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DIRECT: Deep Image REConstruction Toolkit

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Software

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Summary

DIRECT is a Python, end-to-end pipeline for solving Inverse Problems emerging in Imaging Processing. It is built with PyTorch (Paszke et al., 2019) and stores state-of-the-art Deep Learning imaging inverse problem solvers for solving inverse problems such as denoising, dealiasing, and reconstruction. By defining a base forward linear or non-linear operator, DIRECT can be used for training models for recovering images such as MRIs from partially observed or noisy input data. Additionally, it provides the user with the functionality to load saved weights of pre-trained models to be used for inference. Furthermore, it offers functions for preparing and pre-processing data such as `.h5` files into PyTorch Datasets compatible with the software's training pipeline, but also allows for flexibility to work with any kind of PyTorch Dataset. Additionally, in order for the user to view the process of their experiments, it allows for continuous visualisation of training and validation metrics as well as image predictions utilising Tensorboard (examples are illustrated in Figures 1 and 2).

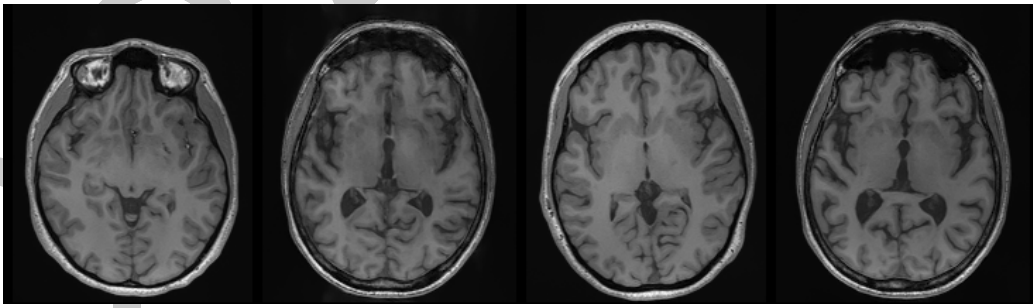

Figure 1: Visualised reconstructions in Tensorboard

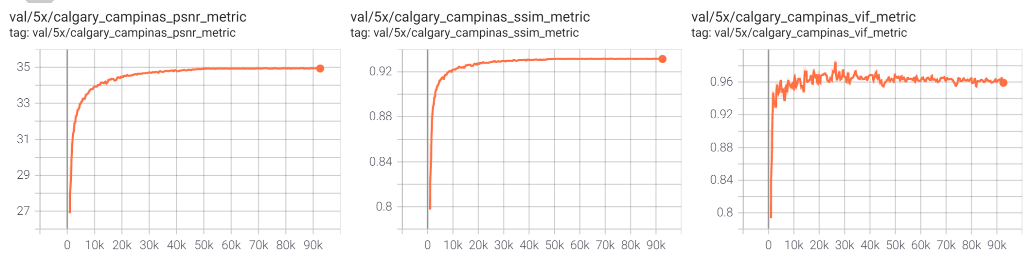

Figure 2: Visualised metrics in Tensorboard

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Statement of need

A plethora of image processing problems arising in biology, chemistry and medicine can be defined as inverse problems. Inverse problems aim in recovering a signal $\vec{x} \in \mathcal{X}$ (e.g. an image) that cannot be directly observed from a set of measurements $\vec{y} \in \mathcal{Y}$ and is subject to a given corruption process known as the forward model:

$$\vec{y} = \mathcal{A}(\vec{x}) + \vec{n}, \tag{1}$$

where $\mathcal{A}$ denotes the forward operator and $\vec{n}$ is some measurement noise, often assumed to be additive and normally distributed. Equation 1 is usually ill-posed and therefore an explicit solution is hard to find. Instead, inverse problems in imaging are typically solved by minimizing an objective function $\mathcal{J}$ which is consisted of a data-fidelity term $\mathcal{L}$ and a regularization term $\mathcal{R}$ (also known as Variational Problems):

$$\vec{\hat{x}} = \min_{\vec{z} \in \mathcal{X}} \mathcal{J}(z) = \min_{\vec{z} \in \mathcal{X}} \mathcal{L}\big(\vec{y}, \mathcal{A}(\vec{z})\big) + \lambda \mathcal{R}(\vec{z}), \quad \lambda \geq 0. \tag{2}$$

Accelerated MRI Reconstruction

Accelerated Magnetic Resonance Image (MRI) Reconstruction, that is, reconstructing an MR image from a set of partially observed (or sub-sampled) k-space measurements from multiple receiver coils, is par excellence an example of inverse problems. The base forward operator of Accelerated MRI Reconstruction is usually the two or three-dimensional Fast Fourier Transform (FFT) denoted as $\mathcal{F}$. Conventional approaches for solving this class of inverse problems include Parallel Imaging (PI) (Larkman & Nunes, 2007) and Compressed Sensing (CS) (Donoho, 2006). Combining these methods with Deep Learning imaging inverse problem solvers can aid in providing reconstructed images with high fidelity from highly sub-sampled measurements.

More specifically, given as input (retrospectively) sub-sampled k-space measurements from n_c coils

$$\vec{y} = \{\vec{y}_1, \ldots, \vec{y}_{n_c}\} = \{U \circ \mathcal{F}(S_i \vec{x})\}_{i=1}^{n_c},$$

these models aim to predict the reconstructed ground truth image $\vec{x}$. The corresponding inverse problem replaces (2) with the following:

$$\vec{\hat{x}} = \min_{\vec{z} \in \mathcal{X}} \sum_{i=1}^{n_c} \mathcal{L}\big(\vec{y}_i, U \circ \mathcal{F}(S_i \vec{z})\big) + \lambda \mathcal{R}(\vec{z}), \tag{3}$$

where S_i denotes a (usually unknown) coil sensitivity map, property of each individual coil, and U denotes a retrospective sub-sampling mask operator which simulates the sub-sampling process in clinical settings. As DIRECT stores several state-of-the-art baselines, it is an essential tool for any research team working with partially observed k-space data.

Functionality

DIRECT allows for easy and flexible experimentation. The user can define a configuration file with the `.yaml` extension to perform any experiments. See Configuration File below for an example of a configuration file. DIRECT can be employed for training and/or validating models on multiple machines and GPUs as it is integrated with PyTorch's `torch.distributed` module and NVIDIA's cuDNN (Chetlur et al., 2014). Besides the already-stored baselines, the user can easily incorporate into DIRECT their own inverse problem solvers.

Configuration File

In a configuration file it should be specified all the experiment parameters including model parameters, physics parameters, training and validation parameters, dataset parameters, etc. The following is a template example of a configuration file:

```yaml
model:
  model_name: <nn_model_path>
  model_parameter_1: <nn_model_paramter_1>
  model_parameter_2: <nn_model_paramter_2>
  ...
additional_models:
  sensitivity_model:
    model_name: <nn_sensitivity_model_path>
    ...
physics:
  forward_operator: fft2(centered=<true_or_false>)
  backward_operator: ifft2(centered=<true_or_false>)
  ...
training:
  datasets:
  - name: Dataset1
    lists:
    - <path_to_list_1_for_Dataset1>
    - <path_to_list_2_for_Dataset1>
    transforms:
      estimate_sensitivity_maps: <true_or_false>
      scaling_key: <scaling_key>
      image_center_crop: <true_or_false>
      masking:
        name: MaskingFunctionName
        accelerations: [acceleration_1, accelaration_2, ...]
        ...
    ...
  - name: Dataset2
    ...
  optimizer: <optimizer>
  lr: <learning_rate>
  batch_size: <batch_size>
  lr_step_size: <lr_step_size>
  lr_gamma: <lr_gamma>
  lr_warmup_iter: <num_warmup_iterations>
  num_iterations: <num_iterations>
  validation_steps: <num_val_steps>
  loss:
    losses:
    - function: <fun1_as_in_model_engine>
      multiplier: <multiplier_1>
    - function: <fun2_as_in_model_engine>
      multiplier: <multiplier_2>
  checkpointer:
    checkpoint_steps: <num_checkpointer_steps>
  metrics: [<metric_1>, <metric_2>, ...]
  ...
validation:
  datasets:
```

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```yaml
  - name: ValDataset1
    transforms:
      ...
      masking:
        ...
    text_description: <val_description_1>
    ...
  - name: ValDataset2
    ...
  batch_size: <val_batch_size>
  metrics:
  - val_metric_1
  - val_metric_2
  - ...
  ...
inference:
  dataset:
    name: InferenceDataset
    lists: ...
    transforms:
      masking:
        ...
      ...
    text_description: <inference_description>
    ...
  batch_size: <batch_size>
  ...
logging:
  tensorboard:
  num_images: <num_images>
```

Baselines Stored

Model Name	Algorithm - Architecture
Recurrent-VarNet	Recurrent Variational Network (Yiasemis, Sánchez, et al., 2021)
RIM	Recurrent Inference Machine (Beauferris et al., 2020; Lønning et al., 2019)
LPDNet	Learned Primal Dual Network (Adler & Oktem, 2018)
EndToEnd-Varnet	End-to-end Variational Network (Sriram et al., 2020)
XPDNet	X - Primal Dual Network (Ramzi et al., 2021)
KIKINet	Kspace-Image-Kspace-Image Network (Eo et al., 2018)
JointICNet	Joint Deep Model-based MR Image and Coil Sensitivity Reconstruction Network (Jun et al., 2021)
MultiDomainNet	Feature-level multi-domain learning with standardization for multi-channel data (Muckley et al., 2021)
UNet2d	U-Net for MRI Reconstruction (Zbontar et al., 2019)

Research projects using DIRECT

DIRECT is the main software used for research by the MRI Reconstruction team of the Innovation Centre for Artificial Intelligence (ICAI) - AI for Oncology group of the Netherlands Cancer Institute (NKI).

Challenges

DIRECT has been used for MRI Reconstruction result submissions in the fastMRI challenge (Muckley et al., 2021) and the Multi-Coil MRI Reconstruction challenge (Beauferris et al., 2020).

Publications

Papers using DIRECT:

- Yiasemis, Zhang, et al. (2021) (presented in SPIE Medical Imaging Conference 2022)
- Yiasemis, Sánchez, et al. (2021) (to be presented in CVPR Conference 2022)

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