repetition of the sequence, especially after issuing a breathing command to the patient **22**.
[0110] In certain embodiments, there may also be actions that only trigger when the selected compliance class indicates a good compliance of the patient **22**. It is, e.g., possible, to only start or resume an imaging sequence when such a compliance class is selected.
[0111] In act S**8**, the medical imaging procedure is adjusted depending on the selected compliance class **25**. It is, e.g., possible to the adjust at least one parameter **51** of the imaging sequence based on the selected compliance class **25**. This may be especially useful when multiple levels of compliance are detected by selecting from more than two possible compliance classes. In this case, multiple compliance classes may allow for the imaging sequence or to continue. It may however be useful to adjust the imaging sequence when the selected compliance class **25** does indicate a sufficient, but not optimal compliance. In this case, it may be possible to modify the imaging sequence to require a shorter breath-hold time, to make it easier for the patient **22** to comply with the desired breathing and/or breath-holding pattern **26**.
[0112] As shown schematically in FIG. **2**, the possible actions triggered by the selection of the compliance class **25** may be separated into the generation of the control signal **64** to control the

imaging sequence, the giving of breathing instructions **65** to the patient **22**, and the outputting of the non-compliance information **27**.
[0113] In the embodiment according to FIG. **1**, both the mapping function **33** used in act S**3** and the classifier **48** used in act S**5** are implemented as a trained machine learning models **36**, **49**. The respective trained machine learning model **36**, **49** may in particular have the structure of a neural network.
[0114] To illustrate the features and working of such a neural network, FIG. **4** displays an embodiment of an artificial neural network **1**. For simplicity's sake, a relatively simple network is shown and discussed.
[0115] For an implementation of the first trained machine learning model **36**, a larger network may be used, that has an input note **6-8** for each measurement of the chronological sequence **31** and an output node **17**, **18** for each of the breathing pattern parameters **35**.
[0116] For an implementation of the second trained machine learning model **49**, the number of input nodes **6-8** may correspond to the number of a breathing pattern parameters **35** and the number of output nodes may correspond to the number of possible compliance classes. Output nodes may then, e.g., output the probability, that an input corresponds to the respective compliance class and the class with the highest probability may be selected as the selected compliance class **35**.
[0117] Alternative terms for "artificial neural network" are "neural network," "artificial neural net," or "neural net."
[0118] The artificial neural network **1** includes nodes **6-18** and edges **19-21**, wherein each edge **19-21** is a directed connection from a first node **6-18** to a second node **6-18**. The first node **6-18** and the second node **6-18** may be different nodes **6-18**. Alternatively, it is also possible that the first node **6-18** and the second node **6-18** are identical. For example, in FIG. **1** the edge **19** is a directed connection from the node **6** to the node **9**, and the edge **20** is a directed connection from the node **7** to the node **9**. An edge **19-21** from a first node **6-18** to a second node **6-18** is also denoted as "ingoing edge" for the second node **6-18** and as "outgoing edge" for the first node **6-18**.
[0119] In this embodiment, the nodes **6-18** of the artificial neural network **1** may be arranged in layers **2-5**, wherein the layers **2-5** may include an intrinsic order introduced by the edges **19-21** between the nodes **6-18**. In particular, edges **19-21** may exist only between neighboring layers of nodes **6-18**. In the displayed embodiment, there is an input layer **2** including only nodes **6-8** without an incoming edge, an output layer **5** including only nodes **17**, **18** without outgoing edges, and hidden layers **3**, **4** in-between the input layer **2** and the output layer **5**. The number of hidden layers **3**, **4** may be chosen arbitrarily. The number of nodes **6-8** within the input layer **2** may relate to the number of input values of the neural network, and the number of nodes **17**, **18** within the output layer **5** may relate to the number of output values of the neural network.
[0120] In particular, a (real) number may be assigned as a value to every node **6-18** of the neural network **1**. Here, x (n); denotes the value of the i-th node **6-18** of the n-th layer **2-5**. The values of the nodes **6-8** of the input layer **2** are equivalent to the input values of the neural network **1**, the values of the nodes **17**, **18** of the output layer **5** are equivalent to the output values of the neural network **1**. Furthermore, each edge **19-21** may include a weight being a real number, in particular, the weight is a real number within the interval [−1, 1] or within the interval [0, 1]. Here, w.sup.(m,n).sub.i,j denotes the weight of the edge between the i-th node **6-18** of the m-th layer **2-5** and the j-th node **6-18** of the n-th layer **2-5**. Furthermore, the abbreviation w.sup.(n).sub.i,j is defined for the weight w.sup.(n,n+1).sub.i,j.
[0121] In particular, to calculate the output values of the neural network **1**, the input values are propagated through the neural network **1**. In particular, the values of the nodes **6-18** of the (n+1)-th layer **2-5** may be calculated based on the values of the nodes **6-18** of the n-th layer **2-5** by:
[00001] $x_j^{(n+1)} = f(\text{.Math.}_i\ x_i^{(n)}\ \text{.Math.}\ w_{i,j}^{(n)})$.
[0122] Herein, the function f is a transfer function (another term is "activation function"). Known transfer functions are step functions, sigmoid function (e.g. the logistic function, the generalized

logistic function, the hyperbolic tangent, the Arctangent function, the error function, the smooth step function) or rectifier functions. The transfer function is mainly used for normalization purposes.

[0123] In particular, the values are propagated layer-wise through the neural network **1**, wherein values of the input layer **2** are given by the input of the neural network **1**, wherein values of the first hidden layer **3** may be calculated based on the values of the input layer **2** of the neural network **1**, wherein values of the second hidden layer **4** may be calculated based in the values of the first hidden layer **3**, etc.

[0124] In order to set the values w.sup.(m,n).sub.i,j for the edges **19-21**, the neural network **1** has to be trained using training data. In particular, training data includes training input data and training output data (denoted as t.sub.i). For a training act, the neural network **1** is applied to the training input data to generate calculated output data. In particular, the training data and the calculated output data include a number of values, the number being equal to the number of nodes **17**, **18** of the output layer **5**.

[0125] In particular, a comparison between the calculated output data and the training data is used to recursively adapt the weights within the neural network **1** (backpropagation algorithm). In particular, the weights are changed according to:

[00002] $w_{i,j}^{(n)} = w_{i,j}^{(n)} - \text{.Math.} \ {}_{j}^{(n)} x_i^{(n)}$

wherein γ is a learning rate, and the numbers δ.sup.(n).sub.j may be recursively calculated as:

[00003] ${}_{j}^{(n)} = (\text{.Math.}_k \ {}_{k}^{(n+1)} \ \text{.Math.} \ w_{j,k}^{(n+1)}) \ \text{.Math.} \ f' (\text{.Math.}_i \ x_i^{(n)} \ \text{.Math.} \ w_{i,j}^{(n)})$

based on δ.sup.(n+1).sub.j, if the (n+1)-th layer is not the output layer **5**, and:

[00004] ${}_{j}^{(n)} = (x_k^{(n+1)} - t_j^{(n+1)}) \ \text{.Math.} \ f' (\text{.Math.}_i \ x_i^{(n)} \ \text{.Math.} \ w_{i,j}^{(n)})$

if the (n+1)-th layer is the output layer **5**, wherein f′ is the first derivative of the activation function, and y.sup.(n+1).sub.j is the comparison training value for the j-th node of the output layer **5**.

[0126] Concrete examples for the training of the first and second trained machine learning model **36**, **49** are now provided with reference to FIGS. **5** and **6**.

[0127] As shown in FIG. **5**, the second trained machine learning model **49** may be trained using a supervised training. In act S**9**, multiple sets **34** of breathing pattern parameters **35** are received as input training data. The respective set **34** may be determined by processing a reference sequence of measurements concerning a respective breathing status of a respective patient by the mapping function **33** that was already discussed with reference to FIGS. **1** and **2**. The respective reference sequence may in particular be a chronological sequence of such measurements that was acquired while monitoring and/or controlling a respective previous medical imaging procedure.

[0128] In act S**10**, a respective associated reference compliance class **54** is received for each one of the sets **34** of breathing pattern parameters **35** as output training data. The reference compliance class corresponds to a compliance class, which may be selected by the second trained machine learning network **49** when it is applied to the respective set **34** of breathing pattern parameters **35** provided as input training data.

[0129] The reference compliance class **54** may be manually assigned to the respective set **34** by a medical expert that evaluates the associated reference sequence and/or the results of the previous medical imaging procedure during which this reference sequence was acquired. Alternatively, the reference compliance class **54** may be automatically determined, e.g., by automatically determining a quality measure for the results of this previous medical imaging procedure and/or by the clustering of the reference sequences, as already discussed herein.

[0130] To determine the parameters **71** parametrizing the second trained machine learning model, e.g. the weights for the different nodes, based on the input training data and the output training data, preliminary values of the parameters **71** are chosen in act S**11** and the temporarily parametrized model is used to determine a probability distribution **72** for the possible compliance classes **25** for each of the sets **34**.

[0131] In act S**13**, the cost function **53** is calculated, e.g., by adding an error term for each one of the sets, wherein the respective error term depends on the diversions of the probability distribution **72** from the correct distribution that is a delta distribution described by the associated reference compliance class.
[0132] The value of the cost function **53** is then minimized by iteratively varying the parameters **71**, e.g., by using a gradient descent and a backpropagation of error.
[0133] As shown in FIG. **6**, the training of the first trained machine learning model **49** may be based on a slightly modified training of an autoencoder **68**.
[0134] In act S**15**, multiple training data sets **37** that include a respective reference sequence **38** of measurements concerning a respective breathing status of a respective patient and a reference class **39** assigned to the respective reference sequence **38** are received. The respective reference sequence **38** may be acquired during a respective reference imaging procedure. The reference class **39** may correspond to a compliance class that may be assigned to the respective reference sequence **38** when the first trained machine learning model **49** is used as the mapping function **33** in the method discussed with reference to FIG. **1**. In principle, the reference class **39** may be manually assigned by a medical expert, e.g., after reviewing the respective reference sequence **38**.
[0135] In the example, the reference class **39** is however automatically determined based on a measure for an image quality **41** of a medical image dataset **42** acquired during a reference imaging procedure. the measure for the image quality **41** is determined in act S**14** and used to provide the respective training data set **37** in act S**15**.
[0136] Acts S**16** to S**20** may correspond to the training of an autoencoder **68**.
[0137] In act S**16**, the mapping function **33** and therefore the model that is trained to form the first trained machine learning model **36** is used to encode each one of the reference sequences **38** into a respective set **34** of breathing pattern parameters **35** that are provided in act S**17**.
[0138] The breathing pattern parameters **35** of each set **34** are then decoded in act S**18** by a decoder **47** to provide a respective output sequence **73** in act S**19** that may closely replicate the associated reference sequence **38** once of the training of the autoencoder **68** is finished.
[0139] The sum of the differences between each reference sequence **38** and the respective output sequence **73** that is generated by the autoencoder **68** from the respective reference sequence **38** is then used as the partial cost function **69** in act S**20**.
[0140] In a training of an autoencoder **68**, the parameters **66**, **67** of the autoencoder **68** and more specifically of the first trained machine learning model **36** and the decoder **47** may be iteratively varied to minimize this partial cost function **69**.
[0141] The training shown in FIG. **6** does however additionally take a further partial cost function **70** into account. The further partial cost function **70** is determined in act S**21**. The overall cost function **40** that may be a sum or a weighted sum of the partial cost functions, may then be minimized to determine the parameters of **66**, **67**. As previously discussed, this minimization and therefore of the training may be performed by a backpropagation of error, e.g., by gradient descent.
[0142] The partial cost function **70** depends on the distances of the positions of the various sets **34** of breathing pattern parameters **35** and therefore on the distance between positions associated with a respective one of the reference sequences **38** in the breathing pattern parameter space **43**. It may be possible to use a Euclidean distance or any other distance measure.
[0143] The partial cost function **70** is chosen in such a way that the cost may be lowered when positions associated with reference sequences **38** having the same associated reference class **39** are a grouped closer together. Additionally, the cost may be reduced when positions associated with reference sequences **38** having mutually different reference classes **39** are spaced further part.
[0144] When the reference classes **39** at least approximately correspond to compliance classes **25**, that may result when the respective reference sequence **38** is processed as discussed with reference to FIG. **1**, the use of the additional partial cost function **70** therefore trains the mapping function **33** to group chronological sequences **24** for which the same compliance class **25** may be selected in

close vicinity to each other while separating them from chronological sequences **24** that are classified differently from each other in the breathing pattern parameters space **43**. This allows for a more robust classification.

[0145] FIG. **7** shows a flowchart of a further approach for determining the selected compliance class **25** for a given chronological sequence **31**. Acts S**26** to S**28** implement this selection and may replace act S**2** to S**5** in the embodiment shown in FIG. **1**.

[0146] Acts S**23** to S**25** are training acts that are used to determine a cluster information that is used in act S**28** to select the compliance class **25**. These acts are not necessarily included in the computer-implemented method for monitoring and/or controlling a medical imaging procedure and may be considered to form a separate method.

[0147] In act S**23**, multiple sample sequences **44** of measurements concerning a respective breathing status of a respective patient are provided. The provision of such sample sequences **44** is no different from, e.g., the provision of the reference sequences **38** that was already discussed.

[0148] In act S**24**, a respective set **34** of breathing pattern parameters **35** is determined by the mapping function **33**. Act S**24** may be equivalent to the repeated performance of act S**3** shown in FIG. **1** for each of the sample sequences **44**.

[0149] In act S**25**, a cluster analysis **45**, e.g., a k-means clustering, is performed to determine a cluster information concerning multiple clusters **46** in the parameter space **43** spanned by the breathing pattern parameters **35**. Each of these clusters is assigned to one of the possible compliance classes. This may be achieved by manually inspecting the various sample sequences **44** by a medical expert. It is however also possible to use an approach based on image quality analysis for images resulting from acquisition during which the respective sample sequence **44** was acquired. This approach was already discussed with respect to act S**14** in FIG. **6**.

[0150] Parameters of the provided clusters **46**, especially the center of the respective cluster, may then be provided as the cluster information used for the classification in act S**28**.

[0151] For this purpose, the chronological sequence **31**, which is provided in act S**26**, is processed by the mapping function **33** in act S**27** to provide a set **34** of breathing pattern parameters **35** and therefore a position in the breathing pattern parameter space **43**.

[0152] Based on the relative position of this position to the positions of the various clusters **46** described by the cluster information, it may be determined to which cluster the chronic logical sequence **31** belongs and therefore the compliance class **25** associated with this cluster **46** may be selected.

[0153] Although the present disclosure has been described in detail with reference to various embodiments, the present disclosure is not limited by the disclosed examples from which the skilled person is able to derive other variations without departing from the scope of the disclosure.

[0154] It is to be understood that the elements and features recited in the appended claims may be combined in different ways to produce new claims that likewise fall within the scope of the present disclosure. Thus, whereas the dependent claims appended below depend on only a single independent or dependent claim, it is to be understood that these dependent claims may, alternatively, be made to depend in the alternative from any preceding or following claim, whether independent or dependent, and that such new combinations are to be understood as forming a part of the present specification.

[0155] While the present disclosure has been described above by reference to various embodiments, it may be understood that many changes and modifications may be made to the described embodiments. It is therefore intended that the foregoing description be regarded as illustrative rather than limiting, and that it be understood that all equivalents and/or combinations of embodiments are intended to be included in this description.

[0156] Independent of the grammatical term usage, individuals with male, female or other gender identities are included within the term.

Claims

1. A computer-implemented method for monitoring and/or controlling a medical imaging procedure on a patient, the computer-implemented method comprising: receiving breathing information comprising a breathing pattern of the patient; selecting a compliance class from at least two possible compliance classes based on the breathing information, wherein at least one compliance class of the at least two possible compliance classes corresponds to a compliance of the breathing information with a given desired breathing and/or breath-holding pattern; and controlling the medical imaging procedure depending on the selected compliance class; and/or outputting a non-compliance information to a user and/or storing the non-compliance information with an acquired medical image data when the selected compliance class does not indicate a compliance of the breathing information with the given desired breathing and/or breath-holding pattern.
2. The computer-implemented method of claim 1, wherein the breathing information describes a chronological sequence of multiple measurements concerning a respective breathing status, wherein a mapping function is used to map the multiple measurements to a number of breathing pattern parameters, and wherein the number of breathing pattern parameters is smaller than a number of the multiple measurements in the chronological sequence.
3. The computer-implemented method of claim 2, wherein the mapping function comprises a first trained machine learning model based on multiple training data sets comprising a respective reference sequence of measurements concerning a respective breathing status of a respective patient.
4. The computer-implemented method of claim 3, further comprising: receiving multiple training data sets comprising a respective reference sequence of measurements concerning a respective breathing status of a respective patient as input training data; training a machine learning model based on the input training data to determine the first trained machine learning model; and providing the first trained machine learning model.
5. The computer-implemented method of claim 3, wherein the first trained machine learning model is additionally based on a respective reference class assigned to the respective reference sequence, and wherein a cost function depends on a measure of a distance between: (1) the breathing pattern parameters for different reference sequences having a same assigned reference class; and/or (2) the breathing pattern parameters for different reference sequences having a mutually different assigned reference class.
6. The computer-implemented method of claim 5, wherein the reference class assigned to the respective reference sequence is based on: (1) a measure for an image quality of a medical image dataset acquired during a reference imaging procedure for which the respective reference sequence was acquired; and/or (2) a k-means clustering of the reference sequences.
7. The computer-implemented method of claim 6, wherein the clustering of the reference sequences depends on a dynamic time warping distance between the different reference sequences or between partial sequences of the different reference sequences as a distance measure.
8. The computer-implemented method of claim 2, further comprising: receiving or determining a cluster information concerning multiple clusters in a parameter space spanned by the breathing pattern parameters, wherein the cluster information is based on a cluster analysis or a k-means clustering of multiple sets of breathing pattern parameters, wherein the respective set of the breathing pattern parameters is determined by a mapping of a respective sample sequence of measurements concerning a respective breathing status of a respective patient to this parameter space using the mapping function, wherein each cluster of the multiple clusters corresponds to a compliance class of the at least two possible compliance classes, wherein the compliance class for the chronological sequence is determined by determining, based on the cluster information, to which cluster of the multiple clusters the set of breathing pattern parameters, to which the

chronological sequence is mapped by the mapping function, belongs.

9. The computer-implemented method of claim 8, wherein the cluster analysis of the multiple sets of breathing pattern parameters depends on a dynamic time warping distance between different reconstructed sequences reconstructed from the respective set of breathing pattern parameters using a decoder, or between partial sequences of the different reconstructed sequences as a distance measure.

10. The computer-implemented method of claim 2, further comprising: selecting the compliance class using a classifier that processes the breathing pattern parameters as input data, wherein the classifier comprises a second trained machine learning model.

11. The computer-implemented method of claim 10, further comprising: receiving multiple sets of breathing pattern parameters as input training data; receiving a respective associated reference compliance class for each set of the multiple sets of breathing pattern parameters as output training data; training a machine learning model based on the input training data and the output training data to determine the second trained machine learning model; and providing the second trained machine learning model.

12. The computer-implemented method of claim 1, wherein the medical imaging procedure is controlled by: (1) starting and/or stopping and/or continuing and/or restarting an imaging sequence and/or issuing a breathing command to the patient when a respective trigger condition that depends on the selected compliance class is fulfilled; and/or (2) adjusting at least one parameter of the imaging sequence based on the selected compliance class.

13. The computer-implemented method of claim 1, wherein the selection of the compliance class additionally depends on: (1) at least one additional parameter comprising a timing of instructions concerning the desired breathing and/or breath-holding pattern given to the patient; (2) an imaging sequence used to control at least one medical imaging device during the medical imaging procedure; (3) a size and/or a weight of the patient; (4) a diagnostic information concerning the patient; or (5) a combination thereof.

14. A data processing system comprising: a programmable processor and a memory configured to: receive breathing information comprising a breathing pattern of a patient; select a compliance class from at least two possible compliance classes based on the breathing information, wherein at least one compliance class of the at least two possible compliance classes corresponds to a compliance of the breathing information with a given desired breathing and/or breath-holding pattern; and control a medical imaging procedure depending on the selected compliance class; and/or output a non-compliance information to a user and/or store the non-compliance information with an acquired medical image data when the selected compliance class does not indicate a compliance of the breathing information with the given desired breathing and/or breath-holding pattern.

15. A computer-implemented method for providing a trained machine learning model, the computer-implemented method comprising: receiving multiple training data sets comprising: (1) a respective reference sequence of measurements concerning a respective breathing status of a respective patient or (2) breathing pattern parameters as input training data; optionally receiving a respective associated reference compliance class for each set of the multiple training data sets of the breathing pattern parameters as output training data; training a machine learning model based on: (1) the input training data or (2) the input training data and the output training data to determine the trained machine learning model; and providing the trained machine learning model.
