Universal Model for Cardiac MRI Reconstruction Challenge: Structured description of the challenge design

CHALLENGE ORGANIZATION

Title

Use the title to convey the essential information on the challenge mission.

Universal Model for Cardiac MRI Reconstruction Challenge

Challenge acronym

Preferable, provide a short acronym of the challenge (if any).

CMRxUniversalRecon

Challenge abstract

Provide a summary of the challenge purpose. This should include a general introduction in the topic from both a biomedical as well as from a technical point of view and clearly state the envisioned technical and/or biomedical impact of the challenge.

Cardiac magnetic resonance imaging (CMR) has emerged as a crucial imaging technique for diagnosing cardiac diseases, thanks to its excellent soft tissue contrast and non-invasive nature. However, a notable limitation of MRI is its slow imaging speed, which causes patient discomfort and introduces motion artifacts into the images.
To accelerate image acquisition, CMR image reconstruction (recovering high-quality clinical interpretable images from highly under-sampled k-space data) has gained significant attention in recent years. Particularly, AI-based image reconstruction algorithms have shown great potential in improving imaging performance by utilizing highly under-sampled data. However, the field of CMR reconstruction lacks publicly available, standardized, and high-quality datasets for the development and assessment for AI-based CMR reconstruction.
CMR imaging has the nature of multi-contrast, e.g., cardiac cine, mapping, tagging, phase-contrast, and dark-blood imaging. It also includes imaging of different anatomical views such as long-axis (2-chamber, 3-chamber, and 4-chamber), short-axis, outflow tract, and aortic (cross-sectional and sagittal views). Additionally, accelerated imaging trajectories, including uniformly undersampling and variable-density sampling, are employed. Unfortunately, conventional CNN-based reconstruction models often require training and deployment for each specific imaging scenario (imaging sequence, view, and device vendor), limiting their clinical application in the real world.
The objective of establishing the 'CMRxUniversalRecon' challenge is to provide a benchmark that enables the broader research community to contribute to the important work of accelerated CMR imaging with universal approaches that allow more diverse applications and better performance in real-world deployment in various environments. To achieve this goal, in the first run of the 'CMRxRecon' challenge (MICCAI 2023) we provided training and test data from a total of 200 subjects and the technical infrastructure as well as a baseline model for CMR reconstruction on muti-contrast imaging. The results of 'CMRxRecon' 2023 demonstrated the feasibility of highly sub-sampled k-space reconstruction on dedicated pre-trained models.

In this second run of the CMR reconstruction challenge we aim to make an important step towards clinical implementation by extending the challenge scope in two directions:
1) trustworthy reconstruction on multi-contrast CMR imaging using a universal pre-trained reconstruction model;
2) robust reconstruction with diverse and even unseen k-space trajectory and various acceleration factors using a universal model.

Challenge keywords

List the primary keywords that characterize the challenge.challenge_

Cardiac MRI, image reconstruction, universal model, fast imaging, multi-contrast imaging

Year

The challenge will take place in 2024

FURTHER INFORMATION FOR CONFERENCE ORGANIZERS

Workshop

If the challenge is part of a workshop, please indicate the workshop.

This challenge could potentially be part of the Statistical Atlases and Computational Modeling of the Heart (STACOM) workshop.

Duration

How long does the challenge take?

Half day.

Expected number of participants

Please explain the basis of your estimate (e.g. numbers from previous challenges) and/or provide a list of potential participants and indicate if they have already confirmed their willingness to contribute.

We expect participation from 20-40 teams at MICCAI 2024. This is estimated from the previous 'CMRxRecon' 2023 challenge, in which 26 teams participated in all stages of the challenge, including the submission of the final Docker. According to the post-post-event survey conducted last year, all the 26 participating teams who filled out the questionnaire expressed their willingness to continue participating in the challenge. We expect a considerable increase of participants this year, due to the fast growing research communities of CMR, inverse problems, generative AI, and foundation models. This anticipation is also based on the growing popularity of the CMRxRecon 2023 dataset after the challenge.

Publication and future plans

Please indicate if you plan to coordinate a publication of the challenge results.

After the challenge, we will consolidate the results in a challenge paper and submit it to a high-impact journal (e.g., Medical Image Analysis, IEEE Transactions on Medical Imaging).

Space and hardware requirements

Organizers of on-site challenges must provide a fair computing environment for all participants. For instance, algorithms should run on the same computing platform provided to all.

Participants are expected to train models in their local computational environments and to submit docker containers on Synapse platform. Training and validation data are available for registered teams to download. A leaderboard will be maintained on the Synapse platform during the validation phase. For testing as part of the challenge, participants need to submit their docker containers on Synapse platform and we will use the organizers' servers for testing. We will also require the teams to report their computational cost and optionally carbon footprint for model development.
For the on-site day, we will take a hybrid form to guarantee the participation of all the teams and audiences. We will reveal the challenge outcome and invite the winning teams to present

TASK 1: Multi-contrast CMR reconstruction

SUMMARY

Abstract

Provide a summary of the challenge purpose. This should include a general introduction in the topic from both a biomedical as well as from a technical point of view and clearly state the envisioned technical and/or biomedical impact of the challenge.

Multi-contrast CMR imaging, which involves acquiring multiple imaging sequences with different contrast weightings, provides valuable information for comprehensive cardiac structural and functional assessment. However, the acquisition of multiple contrast-weighted images significantly increases the scan time, leading to longer patient discomfort and greater susceptibility to motion artifacts. Therefore, to reduce image acquisition time, there is a growing need for data-efficient and reliable reconstruction methods to enable accelerated and high-quality multi-contrast CMR imaging.
The objective of this challenge is to develop a universal model that 1) provide high-quality image reconstruction for highly-accelerated (undersampled) MRI acquisitions; 2) being able to process multiple contrast measurements, views, and scanning protocols using a single universal model.
The development of a universal pre-trained reconstruction model is essential to tackle the diverse range of cardiac imaging applications. Traditional reconstruction methods often require specialized algorithms for different imaging sequences, making them less flexible and time-consuming to implement. By contrast, a universal pre-trained model can offer a unified framework that can handle various imaging contrasts, allowing for faster and more robust reconstructions across different CMR protocols. This approach not only improves efficiency but also promotes consistency and standardization in multi-contrast CMR reconstruction.
The CMRxUniversalRecon Challenge aims to foster advancements in multi-contrast CMR reconstruction by providing a platform for researchers to develop and evaluate reconstruction methods. The dataset will include multi-contrast k-space data, consisting of cardiac cine, mapping, tagging, phase-contrast, and dark-blood imaging. The dataset also includes imaging of different anatomical views like long-axis (2-chamber, 3-chamber, and 4-chamber), short-axis, outflow tract, and aortic (cross-sectional and sagittal views). The challenge encourages participants to develop innovative approaches, such as the use of universal pre-trained models, to tackle the complexities of multi-contrast CMR imaging. The envisioned technical impact of this challenge is the development of reliable and data-efficient reconstruction methods that can enhance both the patient experience and the diagnostic quality of multi-contrast CMR images, enabling more accurate and comprehensive cardiac assessment.

Keywords

List the primary keywords that characterize the task.

Multi-contrast imaging, cardiac image reconstruction, under-sampling, universal model

ORGANIZATION

Organizers

a) Provide information on the organizing team (names and affiliations).

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b) Provide information on the primary contact person.

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Life cycle type

Define the intended submission cycle of the challenge. Include information on whether/how the challenge will be continued after the challenge has taken place.Not every challenge closes after the submission deadline (one-time event). Sometimes it is possible to submit results after the deadline (open call) or the challenge is repeated with some modifications (repeated event).

Examples:

- One-time event with fixed conference submission deadline
- Open call (challenge opens for new submissions after conference deadline)
- Repeated event with annual fixed conference submission deadline

One-time event with fixed submission deadline.

Challenge venue and platform

a) Report the event (e.g. conference) that is associated with the challenge (if any).

N/A

b) Report the platform (e.g. grand-challenge.org) used to run the challenge.

synapse.org

c) Provide the URL for the challenge website (if any).

This is last year's website: https://cmrxrecon.github.io. The website for this year is under active construction.

Participation policies

a) Define the allowed user interaction of the algorithms assessed (e.g. only (semi-) automatic methods allowed).

Fully automatic.

b) Define the policy on the usage of training data. The data used to train algorithms may, for example, be restricted to the data provided by the challenge or to publicly available data including (open) pre-trained nets.

It should be restricted to the data provided by this challenge as well as data from the 'fastMRI' challenge (the most related public dataset), under the terms and conditions associated with the data usage.

c) Define the participation policy for members of the organizers' institutes. For example, members of the organizers' institutes may participate in the challenge but are not eligible for awards.

May participate but not eligible for awards and not listed in the leaderboard.

d) Define the award policy. In particular, provide details with respect to challenge prizes.

The top 5 winners receive monetary awards. We are in negotiation with the sponsor about the value (approximately $2000 in total).

e) Define the policy for result announcement.

Examples:

- Top 3 performing methods will be announced publicly.
- Participating teams can choose whether the performance results will be made public.

All submissions will be reported in the leaderboard. Participating teams can opt out of publication of their results in the leaderboard.
Prize-winning methods will be announced publicly as part of a scientific session at the MICCAI annual meeting.

f) Define the publication policy. In particular, provide details on ...

- ... who of the participating teams/the participating teams' members qualifies as author
- ... whether the participating teams may publish their own results separately, and (if so)
- ... whether an embargo time is defined (so that challenge organizers can publish a challenge paper first).

Participating teams with a valid submission can nominate their team members as co-authors for the challenge paper. We reserve the right to exclude teams if they break the challenge rules. Participating teams can publish their own results but after a 3-month embargo period.

Submission method

a) Describe the method used for result submission. Preferably, provide a link to the submission instructions.

Examples:

- Docker container on the Synapse platform. Link to submission instructions: <URL>
- Algorithm output was sent to organizers via e-mail. Submission instructions were sent by e-mail.

Docker container will be accepted as submission through the Synapse platform. Submission details will be published at the time point of challenge announcement.

b) Provide information on the possibility for participating teams to evaluate their algorithms before submitting final results. For example, many challenges allow submission of multiple results, and only the last run is officially counted to compute challenge results.

Participating teams are allowed 3 submissions per task. Only the last run submission is officially counted to rank challenge results. Before the final submission on the test set, participants can test their docker containers on the

validation dataset to avoid submission errors.

Challenge schedule

Provide a timetable for the challenge. Preferably, this should include

- the release date(s) of the training cases (if any)
- the registration date/period
- the release date(s) of the test cases and validation cases (if any)
- the submission date(s)
- associated workshop days (if any)
- the release date(s) of the results

[Apr 1, 2024] website opens for registration, release training and validation images
[Apr 10, 2024] submission system opens for validation
[Aug 1, 2024] submission system opens for testing
[Sept 1, 2024] registration and docker submission deadline
[Oct 8, 2024] release final results

Ethics approval

Indicate whether ethics approval is necessary for the data. If yes, provide details on the ethics approval, preferably institutional review board, location, date and number of the ethics approval (if applicable). Add the URL or a reference to the document of the ethics approval (if available).

We have received ethics approval from the local ethics committee of School of Basic Medical Sciences, Fudan University granted on 17/11/2021, No. 2021-Y060.

Data usage agreement

Clarify how the data can be used and distributed by the teams that participate in the challenge and by others during and after the challenge. This should include the explicit listing of the license applied.

Examples:

- CC BY (Attribution)
- CC BY-SA (Attribution-ShareAlike)
- CC BY-ND (Attribution-NoDerivs)
- CC BY-NC (Attribution-NonCommercial)
- CC BY-NC-SA (Attribution-NonCommercial-ShareAlike)
- CC BY-NC-ND (Attribution-NonCommercial-NoDerivs)

CC BY-NC-ND.

Code availability

a) Provide information on the accessibility of the organizers' evaluation software (e.g. code to produce rankings). Preferably, provide a link to the code and add information on the supported platforms.

We have released the source code for evaluating and ranking the results at Github: https://github.com/CmrxRecon/CMRxRecon

b) In an analogous manner, provide information on the accessibility of the participating teams' code.

The participating teams are suggested to provide links to their code on our website for reproducibility study. However, it is not a condition of participation.

Conflicts of interest

Provide information related to conflicts of interest. In particular provide information related to sponsoring/funding of the challenge. Also, state explicitly who had/will have access to the test case labels and when.

We declare no conflicts of interest. Test images will only be accessible to the challenge organizers.

MISSION OF THE CHALLENGE

Field(s) of application

State the main field(s) of application that the participating algorithms target.

Examples:

- Diagnosis
- Education
- Intervention assistance
- Intervention follow-up
- Intervention planning
- Prognosis
- Research
- Screening
- Training
- Cross-phase

Research, Diagnosis.

Task category(ies)

State the task category(ies)

Examples:

- Classification
- Detection

- Localization
- Modeling
- Prediction
- Reconstruction
- Registration
- Retrieval
- Segmentation
- Tracking

Reconstruction.

Cohorts

We distinguish between the target cohort and the challenge cohort. For example, a challenge could be designed around the task of medical instrument tracking in robotic kidney surgery. While the challenge could be based on ex vivo data obtained from a laparoscopic training environment with porcine organs (challenge cohort), the final biomedical application (i.e. robotic kidney surgery) would be targeted on real patients with certain characteristics defined by inclusion criteria such as restrictions regarding sex or age (target cohort).

a) Describe the target cohort, i.e. the subjects/objects from whom/which the data would be acquired in the final biomedical application.

The target cohort is patients requiring multi-contrast CMR exams, especially patients with arrhythmia and those who cannot adhere to standard imaging protocols.

b) Describe the challenge cohort, i.e. the subject(s)/object(s) from whom/which the challenge data was acquired.

A total of 200 volunteers with multi-contrast CMR imaging from our medical center will be included. The dataset will include multi-contrast k-space data, consist of cardiac cine, mapping, tagging, phase-contrast, and dark-blood imaging. The dataset also includes imaging of different anatomical views like long-axis (2-chamber, 3-chamber, and 4-chamber), short-axis, outflow tract, and aortic (cross-sectional and sagittal views).

Imaging modality(ies)

Specify the imaging technique(s) applied in the challenge.

Magnetic Resonance Imaging

Context information

Provide additional information given along with the images. The information may correspond ...

a) ... directly to the image data (e.g. tumor volume).

none

b) ... to the patient in general (e.g. sex, medical history).

none

Target entity(ies)

a) Describe the data origin, i.e. the region(s)/part(s) of subject(s)/object(s) from whom/which the image data would be acquired in the final biomedical application (e.g. brain shown in computed tomography (CT) data, abdomen shown in laparoscopic video data, operating room shown in video data, thorax shown in fluoroscopy video). If necessary, differentiate between target and challenge cohort.

Multi-contrast CMR data is acquired from the heart and aorta.

b) Describe the algorithm target, i.e. the structure(s)/subject(s)/object(s)/component(s) that the participating algorithms have been designed to focus on (e.g. tumor in the brain, tip of a medical instrument, nurse in an operating theater, catheter in a fluoroscopy scan). If necessary, differentiate between target and challenge cohort.

The algorithm target is to assess the reconstruction performance on multi-contrast CMR imaging based on a universal pre-trained reconstruction model. In the challenge cohort, we recruit volunteers to be scanned with fixed k-space trajectories and accelerating factors.

Assessment aim(s)

Identify the property(ies) of the algorithms to be optimized to perform well in the challenge. If multiple properties are assessed, prioritize them (if appropriate). The properties should then be reflected in the metrics applied (see below, parameter metric(s)), and the priorities should be reflected in the ranking when combining multiple metrics that assess different properties.

- Example 1: Find highly accurate liver segmentation algorithm for CT images.
- Example 2: Find lung tumor detection algorithm with high sensitivity and specificity for mammography images.

Corresponding metrics are listed below (parameter metric(s)).

To find a data-efficient and reliable CMR reconstruction algorithm that can accommodate multiple contrasts and views, under high acceleration (undersampling) rate.
Corresponding metrics are listed below (parameter metric(s)).
Peak signal-to-noise ratio (PSNR)[1], structural similarity index measure (SSIM)[1] and normalized mean squared error (NMSE)[2] between reconstructed images and ground truth images (fully sampled data).
1. When evaluating SSIM, we will narrow down the assessment field-of-view to the region where the heart is located, to avoid interference from the background area.
2. During the testing and ranking phase, we will invite three radiologists to independently score the top five teams ranked by SSIM. The scoring will cover three aspects: image quality, image artifacts, and clinical utility. We will consider both the radiologists' scores and the SSIM results to generate a comprehensive ranking.
Reference:
[1] Hore A, Ziou D. Image quality metrics: PSNR vs. SSIM[C]//2010 20th international conference on pattern recognition. IEEE, 2010: 2366-2369.
[2] Hameed A, Abotiheen M H A, Abdulzahra R. Quality measurement of blurred images using NMSE and SSIM metrics in HSV and RGB color spaces[J]. Physics Journal, 2015, 1: 105-111.

DATA SETS

Data source(s)

a) Specify the device(s) used to acquire the challenge data. This includes details on the device(s) used to acquire the imaging data (e.g. manufacturer) as well as information on additional devices used for performance assessment (e.g.

tracking system used in a surgical setting).

Siemens 3.0T MRI scanner (MAGNETOM Vida)

b) Describe relevant details on the imaging process/data acquisition for each acquisition device (e.g. image acquisition protocol(s)).

We follow the recommendations of CMR exams reported in the previous publication (doi: 10.1007/s43657-02100018x, 10.1007/s43657-021-00018-x). We use 'TrueFISP' for cine, PC and tagging, and 'FLASH' for mapping and dark-blood imaging. The collected imaging planes include long-axis (2-chamber, 3-chamber, and 4-chamber), short-axis, outflow tract, and aortic (cross-sectional and sagittal views). Typically 5-15 slices are acquired. For mapping, signal data were collected at the end of the diastole with ECG triggering. The cardiac cycle is segmented into 15-25 phases with a temporal resolution of around 50 ms. Typical geometrical parameters include: spatial resolution 2.0×2.0 mm2, slice thickness 8.0 mm, and slice gap 4.0 mm.

c) Specify the center(s)/institute(s) in which the data was acquired and/or the data providing platform/source (e.g. previous challenge). If this information is not provided (e.g. for anonymization reasons), specify why.

Zhangjiang Imaging Center, Fudan University, China

d) Describe relevant characteristics (e.g. level of expertise) of the subjects (e.g. surgeon)/objects (e.g. robot) involved in the data acquisition process (if any).

Data are acquired with a team of radiographers and clinical advisors as appropriate.

Training and test case characteristics

a) State what is meant by one case in this challenge. A case encompasses all data that is processed to produce one result that is compared to the corresponding reference result (i.e. the desired algorithm output).

Examples:

- Training and test cases both represent a CT image of a human brain. Training cases have a weak annotation (tumor present or not and tumor volume (if any)) while the test cases are annotated with the tumor contour (if any).
- A case refers to all information that is available for one particular patient in a specific study. This information always includes the image information as specified in data source(s) (see above) and may include context information (see above). Both training and test cases are annotated with survival (binary) 5 years after (first) image was taken.

Training cases include fully sampled k-space data and auto-calibration lines (ACS, 24 lines) will be provided in '.mat' format.
Validation cases include under-sampled k-space data, sampling trajectories, and auto-calibration lines (ACS, 24 lines) with various acceleration factors in '.mat' format.
Test cases include fully sampled k-space data, under-sampled k-space data, sampling trajectories and auto-calibration lines (ACS, 24 lines). Test cases will not be released before the challenge ends.

b) State the total number of training, validation and test cases.

200 cases in total (100 cases for training, 50 validation cases and 50 test cases).

c) Explain why a total number of cases and the specific proportion of training, validation and test cases was chosen.

The sample size of training dataset is reasonable for training deep learning reconstruction networks for CMR imaging according to previous literature and our experience. The sample size of validation and test dataset would well represent the distribution of the data cohort and achieve robust evaluation of the models according to last year's 'CMRxRecon' challenge results, in which 60 cases were used for validation (the website is not allowed to be put here due to special character, you can search 'CMRxRecon' on synapse.org).

d) Mention further important characteristics of the training, validation and test cases (e.g. class distribution in classification tasks chosen according to real-world distribution vs. equal class distribution) and justify the choice.

All subjects are healthy adults and we will aim for an age and gender balance between the training and test data.

Annotation characteristics

a) Describe the method for determining the reference annotation, i.e. the desired algorithm output. Provide the information separately for the training, validation and test cases if necessary. Possible methods include manual image annotation, in silico ground truth generation and annotation by automatic methods.

If human annotation was involved, state the number of annotators.

N.A.

b) Provide the instructions given to the annotators (if any) prior to the annotation. This may include description of a training phase with the software. Provide the information separately for the training, validation and test cases if necessary. Preferably, provide a link to the annotation protocol.

N.A.

c) Provide details on the subject(s)/algorithm(s) that annotated the cases (e.g. information on level of expertise such as number of years of professional experience, medically-trained or not). Provide the information separately for the training, validation and test cases if necessary.

N.A.

d) Describe the method(s) used to merge multiple annotations for one case (if any). Provide the information separately for the training, validation and test cases if necessary.

N.A.

Data pre-processing method(s)

Describe the method(s) used for pre-processing the raw training data before it is provided to the participating teams. Provide the information separately for the training, validation and test cases if necessary.

The raw k-space data exported from the scanner will be processed and transformed to '.mat' format using the script provided by our vendor. A readme file will be provided to describe the content and usage of the data.

Sources of error

a) Describe the most relevant possible error sources related to the image annotation. If possible, estimate the magnitude (range) of these errors, using inter-and intra-annotator variability, for example. Provide the information separately for the training, validation and test cases, if necessary.

N.A.

b) In an analogous manner, describe and quantify other relevant sources of error.

N.A.

ASSESSMENT METHODS

Metric(s)

a) Define the metric(s) to assess a property of an algorithm. These metrics should reflect the desired algorithm properties described in assessment aim(s) (see above). State which metric(s) were used to compute the ranking(s) (if any).

- Example 1: Dice Similarity Coefficient (DSC)
- Example 2: Area under curve (AUC)

PSNR, SSIM and NMSE between reconstructed images and ground truth images (fully sampled data).
1. When evaluating SSIM, we will narrow down the assessment field-of-view to the region where the heart is located, to avoid interference from the background area.
2. During the testing and ranking phase, we will invite three radiologists to independently score the top five teams ranked by SSIM. The scoring will cover three aspects: image quality, image artifacts, and clinical utility. We will consider both the radiologists' scores and the SSIM results to generate a comprehensive ranking.

b) Justify why the metric(s) was/were chosen, preferably with reference to the biomedical application.

We keep these metrics aligned with the 'fastMRI' challenge evaluation metrics for fair evaluations.

Ranking method(s)

a) Describe the method used to compute a performance rank for all submitted algorithms based on the generated metric results on the test cases. Typically the text will describe how results obtained per case and metric are aggregated to arrive at a final score/ranking.

PSNR, SSIM and NMSE between reconstructed images and ground truth images (fully sampled data).
1. When evaluating SSIM, we will narrow down the assessment field-of-view to the region where the heart is located, to avoid interference from the background area.
2. During the testing and ranking phase, we will invite three radiologists to independently score the top five teams ranked by SSIM. The scoring will cover three aspects: image quality, image artifacts, and clinical utility. We will consider both the radiologists' scores and the SSIM results to generate a comprehensive ranking.

b) Describe the method(s) used to manage submissions with missing results on test cases.

Participating teams are required to submit docker containers and process all the cases in the test set on our server. For the cases without valid output, we will assign it to the lowest value of metric.

c) Justify why the described ranking scheme(s) was/were used.

PSNR, SSIM and NMSE between reconstructed images and ground truth images (fully sampled data).
1. When evaluating SSIM, we will narrow down the assessment field-of-view to the region where the heart is located, to avoid interference from the background area.
2. During the testing and ranking phase, we will invite three radiologists to independently score the top five teams ranked by SSIM. The scoring will cover three aspects: image quality, image artifacts, and clinical utility. We will consider both the radiologists' scores and the SSIM results to generate a comprehensive ranking.

Statistical analyses

a) Provide details for the statistical methods used in the scope of the challenge analysis. This may include

- description of the missing data handling,
- details about the assessment of variability of rankings,
- description of any method used to assess whether the data met the assumptions, required for the particular statistical approach, or
- indication of any software product that was used for all data analysis methods.

See the description of metrics and ranking methods above.

b) Justify why the described statistical method(s) was/were used.

See the description of metrics and ranking methods above.

Further analyses

Present further analyses to be performed (if applicable), e.g. related to

- combining algorithms via ensembling,
- inter-algorithm variability,
- common problems/biases of the submitted methods, or
- ranking variability.

N/A

TASK 2: Random sampling CMR reconstruction

SUMMARY

Abstract

Provide a summary of the challenge purpose. This should include a general introduction in the topic from both a biomedical as well as from a technical point of view and clearly state the envisioned technical and/or biomedical impact of the challenge.

CMR imaging is time-consuming due to the acquisition of a large amount of raw data in the k-space (raw signal measurement). To address this limitation, accelerated imaging techniques have been developed, which rely on sub-Nyquist undersampling the k-space data. Random (incoherent) undersampling of the k-space trajectory is one such approach that offers acceleration and potential for improved image quality. The need for a universal model therefore arises from the diverse sampling schemes of cardiac image acquisition: Different CMR protocols often require distinct k-space sampling trajectories and acceleration factors. Traditional reconstruction methods struggle to adapt to these variations, as they typically rely on sampling-specific algorithms. A universal model offers a unified framework that can handle different sampling trajectories and acceleration factors, providing flexibility and efficiency in the reconstruction process. This approach is necessary to achieve consistent and reliable reconstructions across diverse CMR imaging scenarios.
The primary objective of this research is to develop a universal model that can robustly reconstruct CMR images from randomly-sampled k-space trajectories (uniformly sampling and variable-density sampling) at different acceleration factors (acceleration factors from 3x to 20x). The proposed approach is supposed to leverage deep learning algorithms to exploit the potential of random sampling, enabling faster acquisition times while maintaining high-quality image reconstructions.
The CMRxUniversalRecon Challenge aims to advance the field of CMR reconstruction by providing a platform for researchers to develop and evaluate reconstruction methods for randomly-sampled and unseen k-space trajectories and various acceleration factors. The challenge encourages participants to explore the capabilities of universal models in robustly reconstructing CMR images, considering the complexities associated with different sampling trajectories and acceleration factors. From a technical perspective, the challenge envisions the development of innovative deep learning approaches that can enhance the data-efficiency, generalizability, and accuracy of CMR reconstruction. Biomedically, the challenge has the potential to improve patient care by enabling faster and more reliable diagnosis of cardiovascular diseases through accelerated CMR imaging techniques.

Keywords

List the primary keywords that characterize the task.

Cardiac image reconstruction, random sampling, universal model

ORGANIZATION

Organizers

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Nan Jiang
Jiangsu Industrial Technology Research Institute & National Innovation Center Par Excellence, China

Guang Yang, Fanwen Wang
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He Wang, Hao Li, Zhensen Chen
Institute of Science and Technology for Brain-inspired Intelligence, Fudan University, China

Xiahai Zhuang
School of Data Science, Fudan University, China

Cheng Ouyang
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Life cycle type

Define the intended submission cycle of the challenge. Include information on whether/how the challenge will be continued after the challenge has taken place.Not every challenge closes after the submission deadline (one-time event). Sometimes it is possible to submit results after the deadline (open call) or the challenge is repeated with some modifications (repeated event).

Examples:

- One-time event with fixed conference submission deadline
- Open call (challenge opens for new submissions after conference deadline)
- Repeated event with annual fixed conference submission deadline

One-time event with fixed submission deadline.

Challenge venue and platform

a) Report the event (e.g. conference) that is associated with the challenge (if any).

N/A

b) Report the platform (e.g. grand-challenge.org) used to run the challenge.

synapse.org

c) Provide the URL for the challenge website (if any).

This is last year's website: https://cmrxrecon.github.io. The website for this year is under active construction.

Participation policies

a) Define the allowed user interaction of the algorithms assessed (e.g. only (semi-) automatic methods allowed).

Fully automatic.

b) Define the policy on the usage of training data. The data used to train algorithms may, for example, be restricted to the data provided by the challenge or to publicly available data including (open) pre-trained nets.

It should be restricted to the data provided by this challenge as well as data from the 'fastMRI' challenge (the most related public dataset), following the terms and conditions associated with the data usage.

c) Define the participation policy for members of the organizers' institutes. For example, members of the organizers' institutes may participate in the challenge but are not eligible for awards.

May participate but not eligible for awards and not listed in the leaderboard.

d) Define the award policy. In particular, provide details with respect to challenge prizes.

The top 5 winners receive monetary awards. We are in negotiation with the sponsor about the value (approximately $2000 in total).

e) Define the policy for result announcement.

Examples:

- Top 3 performing methods will be announced publicly.
- Participating teams can choose whether the performance results will be made public.

All submissions will be reported in the leaderboard. Participating teams can opt out of publication of their results in the leaderboard.
Prize-winning methods will be announced publicly as part of a scientific session at the MICCAI annual meeting.

f) Define the publication policy. In particular, provide details on ...

- ... who of the participating teams/the participating teams' members qualifies as author
- ... whether the participating teams may publish their own results separately, and (if so)
- ... whether an embargo time is defined (so that challenge organizers can publish a challenge paper first).

Participating teams with a valid submission can nominate their team members as co-authors for the challenge paper. We reserve the right to exclude teams if they break the challenge rules. Participating teams can publish their own results but after a 3-month embargo period.

Submission method

a) Describe the method used for result submission. Preferably, provide a link to the submission instructions.

Examples:

- Docker container on the Synapse platform. Link to submission instructions: <URL>
- Algorithm output was sent to organizers via e-mail. Submission instructions were sent by e-mail.

Docker container will be accepted as submission through the Synapse platform. Submission details will be published at the time point of challenge announcement.

b) Provide information on the possibility for participating teams to evaluate their algorithms before submitting final results. For example, many challenges allow submission of multiple results, and only the last run is officially counted to compute challenge results.

Participating teams are allowed 3 submissions per task. Only the last run submission is officially counted to rank challenge results. Before the final submission on the test set, participants can test their docker containers on the validation dataset to avoid submission errors.

Challenge schedule

Provide a timetable for the challenge. Preferably, this should include

- the release date(s) of the training cases (if any)
- the registration date/period
- the release date(s) of the test cases and validation cases (if any)
- the submission date(s)
- associated workshop days (if any)
- the release date(s) of the results

[Apr 1, 2024] website opens for registration, release training and validation images
[Apr 10, 2024] submission system opens for validation
[Aug 1, 2024] submission system opens for testing
[Sept 1, 2024] registration and docker submission deadline
[Oct 8, 2024] release final results

Ethics approval

Indicate whether ethics approval is necessary for the data. If yes, provide details on the ethics approval, preferably institutional review board, location, date and number of the ethics approval (if applicable). Add the URL or a reference to the document of the ethics approval (if available).

We have received ethics approval from the local ethics committee of School of Basic Medical Sciences, Fudan University granted on 17/11/2021, No. 2021-Y060.

Data usage agreement

Clarify how the data can be used and distributed by the teams that participate in the challenge and by others during and after the challenge. This should include the explicit listing of the license applied.

Examples:

- CC BY (Attribution)
- CC BY-SA (Attribution-ShareAlike)
- CC BY-ND (Attribution-NoDerivs)
- CC BY-NC (Attribution-NonCommercial)
- CC BY-NC-SA (Attribution-NonCommercial-ShareAlike)
- CC BY-NC-ND (Attribution-NonCommercial-NoDerivs)

CC BY-NC-ND.

Code availability

a) Provide information on the accessibility of the organizers' evaluation software (e.g. code to produce rankings). Preferably, provide a link to the code and add information on the supported platforms.

We have released the source code for evaluating and ranking the results at Github: https://github.com/CmrxRecon/CMRxRecon

b) In an analogous manner, provide information on the accessibility of the participating teams' code.

The participating teams are suggested to provide links to their code on our website for reproducibility study. However, it is not a condition of participation.

Conflicts of interest

Provide information related to conflicts of interest. In particular provide information related to sponsoring/funding of the challenge. Also, state explicitly who had/will have access to the test case labels and when.

We declare no conflicts of interest. Test images will only be accessible to the challenge organizers.

MISSION OF THE CHALLENGE

Field(s) of application

State the main field(s) of application that the participating algorithms target.

Examples:

- Diagnosis
- Education
- Intervention assistance
- Intervention follow-up
- Intervention planning
- Prognosis
- Research
- Screening
- Training
- Cross-phase

Research, Diagnosis.

Task category(ies)

State the task category(ies)

Examples:

- Classification
- Detection
- Localization
- Modeling
- Prediction
- Reconstruction

- Registration
- Retrieval
- Segmentation
- Tracking

Reconstruction.

Cohorts

We distinguish between the target cohort and the challenge cohort. For example, a challenge could be designed around the task of medical instrument tracking in robotic kidney surgery. While the challenge could be based on ex vivo data obtained from a laparoscopic training environment with porcine organs (challenge cohort), the final biomedical application (i.e. robotic kidney surgery) would be targeted on real patients with certain characteristics defined by inclusion criteria such as restrictions regarding sex or age (target cohort).

a) Describe the target cohort, i.e. the subjects/objects from whom/which the data would be acquired in the final biomedical application.

The target cohort is patients requiring CMR exams with various undersampling strategies, especially patients with arrhythmia and those who cannot adhere to standard imaging protocols.

b) Describe the challenge cohort, i.e. the subject(s)/object(s) from whom/which the challenge data was acquired.

A total of 200 volunteers with multi-contrast CMR imaging from our medical center will be included. The dataset will include multi-contrast k-space data, consist of cardiac cine and mapping. The k-space data is acquired with random sampled trajectory and various acceleration factors.

Imaging modality(ies)

Specify the imaging technique(s) applied in the challenge.

Magnetic Resonance Imaging

Context information

Provide additional information given along with the images. The information may correspond ...

a) ... directly to the image data (e.g. tumor volume).

none

b) ... to the patient in general (e.g. sex, medical history).

none

Target entity(ies)

a) Describe the data origin, i.e. the region(s)/part(s) of subject(s)/object(s) from whom/which the image data would be acquired in the final biomedical application (e.g. brain shown in computed tomography (CT) data, abdomen shown in laparoscopic video data, operating room shown in video data, thorax shown in fluoroscopy video). If necessary, differentiate between target and challenge cohort.

Data is acquired from the heart and aorta.

b) Describe the algorithm target, i.e. the structure(s)/subject(s)/object(s)/component(s) that the participating algorithms have been designed to focus on (e.g. tumor in the brain, tip of a medical instrument, nurse in an operating theater, catheter in a fluoroscopy scan). If necessary, differentiate between target and challenge cohort.

The algorithm target is to assess the reconstruction performance on various k-space sampling based on a universal pre-trained reconstruction model. In the challenge cohort, we recruit volunteers to be scanned with different k-space trajectories and accelerating factors.

Assessment aim(s)

Identify the property(ies) of the algorithms to be optimized to perform well in the challenge. If multiple properties are assessed, prioritize them (if appropriate). The properties should then be reflected in the metrics applied (see below, parameter metric(s)), and the priorities should be reflected in the ranking when combining multiple metrics that assess different properties.

- Example 1: Find highly accurate liver segmentation algorithm for CT images.
- Example 2: Find lung tumor detection algorithm with high sensitivity and specificity for mammography images.

Corresponding metrics are listed below (parameter metric(s)).

PSNR, SSIM and NMSE between reconstructed images and ground truth images (fully sampled data).
1. When evaluating SSIM, we will narrow down the assessment field-of-view to the region where the heart is located, to avoid interference from the background area.
2. During the testing and ranking phase, we will invite three radiologists to independently score the top five teams ranked by SSIM. The scoring will cover three aspects: image quality, image artifacts, and clinical utility. We will consider both the radiologists' scores and the SSIM results to generate a comprehensive ranking.

DATA SETS

Data source(s)

a) Specify the device(s) used to acquire the challenge data. This includes details on the device(s) used to acquire the imaging data (e.g. manufacturer) as well as information on additional devices used for performance assessment (e.g. tracking system used in a surgical setting).

Siemens 3.0T MRI scanner (MAGNETOM Vida)

b) Describe relevant details on the imaging process/data acquisition for each acquisition device (e.g. image acquisition protocol(s)).

We follow the recommendations of CMR exams reported in the previous publication (doi: 10.1007/s43657-02100018x, 10.1007/s43657-021-00018-x). We use 'TrueFISP' for cine, PC and tagging, and 'FLASH' for mapping and dark-blood imaging. The collected imaging planes include long-axis (2-chamber, 3-chamber, and 4-chamber), short-axis, outflow tract, and aortic (cross-sectional and sagittal views). Typically 5-15 slices are acquired. For mapping, signal data were collected at the end of the diastole with ECG triggering. The cardiac cycle is segmented into 15-25 phases with a temporal resolution of around 50 ms. Typical geometrical parameters include: spatial resolution 2.0×2.0 mm2, slice thickness 8.0 mm, and slice gap 4.0 mm.

c) Specify the center(s)/institute(s) in which the data was acquired and/or the data providing platform/source (e.g. previous challenge). If this information is not provided (e.g. for anonymization reasons), specify why.

Zhangjiang Imaging Center, Fudan University, China

d) Describe relevant characteristics (e.g. level of expertise) of the subjects (e.g. surgeon)/objects (e.g. robot) involved in the data acquisition process (if any).

Data are acquired with a team of radiographers and clinical advisors as appropriate.

Training and test case characteristics

a) State what is meant by one case in this challenge. A case encompasses all data that is processed to produce one result that is compared to the corresponding reference result (i.e. the desired algorithm output).

Examples:

- Training and test cases both represent a CT image of a human brain. Training cases have a weak annotation (tumor present or not and tumor volume (if any)) while the test cases are annotated with the tumor contour (if any).
- A case refers to all information that is available for one particular patient in a specific study. This information always includes the image information as specified in data source(s) (see above) and may include context information (see above). Both training and test cases are annotated with survival (binary) 5 years after (first) image was taken.

Training cases include fully sampled k-space data and auto-calibration lines (ACS, 24 lines) will be provided in '.mat' format.
Validation cases include under-sampled k-space data, sampling trajectories, and auto-calibration lines (ACS, 24 lines) with various acceleration factors in '.mat' format.
Test cases include fully sampled k-space data, under-sampled k-space data, sampling trajectories and auto-calibration lines (ACS, 24 lines). Test cases will not be released before the challenge ends.

b) State the total number of training, validation and test cases.

200 cases in total (100 cases for training, 50 validation cases and 50 test cases).

c) Explain why a total number of cases and the specific proportion of training, validation and test cases was chosen.

The sample size of training dataset is reasonable for training deep learning reconstruction networks for CMR imaging according to previous literature and our experience. The sample size of validation and test dataset would well represent the distribution of the data cohort and achieve robust evaluation of the models according to last year's 'CMRxRecon' challenge results, in which 60 cases were used for validation (the website is not allowed to be put here due to special character, you can search 'CMRxRecon' on synapse.org).

d) Mention further important characteristics of the training, validation and test cases (e.g. class distribution in classification tasks chosen according to real-world distribution vs. equal class distribution) and justify the choice.

All subjects are healthy adults and we will aim for an age and gender balance between the training and test data.

Annotation characteristics

a) Describe the method for determining the reference annotation, i.e. the desired algorithm output. Provide the information separately for the training, validation and test cases if necessary. Possible methods include manual image annotation, in silico ground truth generation and annotation by automatic methods.

If human annotation was involved, state the number of annotators.

N.A.

b) Provide the instructions given to the annotators (if any) prior to the annotation. This may include description of a training phase with the software. Provide the information separately for the training, validation and test cases if necessary. Preferably, provide a link to the annotation protocol.

N.A.

c) Provide details on the subject(s)/algorithm(s) that annotated the cases (e.g. information on level of expertise such as number of years of professional experience, medically-trained or not). Provide the information separately for the training, validation and test cases if necessary.

N.A.

d) Describe the method(s) used to merge multiple annotations for one case (if any). Provide the information separately for the training, validation and test cases if necessary.

N.A.

Data pre-processing method(s)

Describe the method(s) used for pre-processing the raw training data before it is provided to the participating teams. Provide the information separately for the training, validation and test cases if necessary.

The raw k-space data exported from the scanner will be processed and transformed to '.mat' format using the script provided by our vendor. A readme file will be provided to describe the content and usage of the data.

Sources of error

a) Describe the most relevant possible error sources related to the image annotation. If possible, estimate the magnitude (range) of these errors, using inter-and intra-annotator variability, for example. Provide the information separately for the training, validation and test cases, if necessary.

N.A.

b) In an analogous manner, describe and quantify other relevant sources of error.

N.A.

ASSESSMENT METHODS

Metric(s)

a) Define the metric(s) to assess a property of an algorithm. These metrics should reflect the desired algorithm properties described in assessment aim(s) (see above). State which metric(s) were used to compute the ranking(s) (if any).

- Example 1: Dice Similarity Coefficient (DSC)
- Example 2: Area under curve (AUC)

PSNR, SSIM and NMSE between reconstructed images and ground truth images (fully sampled data).
1. When evaluating SSIM, we will narrow down the assessment field-of-view to the region where the heart is located, to avoid interference from the background area.
2. During the testing and ranking phase, we will invite three radiologists to independently score the top five teams

ranked by SSIM. The scoring will cover three aspects: image quality, image artifacts, and clinical utility. We will consider both the radiologists' scores and the SSIM results to generate a comprehensive ranking.

b) Justify why the metric(s) was/were chosen, preferably with reference to the biomedical application.

We keep these metrics aligned with the 'fastMRI' challenge evaluation metrics for fair evaluations.

Ranking method(s)

a) Describe the method used to compute a performance rank for all submitted algorithms based on the generated metric results on the test cases. Typically the text will describe how results obtained per case and metric are aggregated to arrive at a final score/ranking.

PSNR, SSIM and NMSE between reconstructed images and ground truth images (fully sampled data).
1. When evaluating SSIM, we will narrow down the assessment field-of-view to the region where the heart is located, to avoid interference from the background area.
2. During the testing and ranking phase, we will invite three radiologists to independently score the top five teams ranked by SSIM. The scoring will cover three aspects: image quality, image artifacts, and clinical utility. We will consider both the radiologists' scores and the SSIM results to generate a comprehensive ranking.

b) Describe the method(s) used to manage submissions with missing results on test cases.

Participating teams are required to submit docker containers and process all the cases in the test set on our server. For the cases without valid output, we will assign it to the lowest value of metric.

c) Justify why the described ranking scheme(s) was/were used.

PSNR, SSIM and NMSE between reconstructed images and ground truth images (fully sampled data).
1. When evaluating SSIM, we will narrow down the assessment field-of-view to the region where the heart is located, to avoid interference from the background area.
2. During the testing and ranking phase, we will invite three radiologists to independently score the top five teams ranked by SSIM. The scoring will cover three aspects: image quality, image artifacts, and clinical utility. We will consider both the radiologists' scores and the SSIM results to generate a comprehensive ranking.

Statistical analyses

a) Provide details for the statistical methods used in the scope of the challenge analysis. This may include

- description of the missing data handling,
- details about the assessment of variability of rankings,
- description of any method used to assess whether the data met the assumptions, required for the particular statistical approach, or
- indication of any software product that was used for all data analysis methods.

See the description of metrics and ranking methods above.

b) Justify why the described statistical method(s) was/were used.

See the description of metrics and ranking methods above.

Further analyses

Present further analyses to be performed (if applicable), e.g. related to

- combining algorithms via ensembling,
- inter-algorithm variability,
- common problems/biases of the submitted methods, or
- ranking variability.

N/A

ADDITIONAL POINTS

References

Please include any reference important for the challenge design, for example publications on the data, the annotation process or the chosen metrics as well as DOIs referring to data or code.

Reference of the CMR imaging acquisition protocol:
1. Wang C, Lyu J, Wang S, et al. CMRxRecon: An open cardiac MRI dataset for the competition of accelerated image reconstruction[J]. arXiv preprint arXiv:2309.10836, 2023.
2. Wang C, Li Y, Lv J, et al. Recommendation for Cardiac Magnetic Resonance Imaging-Based Phenotypic Study: Imaging Part. Phenomics. 2021, 1(4): 151-170. https://doi.org/10.1007/s43657-021-00018-x
Reference for previously developed reconstruction algorithms:
1. Wang C, Jang J, Neisius U, et al. Black blood myocardial T2 mapping. Magnetic resonance in medicine. 2019, 81(1): 153-166. https://doi.org/10.1002/mrm.27360
2. Lyu J, Li G, Wang C, et al. Region-focused multi-view transformer-based generative adversarial network for cardiac cine MRI reconstruction[J]. Medical Image Analysis, 2023: 102760. https://doi.org/10.1016/j.media.2023.102760
3. Qin C, Schlemper J, Caballero J, et al. Convolutional recurrent neural networks for dynamic MR image reconstruction. IEEE transactions on medical imaging, 2018, 38(1): 280-290. https://doi.org/10.1109/TMI.2018.2863670.
4. Qin C, Duan J, Hammernik K, et al. Complementary time-frequency domain networks for dynamic parallel MR image reconstruction. Magnetic Resonance in Medicine, 2021, 86(6): 3274-3291. https://doi.org/10.1002/mrm.28917
5. Lyu J, Tong X, Wang C. Parallel Imaging With a Combination of SENSE and Generative Adversarial Networks (GAN). Quantitative Imaging in Medicine and Surgery. 2020, 10(12): 2260-2273. https://doi.org/10.21037/qims-20-518.
6. Lyu J, Sui B, Wang C, et al. DuDoCAF: Dual-Domain Cross-Attention Fusion with Recurrent Transformer for Fast Multi-contrast MR Imaging. International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2022: 474-484.
7. Ouyang C, Schlemper K, et al. Generalizing Deep Learning MRI Reconstruction across Different Domains, arXiv preprint arXiv: 1902.10815, 2019.

Further comments

Further comments from the organizers.

None