Outline

- Introduction, principles
- Method n°1 : Demons
- Evaluation
- Method n°2 : B-Splines
- **Method n°3 : Deep-learning registration**
- The « sliding » problem
- Method n°4 : TPS (Thin Plate Spline)
- Spatio-temporal deformable registration
- Conclusion

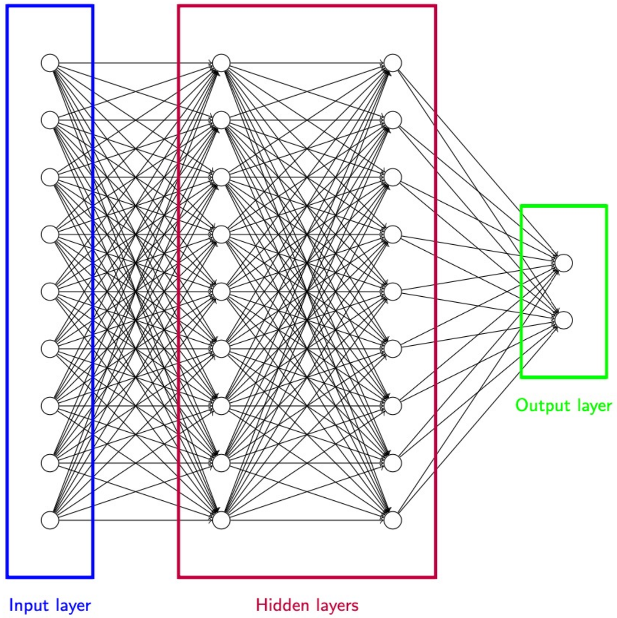
Deep learning image registration

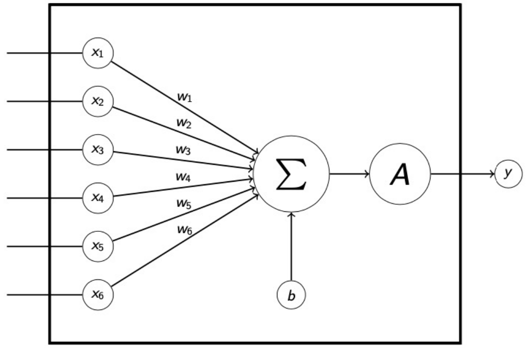
- Can we learn relationship between images and transformations ?
  - Supervised: Learn from known transformations
  - Unsupervised: Use cost function
  - Weakly-supervised : Use known correspondence in training data
- Typically requires lots of data and time to train network
- Once trained, registration results can be produced very quickly for new images

From: UCL MPHY0025 (Jamie Mcclelland)

Deep learning (1/2)

- Model: layers, neurons, input, output
- Loss function
- Optimization, backpropagation
- Convolutional Neural Networks





$$A(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{otherwise} \end{cases}$$

$$y = A(w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + w_5x_5 + w_6x_6 + b)$$

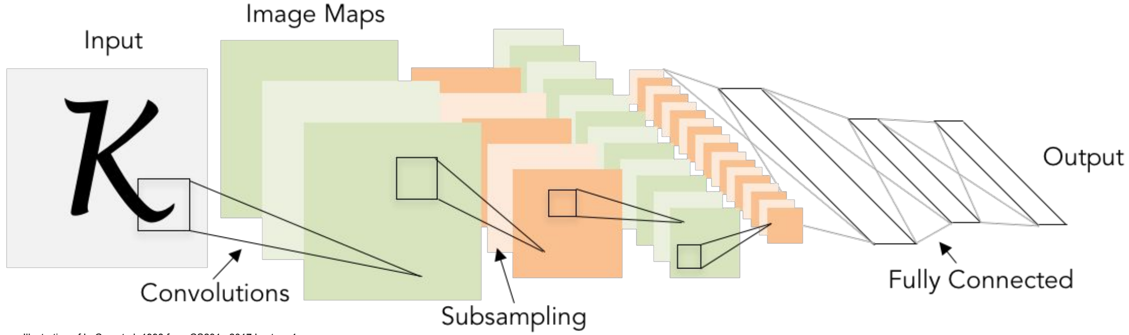


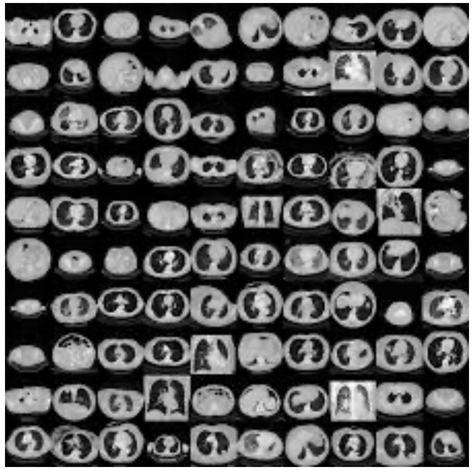
Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

ConvNet:
- preserve spatial structure
- Multi resolution

Deep learning (2/2)

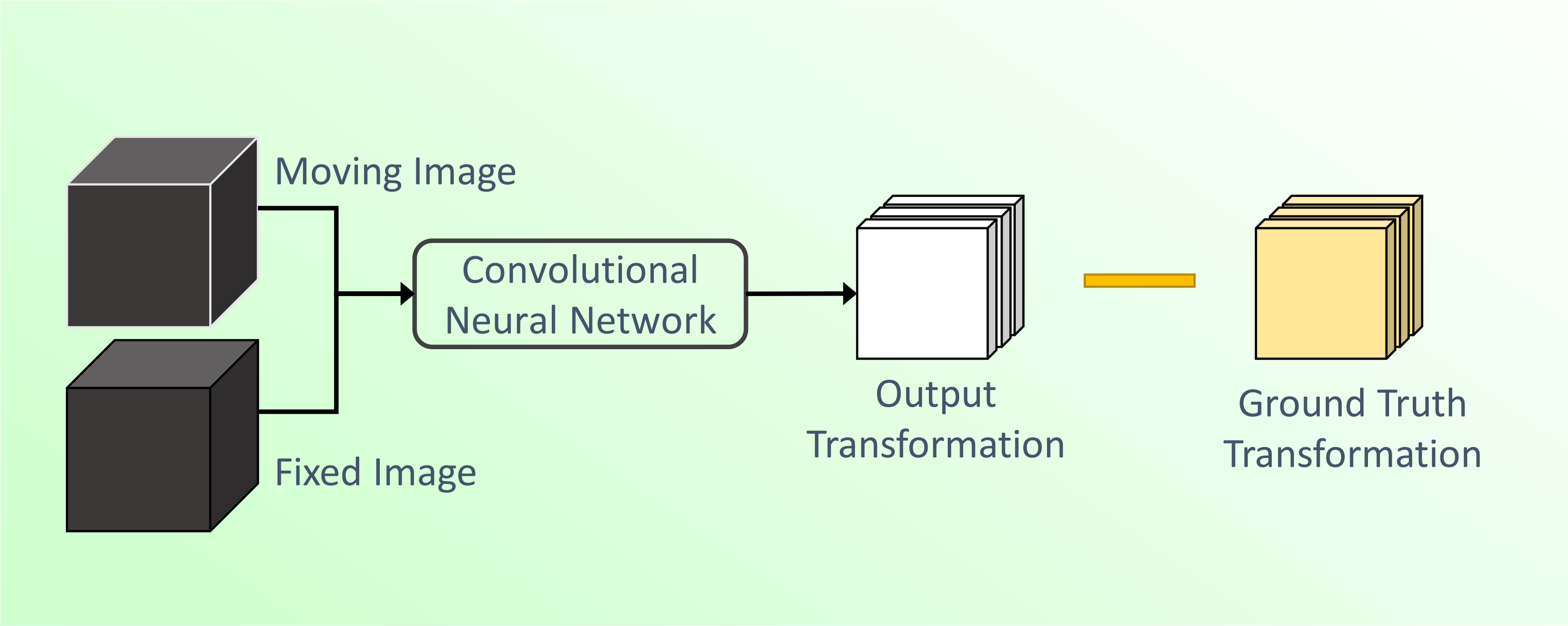
- **Training stage**
  - Optimisation: find the parameters values (neurons)
  - Need large training dataset
  - Need Training/Validation/Test datasets
  - GPU required

- **Inference stage**
  - Send input to model, get output
  - Very fast



(1/3) Supervised

- Required ground truth transformation
  – Simulation, manual alignment, classical image registration



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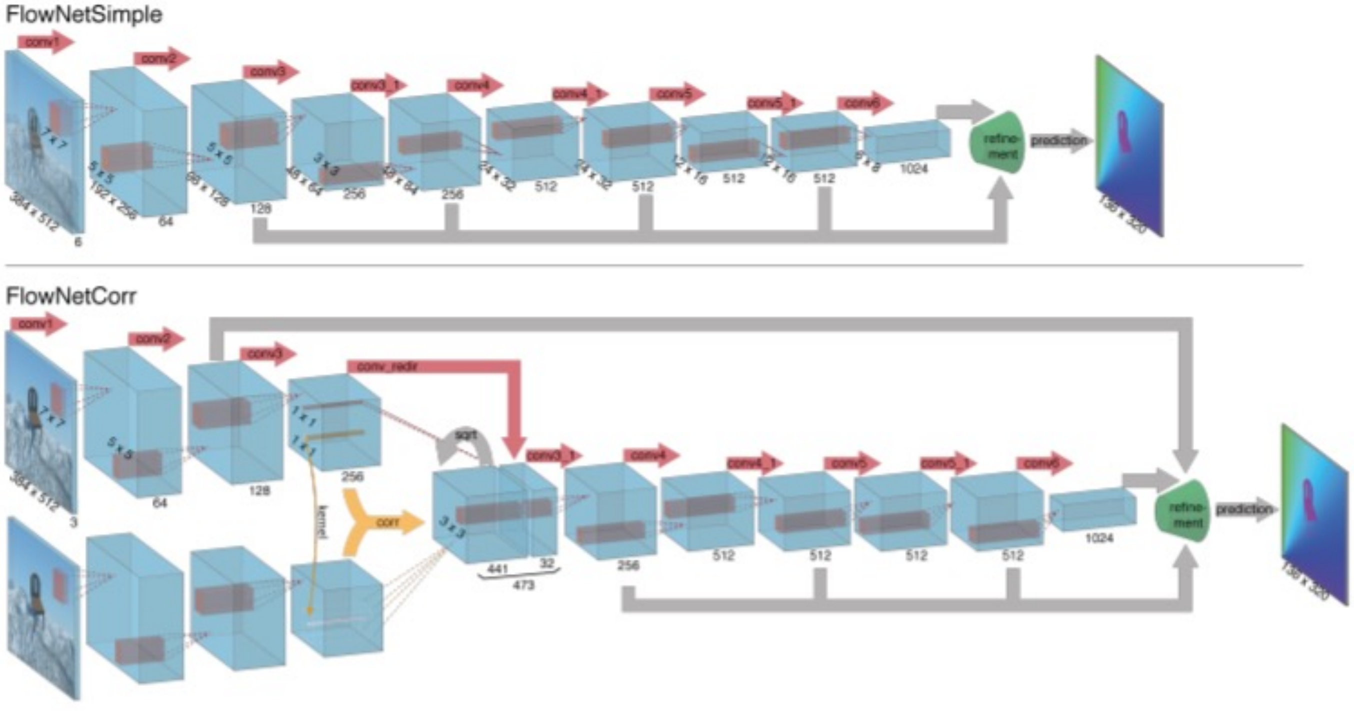
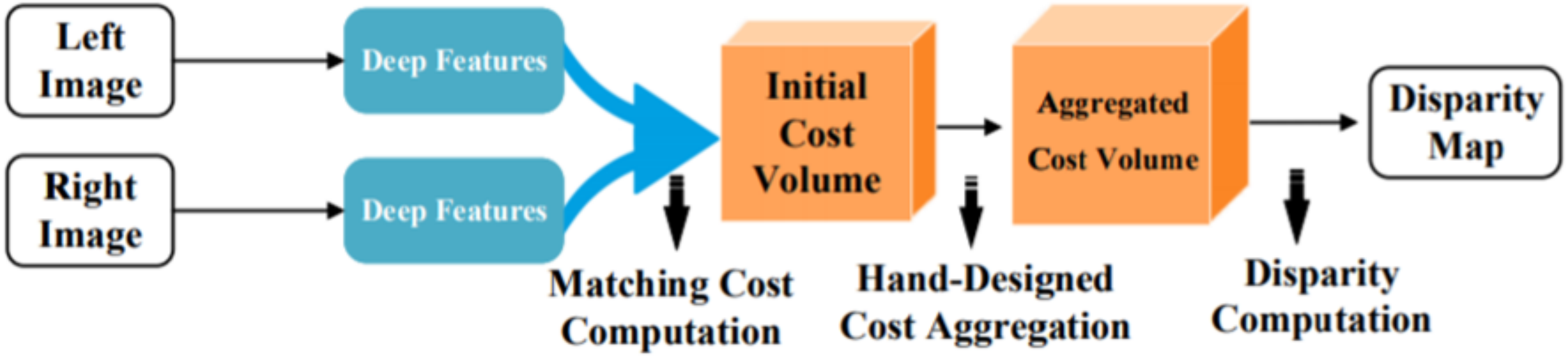




A: The Typical Deep Stereo Matching Architecture

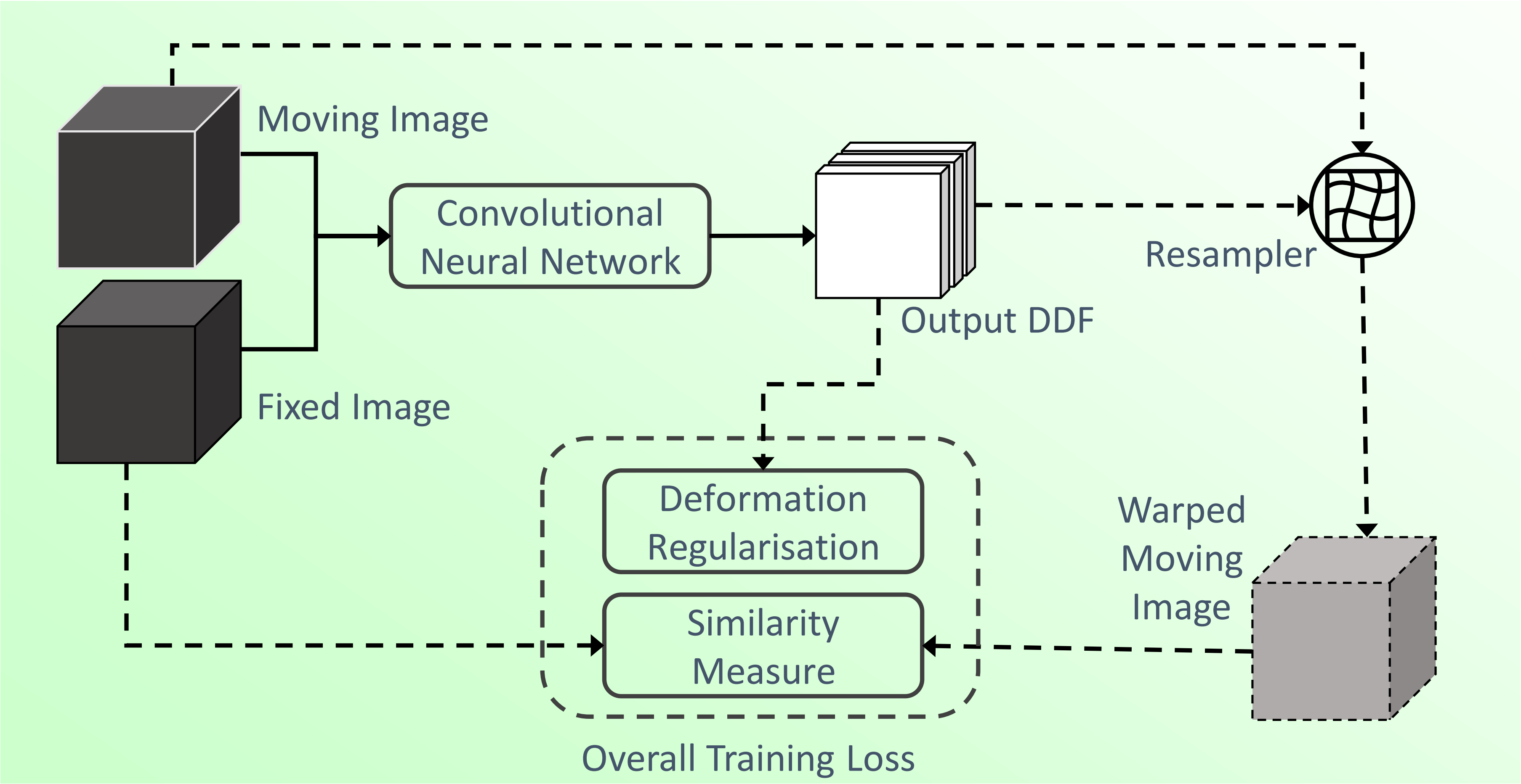
Training dataset for supervised learning

- "Supervised deformable image registration using deep neural networks". PhD thesis. Eppenhof, K. A. J. (2020)

- Training dataset:
  - Real images with ground truth deformation
  - Synthetically deformed clinical images (+augmentation transformations)
  - Variability ?

- (preliminary) Results
  - Very fast
  - Reasonable accuracy

(2/3) Unsupervised



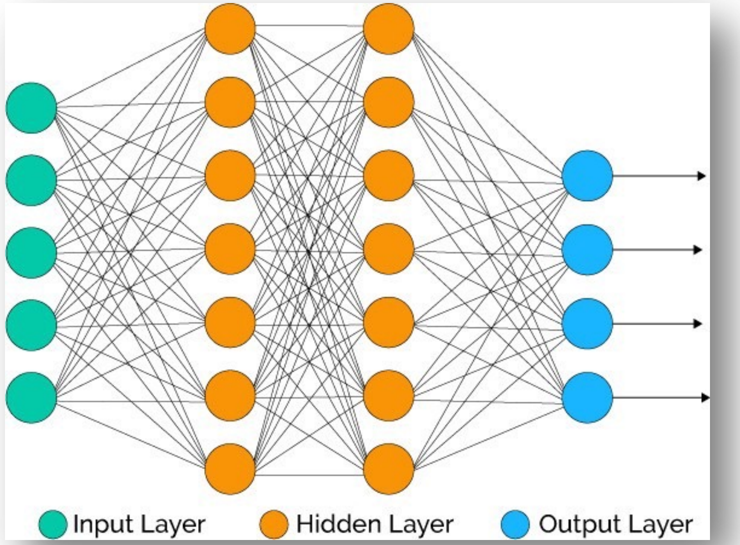
From: UCL MPHY0025 (Jamie Mcclelland)

Deep learning based registration

- One example: Vos et al. 2017

End-to-End Unsupervised Deformable Image Registration with a Convolutional Neural Network

Computer Vision and Pattern Recognition
MICCAI2017



- Principle
  - Unsupervised
  - Input: pairs of images (training dataset)
  - Output: control points displacement as BSpline
  - Simultaneous DIR optimisation of several image pairs
  - Net architecture: layers convolutions, downsampling
  - Backpropagation of image dissimilarity (norm CC)
  - mini-batch stochastic gradient descent (Adam [4])

Deep learning based registration

- Optimisation:
  - Learn weights values that produce Bspline coeff from input
  - Auto differentiation with backpropagation
  - Convolution kernels

- Example with MRI database
  - 45 images (2D+t), 20 timepoints, 256x256
  - Pairs: corresponding slices (diff time)
  - 16 kernels per convolution layer
  - 16x16 control points
  - Bspline or TPSpline
  - Mini batch of 32 pairs, 10k iterations

Example

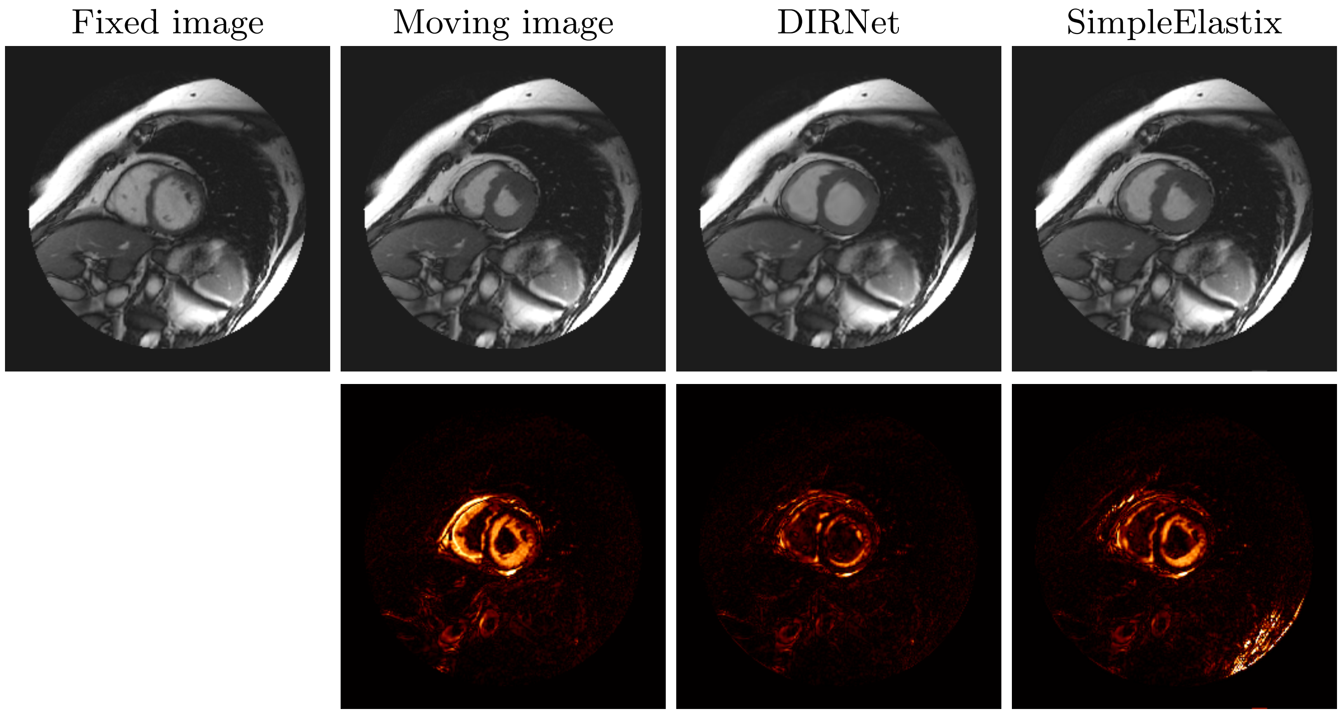
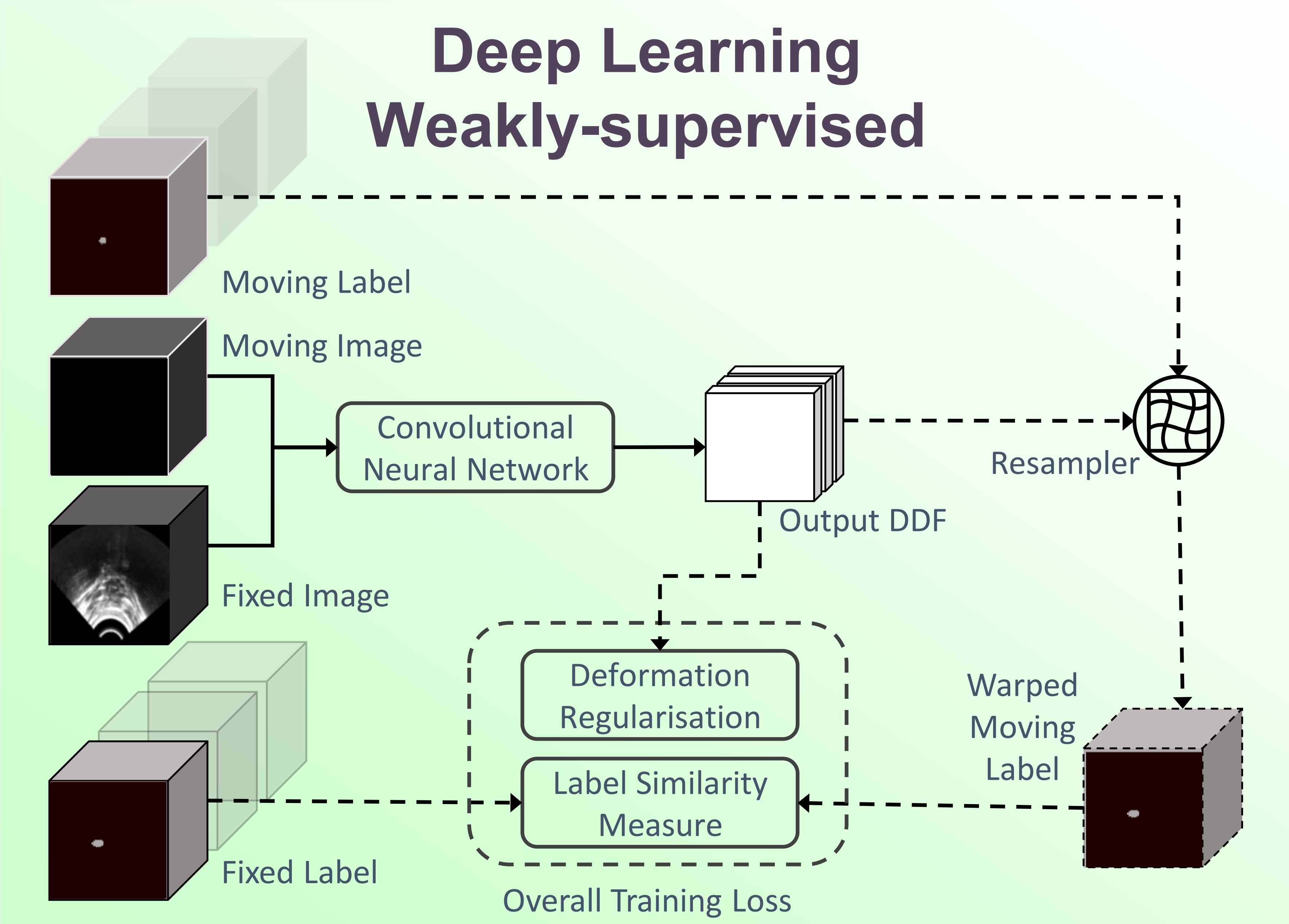


Fig. 4. Top, from left to right: The fixed (ED), the moving (ES), the DIRNet-C1 warped, and the SimpleElastix warped images. Bottom: Heatmaps showing absolute difference images between the fixed image and (from left to right) the original, the DIRNet warped, and the SimpleElastix warped moving images.



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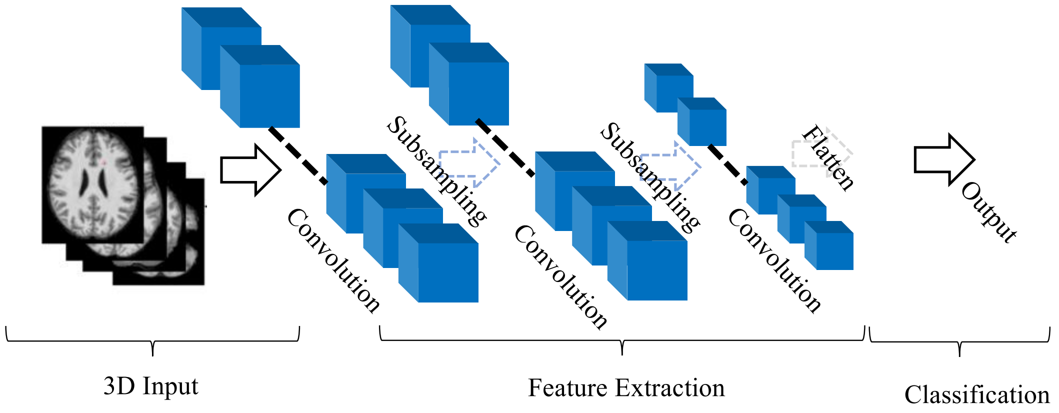
GPU memory issue

- Medical images are (often) 3D
- 3D CNN ? Potential (GPU) memory/time issue
- Alternatives
  - 2D CNN, slices by slices
  - 3D patch (reduced)
  - Slices in different direction: 3 nets to combine
  - Etc ..



Deep learning based registration

Results

- May require pairs of already registered images (**supervised**)
- May **not** require pairs of already registered images (**unsupervised**)
- Results may be comparable to conventional DIR, still WIP
- However, still limited experiments, often 2D only
- Main advantage: speed. One-pass registration.

Reviews

Table 1
DL-based DIR models supervised by reference DVFs.

Authors	Publication Year	Region of interest (ROI)	Modality	Patch-based	Reference DVF Obtained by
Yang et al.[40]	2017	Brain	MR-MR	Yes	LDDMM
Rohé et al.[41]	2017	Heart	MR-MR	No	Surface matching
Cao et al.[42]	2017	Brain	MR-MR	Yes	Syn and Demons
Cao et al.[43]	2018	Brain	MR-MR	Yes	Syn and Demons
Onieva et al.[44]	2018	Lung	CT-CT	No	ANTs
Fan et al.[45]	2019	Brain	MR-MR	Yes	Syn and Demons

Table 2
DL-based DIR models supervised by artificial DVFs.

Authors	Publication Year	ROI	Modality	Patch-based	Reference DVF Obtained by
Sokooti et al.[46]	2017	Lung	CT-CT	No	Mixed spatial frequency
Krebs et al.[47]	2017	Pelvic	MR-MR	No	Statistical deformation models
Eppenhof et al.[48,49]	2018	Lung	CT-CT	No	Random numbers
Sokooti et al.[50]	2019	Lung	CT-CT	No	Mixed spatial frequency

Table 3
Unsupervised and weakly supervised DL-based DIR models.

Authors	Publication Year	ROI	Modality	Patch-based	Supervised by
Sentker et al.[52]	2018	Lung	CT-CT	No	DIS
Cao et al.[43]	2018	Prostate	CT-MR	Yes	DIS, DVF
Hu et al.[53]	2018	Prostate	MR-MR	No	CON, ADV
Fan et al.[54]	2018	Brain	MR-MR	Yes	DIS, DVF, ADV
Kearney et al.[55]	2018	Head and Neck	CBCT-CT	Yes	DIS
Li et al.[56]	2018	Brain	MR-MR	No	DIS, DVF
Krebs et al.[57]	2018	Heart	MR-MR	No	DIS, DVF
Stergios et al.[58]	2018	Lung	MR-MR	No	DIS, DVF
Sun et al.[59]	2018	Brain	MR-US	No	DIS
Zhang et al.[60]	2018	Brain	MR-MR	No	DIS, DVF, INV
Fan et al.[61]	2019	Brain Pelvic	MR-MR	Yes	DIS, DVF, ADV
de Vos et al.[36]	2019	Heart Lung	CT-CT MR-MR	No	DIS, DVF
Balakrishnan et al.[11]	2019	Brain	MR-MR	No	DIS, DVF, CON
Kim et al.[33]	2019	Liver	CT-CT	No	DIS, CYC, IDE
Elmahdy et al.[62]	2019	Prostate	CT-CT	Yes	DIS, CON
Kuang et al.[63]	2019	Brain	MR-MR	No	DIS, DVF, CYC
Yu et al.[64]	2019	Abdomino-pelvic	PET-CT	Yes	DIS
Jiang et al.[35]	2020	Lung	CT-CT	No	DIS, DVF
Fu et al.[34]	2020	Lung	CT-CT	Yes	DIS, DVF, ADV
Fechter et al.[65]	2020	Lung Heart	CT-CT MR-MR	Yes	DIS, DVF, CYC
Lei et al.[66]	2020	Abdomen	CT-CT	Yes	DIS, DVF, ADV

Notes: DIS, Dissimilarity; DVF. DVF regularization; ADV. Adversarial loss; CON. Contour overlapping; INV. Inverse consistency; CYC. Cycle consistency; IDE. Identity loss.

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Review

A review on 3D deformable image registration and its application in dose warping

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Physics in Medicine & Biology

TOPICAL REVIEW

Deep learning in medical image registration: a review

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Ressources

- https://arvidl.github.io/blog/2019/12/04/image-registration-resources-wip
- https://github.com/Duoduo-Qian/Medical-image-registration-Resources
- https://github.com/learn2reg/tutorials2019

- https://github.com/voxelmorph/voxelmorph
- https://github.com/DeepRegNet/DeepReg

- https://colab.research.google.com/drive/1WiqyF7dCdnNBIANEY80Pxw_mVz4fyV-S?usp=sharing

- Introduction to Medical Image Registration with DeepReg, between Old and New
  https://colab.research.google.com/github/DeepRegNet/DeepReg/blob/main/docs/Intro_to_Medical_Image_Registration.ipynb