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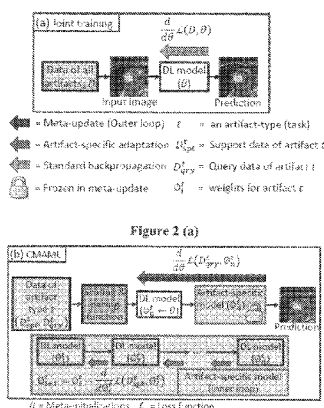


Figure 2 (a)

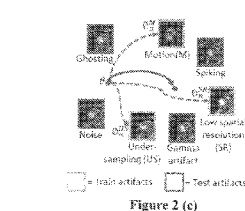


Figure 2 (c)

(57) Abstract: The present invention focuses on enhancing the scan quality of Magnetic Resonance (MR) images by reducing artifacts through a novel deep learning approach. It introduces a Model-Agnostic Meta-Learning (MAML) framework combined with curriculum learning, enabling the system to adaptively learn and restore multiple types of artifacts, such as noise, motion, and undersampling. The method involves receiving an input MR image, processing it through a trained deep learning model, and applying an iterative scheduler component to progressively reduce the magnitude of artifacts. This technique leverages shared knowledge across various artifact types and fine-tunes restoration processes specific to each artifact during training. By improving the clarity and quality of MR images, the invention aids in better image processing, minimizes the need for patient rescans, and enhances MRI workflow efficiency, ultimately leading to a more effective healthcare system.

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METHOD AND APPARATUS FOR ENHANCING THE SCAN QUALITY OF MAGNETIC RESONANCE (MR) IMAGES

TECHNICAL FIELD

The present invention relates to improving the scan quality of the Magnetic Resonance (MR) images, leading to a better decision process by post-processing the acquired image.

BACKGROUND OF THE INVENTION

This section is intended to provide information relating to the field of the invention and thus any approach/functionality described below should not be assumed to be qualified as prior art merely by its inclusion in this section.

Cine Cardiac MRI (CMR) is known as the gold standard when processing images for heart related diseases due to its ability to assess left and right ventricular functions by estimating stroke volume, ejection fraction, end-systolic and end-diastolic volumes. Non-invasive assessment of such quantities aid decision making in various scenarios ranging from the image processing required in detecting heart failure to determining the need for primary prevention implantable cardioverter defibrillators and the timing of surgical intervention in patients with valvular heart disease. However, CMR is highly operator and patient dependent because of the inherent trade-off between spatial and temporal resolution, scan time and signal-to-noise ratio (SNR). For instance, imaging at higher spatial resolution will result in lower SNR or longer scan times. Longer scan time leads to additional artifacts from patient movements. Moreover, this trade-off is further compounded by imaging a moving anatomy. For example, reduced motion artifact, via gated/triggered acquisition, comes at the expense of spatial resolution and adds additional constraints to CMR. In fact, respiratory and cardiac motion during CMR acquisition constitutes a major source of degradation.

The challenge is prospectively addressed by a) avoiding motion by performing breath-holds,

b) suppressing motion by monitoring the motion-cycle. However, case-a is not a feasible solution because multiple breath-holds throughout the acquisition leads to patient discomfort and fatigue. It is also patient dependent and is impossible for paediatric, critically ill, and uncooperative patients. Similarly, case-b involves additional hardware like MR navigators, field probes and pilot tone which is not economical, introduces additional parameters, making

the acquisition complicated and demands a skilled operator to conduct the acquisition. Furthermore, not all artifacts that are clinically relevant like chemical shift can be prospectively addressed. Patient dependent (due to breath holds) and operator dependent (for handling the constraints of additional hardware) nature of the prospective solutions are not feasible and cannot be scaled to every other degradation in CMR. In this wake, data driven learning-based approaches offer a solution as a retrospective/post-processing step.

Existing deep-learning (DL) techniques address the removal of a single type of artifact. However, as MRI is affected by diverse sources of artifacts, training a model separately for each artifact type is not practically possible for deployment because of large computational requirements and cannot be scaled to multiple acquisition settings. Combining all artifact data and training a single DL model is not efficient as it undermines the implicitly available common knowledge shared across various artifacts. So, the existing methods are limited because of the lack of two significant attributes: 1) artifact invariant information that is characterized by the common knowledge shared across images of different artifacts and 2) discriminative artifact-specific restoration that is aided by the artifact invariant information.

Traditional training methods such as Joint training (or) Stochastic Gradient Descent (SGD), combine all artifact data in a single level of optimization as shown in Fig. 2a. Such known methods do not include additional nuances of artifacts (like artifact-type and artifact-amount) that are essential to drive the discriminative artifact-

specific restoration during training.

Thus, conventional deep learning methods are known to deal with removing a specific type of artifact, leading to separately trained models for each artifact type that lack the shared knowledge generalizable across artifacts. Again, training a model for each type and amount of artifact is a tedious process that consumes excessive training time and resources storage for models.

For example, CINENet [3] is known to perform artifact restoration of only under-sampled Cardiac MR (CMR). Several deep neural network architectures are developed specifically for motion correction or super-resolution. However, as MRI is affected by diverse and multiple sources of artifacts, training a model separately for each type of artifact incurs large computational requirements.

Conventional methods for artifact suppression like compressed sensing treat artifacts as aliasing or blur and use non-linear optimization solvers to iteratively recover the image.

There is a long felt need for a technique that imbibes the above attributes to realize a specialized model capable of suppressing multiple artifacts encountered in MRI, including the unseen artifact types.

The present invention proposes a single model that learns a common knowledge across various MRI artifacts and helps to generalize to unseen artifacts with deviated amounts of degradation levels at test time (e.g., under-sampling with unseen acceleration factors different from training data).

OBJECTS OF THE INVENTION

This section is intended to introduce certain objects of the disclosed methods and systems in a simplified form and is not intended to identify the key advantages or features of the present disclosure.

The present invention proposes a Model-agnostic meta-learning (MAML) that is

based on curriculum structure CMAML, a learning process that integrates MAML with curriculum learning to impart the knowledge of variable artifact complexity to adaptively learn restoration of multiple artifacts during training.

The present invention proposes an artifact-invariant information that is characterized by the common knowledge shared across images of different artifacts and incorporates discriminative artifact-specific fine-tuning at train time in order to achieve restoration of various degradations in a single model.

An objective of the present invention is to provide a new technique that overcome the disadvantages associated with the prior art, improves the scan quality, enhancing the scan decision-making process for a better understanding of scanned images, and can potentially be integrated into the MRI workflow.

Another object of the present invention is in restoring artifact affected MRI images for various types of artifacts in a single deep learning model with a training process driven by learning a set of latent representation which is common across artifacts.

Yet another objective of the present invention is to take into account various nuances occurring in the form of artifact-type and artifact-amount that are significant. Moreover, common knowledge present across various different artifacts is to be modeled so that the invention performs reasonably even in the presence of hitherto unseen artifacts.

Other general and specific objectives of the invention will in part be obvious and will in part appear hereinafter.

TECHNICAL ADVANTAGES OF THE PRESENT INVENTION

The present invention can be extensively used in clinical settings, especially in the MRI workflow to correct for the frequent occurrence of artifacts arising from

patient movements and acquisition settings. Improving the scan quality of an artifact image potentially results in better inference on the understanding of images and in reducing the time spent in analyzing the artifact scan, thus, efficiently promoting, for example, a better healthcare system.

The present invention further achieves that long duration MRI acquisition process can be shortened without any loss in the image quality, further resulting in better MRI scanner utilization by increasing the throughput of the number of patients scanned.

The present invention further provides that other degradations arising from the electronic noise of MRI hardware in the form of RF and spiking artifacts does not affect the downstream tasks of analysing the patient.

Other general and specific technical advantages of the invention will in part be obvious and will in part appear hereinafter.

BRIEF DESCRIPTION OF DRAWINGS

Figure 1 illustrates various types of artifacts in MRI acquisition, in accordance with an embodiment of the present invention.

Figure 1 (a) illustrates a qualitative results on motion affected cardiac scan.

Figure 2 illustrates a high-level flowchart of the process during testing, in accordance with an embodiment of the present invention.

Figure 2 (a) illustrates an exemplary method of Joint training in line with embodiments of the present invention.

Figure 2 (b) illustrates a curriculum-MAML for an exemplary neural network in line with present invention.

Figure 3 illustrates a flowchart of the method during training using a representation learning technique, in accordance with an embodiment of the present invention.

Figure 4 illustrates a pacing function in line with the present invention.

Figure 5 illustrates a comparative analysis with respect to SSIM metric on unseen artifact data.

Figure 6 illustrates qualitative results on unseen artifact data.

Figure 7 illustrates qualitative results on composite artifact data.

Figure 8 illustrates an inference pipeline for an exemplary machine learning model having a scheduler component for reducing artifacts during inference stage.

DETAILED DESCRIPTION

In the following description, for the purpose of explanation, numerous specific details have been set forth in order to provide a description of the invention. It will be apparent, however, that the invention may be practiced without these specific details and features.

The present disclosure relates to system and method to improve the scan quality of degraded MRI scan caused by artifacts during acquisition of the MRI scan.

Particularly, the present invention is directed to a method and apparatus for reducing artifacts in MRI scan images during inference by receiving an input MRI scan image, processing the input MRI scan image through a trained deep learning model to generate an output image, applying a scheduler component to iteratively

reduce the magnitude of artifacts in the output image by applying a predefined transformation.

The present invention utilizes a model-agnostic meta-learning (MAML) model as a nested bi-level optimization framework to learn common knowledge across artifacts in an outer level of optimization, and artifact-specific restoration in the inner level.

The present invention proposes that the curriculum-MAML (CMAML) is utilized as a learning process that integrates MAML with curriculum learning to impart the knowledge of variable artifact complexity to adaptively learn restoration of multiple artifacts during training.

In particular, the artifact-specific model of the present invention implements a forward-pass of training process as illustrated in Fig. 2b and effectively promotes a specialized model (θ), based on artifact type, even in the unseen test degradations.

In the MAML framework of the present invention, each type of artifact is treated as a task. The MAML framework as implemented further incorporates a curriculum learning (CL), in order to provide additional knowledge of artifact-complexity during training.

Thus, the present invention implements a level of complexity in curriculum learning [CL] based on the ill-posedness of various artifacts. For instance, in under-sampling artifact, the level of complexity is directly related to the ill-posedness characterized by the amount of acceleration during MRI acquisition. Thus, for two scans where one scan is 3x accelerated and the other is 5x, the former task is less complex than the latter. The proposed learning model of present invention embeds representations based on the nuances in artifacts for a given neural network architecture.

Thus, present invention is able to propose a curriculum-based model-agnostic meta-learning (CMAML) as a training method that performs image restoration of multiple types of artifact- affected MRI scans in a single model. Again, the proposed method establishes an artifact-type as a task and associates the amount of MRI artifact with the task-complexity.

The present invention encompasses analysing multiple MRI artifacts by using multiple artifact representation learning method that provides a single model for improving the scan quality of MRI scans affected by various degradations. The system and method of present invention output a clean counterpart of the artifact affected MRI scan. Further, the present invention encompasses incorporating the nuances of artifact-type and artifact complexity into the training method in determining the artifact free image for a given poor quality MRI scan. Furthermore, the present invention encompasses using multiple artifact data for intelligently updating the model during the course of training to enhance the overall accuracy on various degradations.

Referring to Figure 1, shown are the various types of artifacts that can occur during an MRI acquisition, including, but not limited to, noise artifact, spike artifacts, poor spatial resolution, undersampling artifacts, motion artifacts and ghost artifacts.

Figure 1 (a) illustrates a qualitative results on motion affected cardiac scan.

Figure 2 illustrates a flowchart of the process during testing, in accordance with an embodiment of the present disclosure. As depicted therein, a MRI scan image is processed with the deep-learning module of the present invention which processes the input MRI scan image and results in a scan with improved quality.

Thus, the MRI Scan Image Improvement Using Deep Learning Model broadly comprises three steps:

- The original image obtained from an MRI scan.
- A Deep Learning model that processes the MRI scan image.
- The output is an MRI image with enhanced scan quality.

Figure 3 shows a flowchart of the process during training, in accordance with an embodiment of the present invention.

The process comprises:

- collecting datasets for different types of artifacts (e.g., Artifact 1, Artifact 2, ..., Artifact n)
- pre-processing the collected data to standardize and preparing it for analysis
- assessing the complexity of each artifact using a scoring function. This helps in understanding the severity and nature of the artifacts
- applying a pacing function to gradually introduce data with increasing complexity to the DL model during training. This helps the model learn effectively.
- training the deep learning (DL) model using the pre-processed data and pacing function
- Implementing a correction mechanism within the deep learning DL model to adjust and improve its performance based on artifact-specific challenges
- Developing an artifact-specific model that targets and improves specific types of artifacts identified during training
- Evaluating the improved MRI images using an image quality assessment measure to ensure the enhancements meet the required criteria
- Continuously evaluating the model's performance using an evaluation mechanism
- Checking if the improved image quality meets the set criteria.
 - If “Yes”, finalizing the (deep learning) DL model for deployment.
 - If “No”, iterating through the (deep learning) DL model training and correction

mechanism until the desired quality is achieved.

Thus, as shown in figure 3, dataset(s) of various artifact types are collected. Some exemplary artifact types considered for the process are:

- i) Under-sampling artifact: This type of degradation is induced by the acquisition settings. Usually, the long acquisition duration is shortened at the cost of image quality.
- ii) Motion artifact: Inherent respiratory and cardiac movements degrade the image quality by introducing ghosting artifacts.
- iii) Poor spatial resolution: Artifacts arising due to large in-plane pixel spacing.

Further, data pre-processing includes standardizing the various artifact dataset using following steps:

- i) Cropping: Region of interest (ROI) defined by the cardiac anatomy is extracted within an 128x128 image.
- ii) Normalization: The intensity profile of the heterogeneous dataset is modified such that each image has contrast information fitted within a defined range.

An artifact complexity scoring function is then used to determine a complexity score of an artifact of any type. The complexity score is a value indicating the difficulty in extracting a clean image from the artifact image.

Next, a pacing function is used wherein while initially, the process only uses the easy graded artifacts to perform artifact restoration. At subsequent stages, highly difficult artifacts are cumulatively added to the process so that the knowledge gained from the easy artifacts is used effectively.

In the next step, a deep learning (DL) model provides a parameterized neural network architecture that facilitates a functional mapping from input degraded image to the corresponding clean image at its output. Said model consists of modules including, but not limited to, convolutional layer, batchnorm and nonlinear activation function. The parameters of said modules are appropriately adjusted to

effectively improve the quality of input image.

Further, an artifact-specific model is implemented, where from a single DL model, based on the artifact type, a separate expert model for every available artifact is obtained, using correction mechanism explained herein below.

Correction mechanism also called as backpropagation updates the parameters of a DL model by optimizing an error function. Updating occurs in a way such that the new parameters are better than the old parameters at performing the task of artifact reduction.

Further, the flowchart provides an evaluation mechanism that also uses backpropagation, but instead operates on a hierarchy where, instead of updating, the updated hypothesis is tested for better optimization strategy.

The present invention encompasses inclusion of a biologically motivated method that operates on a spectrum of neural networks and associates a loss function to a training process constituted by the preparation of datasets, applying known artifacts and achieving a highly nonlinear function to map degraded scan to its clean version. This end-to-end learning method based on representation learning is akin to the spirit of biologically evolving systems in the sense of automatically searching (facilitated by feedback as shown in figure 3 in the form of *evaluation mechanism*) and identifying an optimal mechanism (facilitated by coupling evaluation mechanism with correction mechanism in figure 3).

Finally, an image quality assessment measure is used as a metric to quantify the image quality of the output provided by the model.

The present invention based on representation-learning is different in two aspects:

- 1) a single model is designed to effectively improve the quality of scan affected by multiple artifacts and,
- 2) evaluation mechanism is included that boosts the performance of the overall process even in the scenario of unseen artifacts. Whereas the existing system for solving the problem of artifact restoration consists of only training, without

evaluation mechanism, a model for every degradation.

The present invention efficiently utilizes nuances such as artifact type and artifact complexity that provide additional information for improving the scan quality.

The present invention method is designed to work with even a single type of artifact with accuracy all types of artifacts are provided. The method when included in the MRI workflow improves the scan quality, and thus enhances the decision-making process for a better healthcare system.

The data acquisition forward model of the artifact restoration problem [11] is formulated as:

$$Ax + E = y \quad (1)$$

where, $x \in \mathbb{C}^N$ denotes the desired image, $y \in \mathbb{C}^M$ is the measurement from the MRI scanner, $E \in \mathbb{C}^M$ is the noise and $A: \mathbb{C}^N \rightarrow \mathbb{C}^M$ represents the forward operator of MRI acquisition that causes artifacts.

Artifact restoration is ill-posed as the problem is under-determined ($M \ll N$) and the operator A is ill-conditioned. The restoration of MRI artifact scans is achieved by introducing an a-priori knowledge of x into the unconstrained optimization [11]:

$$\min_x ||Ax - y||_2^2 + R(x) \quad (2)$$

where, $||Ax - y||_2^2$ is the data fidelity term and R is a regularization term.

Deep learning-based MRI image restoration involves training a DL model using a single-level optimization on the average loss of all observed artifact data. This supervised joint training can be formulated as:

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \quad \mathbb{E}_{(x_{in}, x) \in \cup_i D_i} [\|x - f(x_{in}; \theta)\|_2^2] \quad (3)$$

where, D_i represents the dataset of artifact i , consisting of ground truth image x and its corresponding degraded image x_{in} . Here, f is a DL model parameterized by θ .

Unlike iterative methods in Eq. 2, statistical expectation ($\mathbb{E}$) analysis in Eq. 3 infers an optimal parameter set θ^* . Artifacts considered for training are motion, super-resolution (SR) and under-sampling (US), each defined with a corresponding operator as:

- (i) **AM (x) = F⁻¹[1+s Ψ_j (F(x))]**, where F and F^{-1} denote 2D Fourier $\mathbb{R}^2 \rightarrow \mathbb{R}^2$ and inverse transforms respectively, Ψ selects k -space data lines of $2s + 1$ frames of CMR .
- (ii) **ASR(x) = U (D(x))**, where D and U denote down-sampling and upsampling operations respectively.
- (iii) **AUS(x) = F⁻¹(M $\circ$ F(x))** where $\circ$ indicate Hadamard product and M is an under-sampling mask.

MAML involves partitioning each task's data into support (x_t, x_{spt}) and query (x_t, x_{qry}) samples.

The parameters of DL model, θ , in Fig. 2b are called meta-initializations. For every task “ t ”, the present invention supports samples to perform a few gradient-descent steps (adaptation) from meta-initializations to obtain task-specific parameters (ϕ_t).

Loss of task-specific parameters on query data is aggregated over all train tasks (T), to provide supervision for meta- initializations. The training method of MAML

[12] is:

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \sum_{t \in \mathcal{T}} ||x_{qry} - f^t(x_{in, qry}; \varphi_t)||_2^2 \quad (4)$$

$$s.t. \quad \varphi_t = \underset{\theta}{\operatorname{argmin}} ||x_{spt} - f(x_{in, spt}^t; \theta)||_2^2 \quad \forall t \in \mathcal{T} \quad (5)$$

In line with the present disclosure of MAML-based artifact image restoration, the present invention considers an artifact-type as a task. On every artifact's support samples, the present invention performs adaptation to result in an artifact-specific model that is characterized by weights φ_t and it constitutes one-level of optimization (inner level, *steps 6 to 12* in Algorithm 1) in the bi-level MAML framework.

The adaptation on an artifact is shown in the Fig. 2b.

After adapting on support samples of all train artifact data, the present invention proposes aggregating the loss incurred by every artifact-specific model using query samples. In the second-level of optimization (outer level, *steps 13 to 16* of Algorithm 1), the present invention proposes backpropagating the total loss to update the meta-initializations and thus completing one end-to-end iteration in the course of training. During the outer level update, the parameters of the artifact-specific model are frozen to perform optimization on only the meta-initializations as shown in Fig. 2b. However, additional nuances in the complexity of various configurations within a type of artifact can embed representations that generalize better for unseen artifacts in test data.

In Curriculum-learning (CL) [10], the present invention proposes 1) a scoring-function that estimates the complexity of a data-sample based on the difficulty of predicting the target associated with the input and 2) a pacing-function that schedules the inclusion of data-samples to DL model across epochs as the training progresses.

During the initial epochs of training in CL, pacing-function provides only low-complexity data-samples based on scoring function to the DL model and as the training progresses, medium to high complexity data-samples are cumulatively included.

Here, the present invention also incorporates CL into MAML framework. Unlike CL, the present invention also defines complexity over a task (Fig. 2b, pink block) and not on data-samples. The scoring-function of a task is parameterized by the ill-posedness of the corresponding forward operator A . The pacing-function used herein is a simple step-function of epoch as in CL, as shown in Fig. 3. The training process of CMAML is described in Algorithm 1 and various notations are explained in detail.

Algorithm 1 CMAML algorithm

Require: α, β and T : Train tasks
Require: $S(T)$: Task scoring-function
Require: $P(T, \cdot)$: Task pacing-function

- 1: Randomly initialize θ
- 2: Sorted tasks: T_{sorted} , in ascending order by $S(T)$
- 3: **for** $e = 1$ **to** max_epochs **do**
- 4: Infer a task mini-batch: $T_{batch}, U = P(T_{sorted}, e)$
- 5: $L_{meta} = 0$
- 6: **for** each training task t in T_{batch} **do**
- 7: Sample a mini-batch of support data
 $D_{spt}^t = \{X_{in,n}^t, X_{..}^t\}_{n=1}^{N_{spt}}$
- 8: Initialize $\varphi_t \leftarrow \theta$
- 9: **for** $u = 1$ **to** U **do** $t >$ Artifact-specific adaptation
- 10: $L_1 = L(\varphi_t, D_{spt}^t)$
- 11: $\varphi_t \leftarrow \varphi_t - \alpha \nabla_{\varphi_t} L_1$
- 12: **end for**
- 13: Sample a mini-batch of query data
 $D_{qry}^t = \{X_{in,n}^t, X_{..}^t\}_{n=1}^{N_{qry}}$
- 14: $L_{meta} \leftarrow L_{meta} + L(\varphi_t, D_{qry}^t)$
- 15: **end for**
- 16: $\theta \leftarrow \theta - Adam[\beta, L_{meta}]$ $t >$ Meta-update
- 17: **end for**

The experimental dataset details are provided herewith.

A. Training Data

For training, the present invention use Multi-Centre, Multi-Vendor & Multi-Disease (M&M) cardiac dataset. The train tasks (T) include artifacts caused by motion, under-sampling and poor spatial resolution.

The present invention in an exemplary embodiment considers three motion artifact tasks with $s = 1, 2$ and 3 in A_M operator, three under-sampling artifact tasks of $2x$, $4x$ and $6x$ acceleration with Cartesian masks, and three scale factors of $2x$, $3x$ and $5x$ as super-resolution tasks.

In each task, the present invention considers 2100 and 500 cardiac images for training and validation respectively.

B. Unseen Artifact Data

In an embodiment, the following unseen artifact data are considered for evaluation: (i) different cardiac dataset i.e., *Automated Cardiac Diagnosis Challenge* (ACDC) [14] dataset (ii) unseen amount of degradation (iii) unseen artifact type.

A combination of three cases is also present in unseen artifact data.

Regarding the different degradations, the present invention selectively chooses $s = 4$ and 6 in A_M operator. Similarly, for undersampling artifact, the present invention selectively chooses $3x$ and $5x$ acceleration in unseen artifact data. Moreover, artifacts not present in training data such as Spiking, Respiratory/Ghosting, Noise and Gamma artifacts are also present in unseen artifact data, simulated using *TorchIO* [15] library.

C. Composite Artifact Data

In an exemplary embodiment, the composite artifact data is characterized by simulating one artifact followed by a different artifact in the same cardiac scan.

For example, in an embodiment five different artifacts on M&M data are considered:

1) Noise and Spiking, 2) Spatial-resolution and Noise, 3) Under-sampling and Spiking, 4) Ghosting and Spiking, and 5) Under-sampling and Noise.

Undersampling artifact consists of $3\times$ acceleration and a $2\times$ factor for spatial resolution.

D. Preprocessing

In an embodiment, M&M and ACDC dataset images are used that consist of three spatial dimensions and one time dimension, along with segmentation maps and end-systolic (ES) [16] time instances of the cardiac cycle.

In the time dimension, except the first and last time points, the rest of the slices are considered for training. The segmentation map of the ES slice consists of the clinically relevant portion of the cardiac scan. A 128×128 region is cropped around the region of interest defined by the segmentation map. Images are normalized for the intensity homogeneity across CMR scans.

In an embodiment, the (deep learning) DL model is a five layer CNN.

Learning rates (α, β) of 0.001 with 200 *max epochs* are chosen in an embodiment. Outer level and inner level use Adam and SGD optimizers respectively. Batch size for support and query data (N_{spt}, N_{qry}) is 5.

Task mini-batch ($|d|$) is chosen to be 3. Pacing functions's cumulative inclusion of artifact data across epochs is shown in Fig. 3 along with easy, medium and hard artifacts. Pacing-function also modulates the number of adaptation steps (U) from 1, 2 & 3 at the cue of adding graded artifacts during training.

The loss function is L_1 norm between the model's prediction and ground truth. All models are trained on 24GB memory *Nvidia RTX-3090*.

The MRI modality is diverse due to its varied acquisition settings and patient conditions. The present invention evaluates the proposed method under deviated scenario of different train and test artifacts and degradations. Details on the unseen artifact data that is used to qualitatively and quantitatively demonstrate the CMAML generalization is given herewith.

The Table I provides quantitative results in terms of SSIM and PSNR (dB) metrics.

From Table I, for M&M dataset, CMAML is consistently better than other methods in terms of SSIM metric that is considered to be close to radiologist scores.

Similarly, in terms of PSNR, CMAML performs better artifact suppression for 83% of unseen degradations on M&M dataset.

Likewise, on ACDC dataset, meta-learning methods outperform SGD for 83% and 67% of artifacts in terms of SSIM and PSNR respectively.

Maximum improvement is present in spiking and gamma artifacts in M&M and ACDC dataset respectively.

Qualitative results with residue images in Fig. 6 indicate that the proposed CMAML is robust with respect to cardiac image perturbations than other methods.

Again, the artifact restoration of motion affected image shown in Fig. 1 indicates

better recovery of details in the left ventricle enclosed by a yellow bounding box in residue. From the boxplot of various artifacts in Fig. 5, the regularization offered by curriculum in MAML framework better aids the restoration of CMR images, especially in spiking and additive noise corruption.

Also for an input image with no artifact, CMAML shows better identity mapping over other methods as shown in Table I below.

TABLE I
QUANTITATIVE RESULTS OF VARIOUS UNSEEN ARTIFACTS. US DENOTES
UNDER-SAMPLING. BOLD FIGURES INDICATE THE BEST SCORES.

Dataset	Artifact	SGD	MAML	CMAML (proposed)
		PSNR/ SSIM	PSNR/ SSIM	PSNR/ SSIM
M&M [13]	Motion	27.47/ 0.9043	27.64/ 0.9068	27.75/ 0.9079
	Gamma	26.25/ 0.9610	26.67/ 0.9659	27.26/ 0.9681
	Ghosting	31.10/ 0.9457	31.17/ 0.9470	31.18/ 0.9471
	Spiking	27.93/ 0.8938	28.30/ 0.9004	28.40/ 0.9010
	US	27.33/ 0.8853	27.32/ 0.8859	27.34/ 0.8862
	Noise	28.59/ 0.8748	28.26/ 0.8663	28.54/ 0.8749
	No artifact	36.73/ 0.9922	37.04/ 0.9928	37.68/ 0.9930
ACDC [14]	Motion	29.30/ 0.9282	29.54/ 0.9305	29.64/ 0.9313
	Gamma	26.57/ 0.9480	27.06/ 0.9526	27.56/ 0.9552
	Ghosting	32.42/ 0.9639	32.51/ 0.9655	32.45/ 0.9656
	Spiking	29.77/ 0.9171	30.12/ 0.9218	30.12/ 0.9212
	US	25.81/ 0.8376	25.83/ 0.8392	25.81/ 0.8393
	Noise	29.92/ 0.8765	29.66/ 0.8693	29.86/ 0.8771
	No artifact	35.38/ 0.9871	36.23/ 0.9897	36.48/ 0.9897

The present invention now describes evaluation on composite artifacts. The scenario of composition of artifacts is described, where the scan containing multiple degradations is prominent in MRI acquisition.

For instance, the ghosting artifact from the respiratory cardiac movement is compounded by the under- sampling artifact arising from acquisition settings.

The present invention evaluates on the test scenario that contains two different artifacts in the same scan as shown in Table II below. Details on the composite artifact data is also described herewin.

From Table II, the CMAML method of the present invention is quantitatively performing better than joint training and MAML in terms of SSIM scores for 80% of composite artifacts. Similarly, in terms of PSNR metric, meta learning methods outperform SGD for 80% of composite artifacts.

For the composite artifact of *ghosting+spiking*, a maximum improvement margin of around 0.006 is noticed for CMAML over SGD.

Qualitative performance of various methods is shown in Fig. 7, including the residue, for a combination of undersampling followed by additive Gaussian noise. The clinically prominent portion of the left ventricle of cardiac is highlighted in the bounding box in the residue images of Fig. 7 and CMAML predicts the artifact suppressed image closer to the normal cardiac scan. For the proposed method, the metrics are statistically significant with $p < 0.05$.

TABLE II
QUANTITATIVE RESULTS OF COMPOSITE ARTIFACTS ON M&M DATASET.
BOLD FIGURES INDICATE THE BEST SCORES.

Composition of artifacts	SGD	MAML	CMAML
	PSNR/ SSIM	PSNR/ SSIM	PSNR/ SSIM
Noise+Spiking	27.48/ 0.8897	27.52/ 0.8883	27.60/ 0.8904
Under-sampling+Spiking	26.70/ 0.8600	26.71/ 0.8612	26.73/ 0.8613
Spatial-resolution+Noise	29.13/ 0.8772	28.77/ 0.8692	28.90/ 0.8750
Ghosting+Spiking	27.21/ 0.9055	27.39/ 0.9106	27.20/ 0.9110
Under-sampling+Noise	25.18/ 0.7988	25.08/ 0.7944	26.13/ 0.8004

Thus, present invention proposes CMAML, a training process based on meta learning, to efficiently consolidate the information of multiple types of artifacts for MRI artifact image restoration. The training process is enabled to embed better representations by associating the artifact's ill-posedness to the complexity and thus

effectively promoting the curriculum fashion of training into meta-learning framework.

For a fixed neural network, the present invention demonstrates increased scalability of CMAML on various nuances of unseen artifacts and composite artifacts in cardiac MRI images qualitatively and quantitatively.

Thus, present invention is trained with deployment perspectives to improve scan quality under various unseen artifacts, and is capable of eliminating models trained separately for each artifact. Moreover, restoring the artifact affected scan within the MRI workflow reduces the burden on the healthcare system by avoiding patient recall and rescan.

Further, Fig. 8 describes an inference pipeline for a machine learning model with a scheduler component that reduces the artifacts progressively during the inference stage.

The exemplary scheduler is designed to iteratively reduce the magnitude of artifacts that might be present in the output of the trained model.

The scheduler modifies the output image by a defined iterative process to achieve the desired reduction in artifacts.

The transformation applied by the scheduler can be represented as:

Input images to the scheduler: CMAML output (I_{out}) CMAML input (I_{in})	Output from the scheduler: $I_{sch} = I_{out} - 0.1 * (I_{out} - I_{in})$
--	--

Although the present invention has been described in considerable detail with reference to certain preferred embodiments and examples thereof, other embodiments and equivalents are possible. Even though numerous characteristics and advantages of the present invention have been set forth in the foregoing description, together with functional and procedural details, the disclosure is

illustrative only, and changes may be made in detail, especially in terms of the structuring and implementation within the principles of the invention to the full extent indicated by the broad general meaning of the terms. Thus, various modifications are possible of the presently disclosed system and method without deviating from the intended scope and spirit of the present invention.

We Claim:

1. A method for reducing artifacts in MRI scan images during inference, comprising:

- receiving an input MRI scan image;
- processing the input MRI scan image through a trained deep learning model to generate an output image;
- applying a scheduler component to iteratively reduce the magnitude of artifacts in the output image by applying a predefined transformation.

2. The method of claim 1, wherein the predefined transformation applied by the scheduler component is represented by the equation:

$$\begin{aligned} & \backslash \\ I_{\{sch\}} &= I_{\{out\}} - 0.1 \times (I_{\{out\}} - I_{\{in\}}) \\ & \backslash \end{aligned}$$

where $(I_{\{in\}})$ is the input image to the trained model, and $(I_{\{out\}})$ is the output image from the trained model.

3. The method of claim 1, wherein the scheduler component operates iteratively until the magnitude of artifacts is reduced to a predetermined threshold.

4. The method of claim 1, further comprising:

- adjusting the transformation parameters based on feedback regarding the reduction of artifacts in the output image.

5. The method of claim 1, further comprising:

- determining the number of iterations required for artifact reduction based on the initial quality of the output image.

6. The method of claim 1, wherein the trained deep learning model is a model-agnostic meta-learning (MAML) model.

7. The method of claim 1, wherein trained deep learning model is configured to

handle multiple types of artifacts including but not limited to noise, spiking artifacts, poor spatial resolution, undersampling artifacts, motion artifacts, and ghost artifacts.

8. An apparatus for reducing artifacts in MRI scan images during inference, comprising:

- a trained deep learning model configured to receive an input image and generate an output image; and
- a scheduler component operatively coupled to the trained deep learning model, wherein the scheduler component iteratively reduces the magnitude of artifacts in the output image by applying a predefined transformation.

9. The apparatus of claim 8, further comprising a feedback mechanism that adjusts the transformation parameters based on the reduction of artifacts in the output image.

10. The apparatus of claim 8, wherein the scheduler component includes a control unit that determines the number of iterations required for artifact reduction based on the initial quality of the output image.

11. A non-transitory computer-readable medium storing instructions that, when executed by a processor, cause the processor to perform a method for reducing artifacts in MRI scan images during inference, the method comprising:

- receiving an input MRI scan image;
- processing the input MRI scan image through a trained deep learning model to generate an output image;
- applying a scheduler component to iteratively reduce the magnitude of artifacts in the output image by applying a predefined transformation.

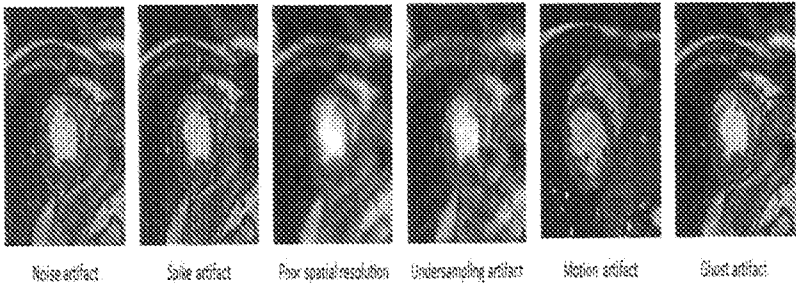


Figure 1

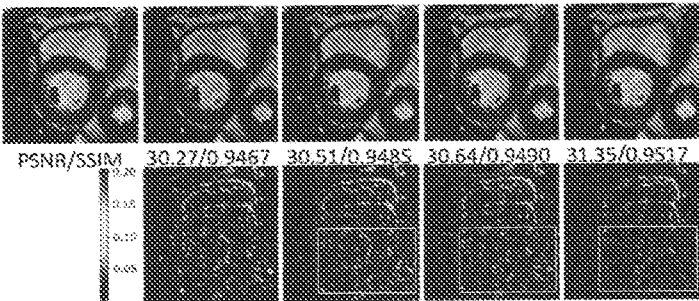


Figure 1 (a)

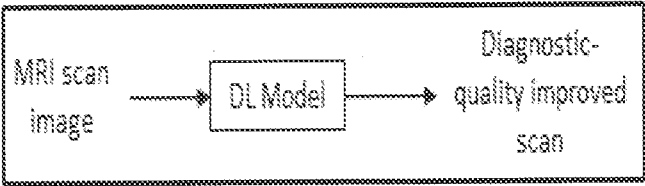


Figure 2

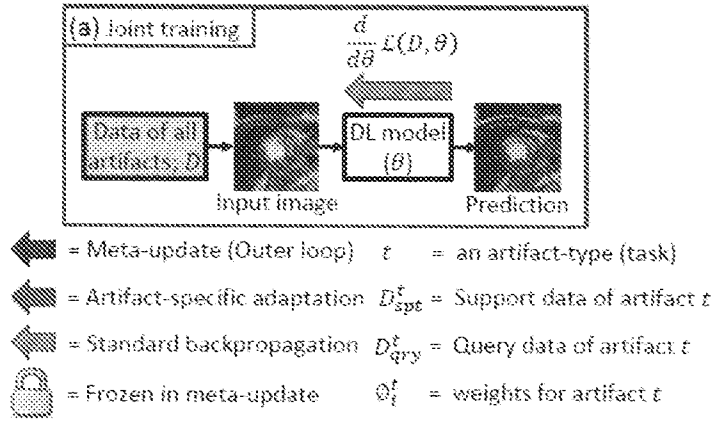


Figure 2 (a)

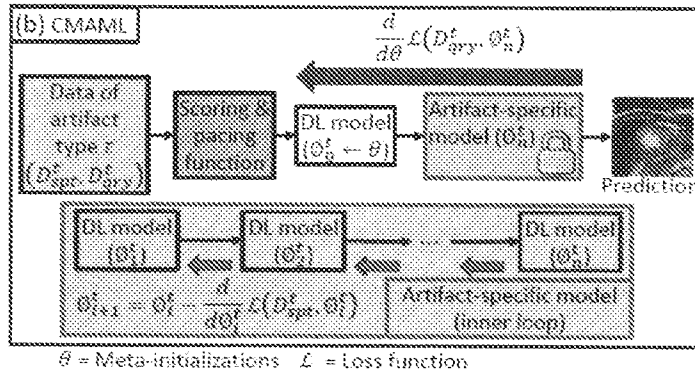


Figure 2 (b)

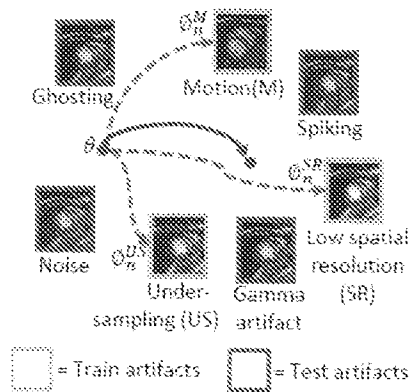


Figure 2 (c)

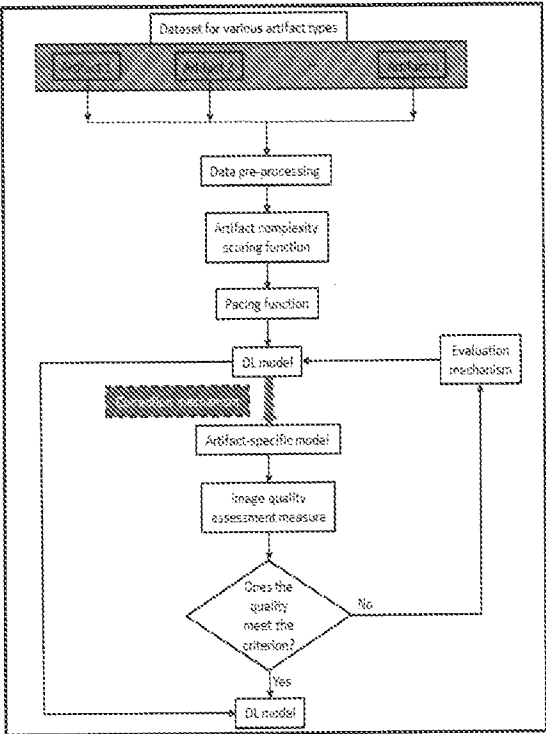


Figure 3

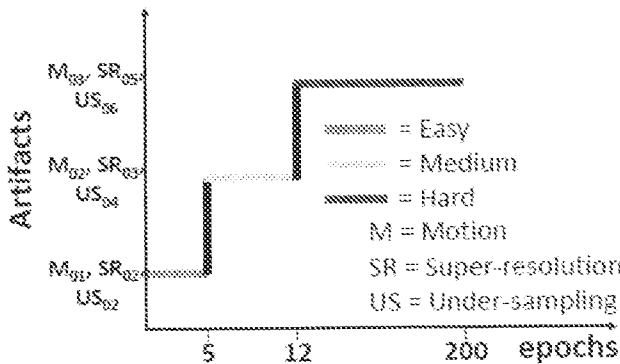


Figure 4

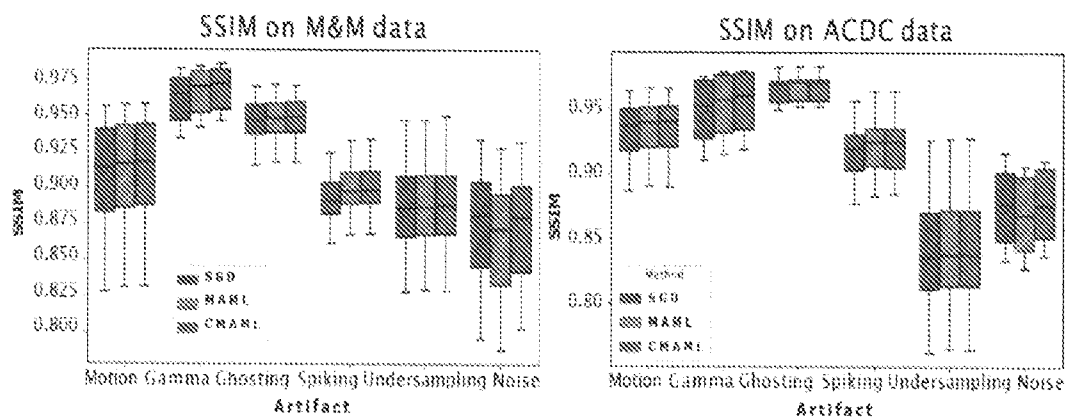


Figure 5

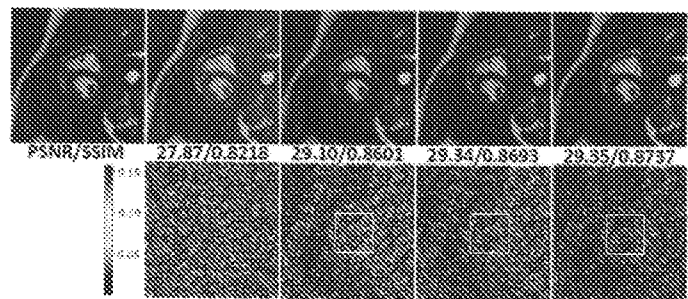


Figure 6

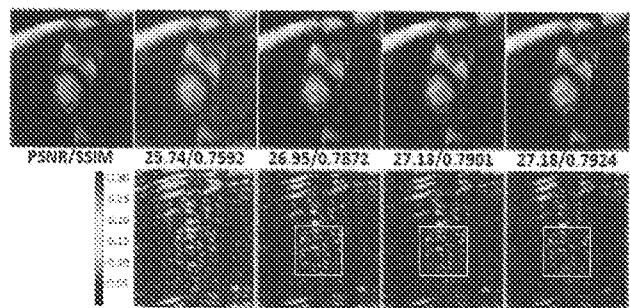


Figure 7

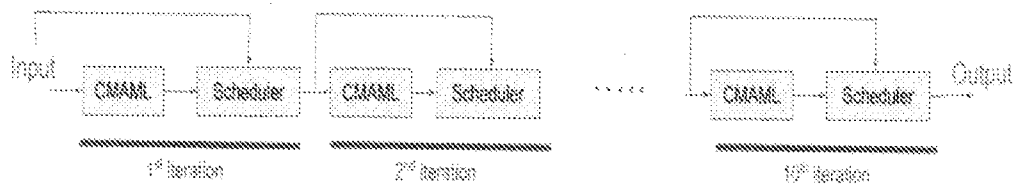


Figure 8

INTERNATIONAL SEARCH REPORT

International application No.
PCT/IN2024/051408

A. CLASSIFICATION OF SUBJECT MATTER

G01R33/565, A61B5/055, G01R33/56, G01R33/54, G01R33/48 Version=2024.01

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

G01R, A61B

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic database consulted during the international search (name of database and, where practicable, search terms used)

PatSeer, IPO Internal Database

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y	A. Palla, S. Ramanarayanan, K. Ram and M. Sivaprakasam, "Generalizable Deep Learning Method for Suppressing Unseen and Multiple MRI Artifacts Using Meta-learning," " https://doi.org/10.48550/arXiv.2304.06378 "; 13 April, 2023 (13-04-2023) Abstract, Introduction, Methodology, figure 2	1-11
Y	Chen, Z., Pawar, K., Ekanayake, M. et al.; "Deep Learning for Image Enhancement and Correction in Magnetic Resonance Imaging-State-of-the-Art and Challenges"; J Digit Imaging 36, 204-230 (2023); https://doi.org/10.1007/s10278-022-00721-9 , 02 November, 2022 (02-11-2022) Abstract, Introduction, page 206, figure 1, Network Training	1-11

☐ Further documents are listed in the continuation of Box C. ☐ See patent family annex.

* Special categories of cited documents:

"A" document defining the general state of the art which is not considered to be of particular relevance

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"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"I" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search

22-11-2024

Date of mailing of the international search report

22-11-2024

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