Semi-supervised Image-to-Image Translation for Robust Image Registration

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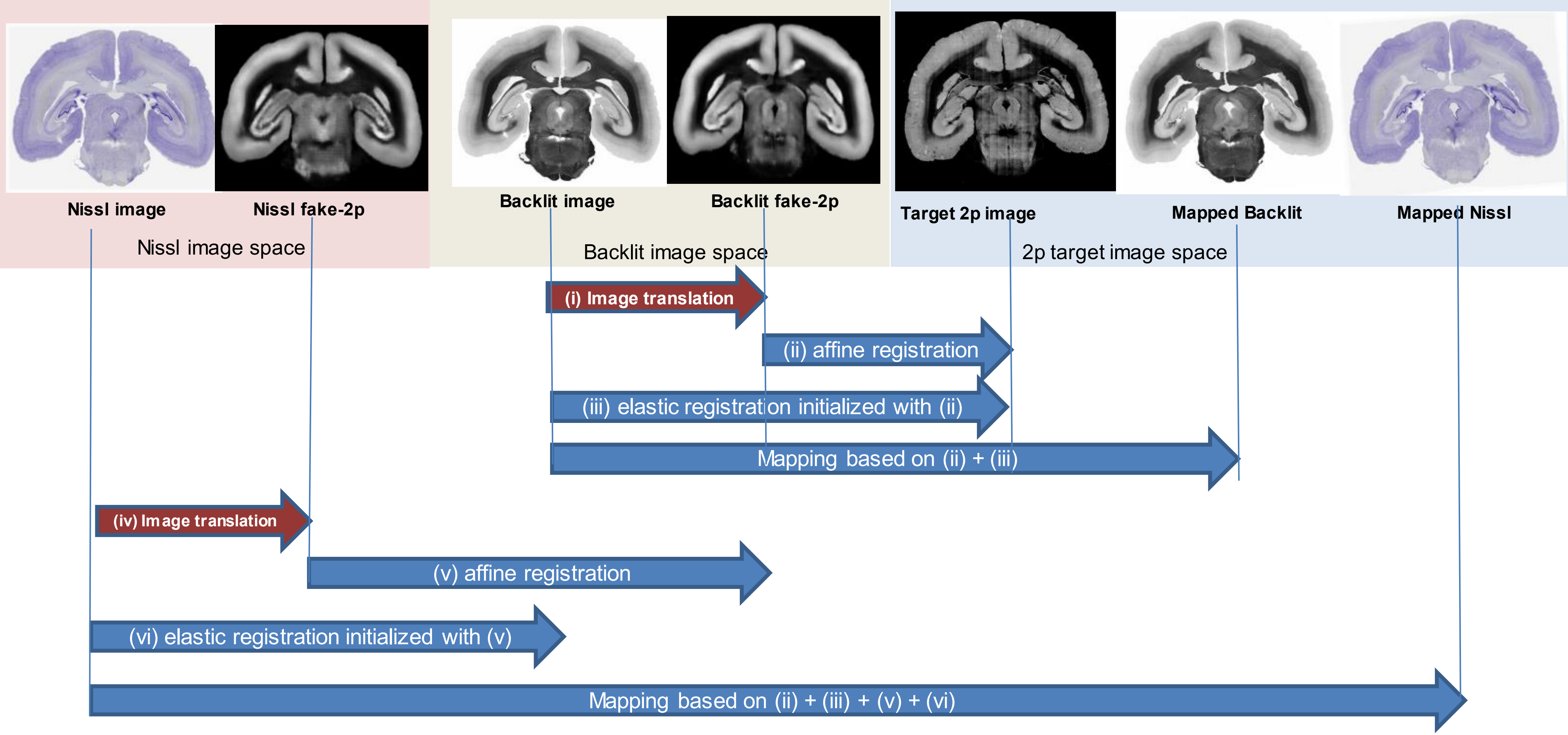
3) Okinawa Institute of Science and Technology, Neural Computation Unit, Japan
4) Kyoto University, Ishii-lab, Japan



Training set

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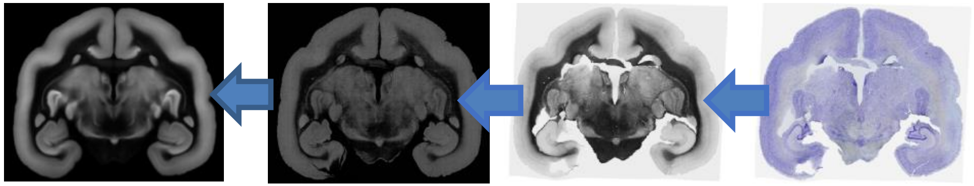
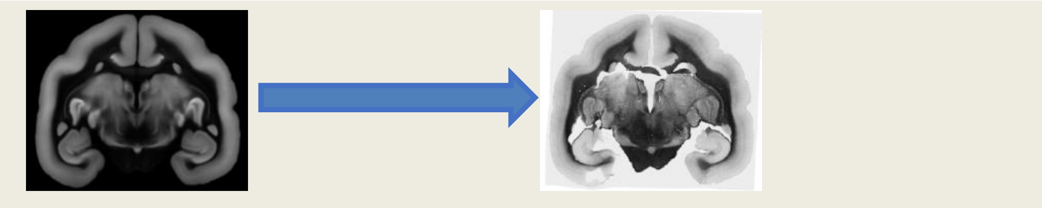
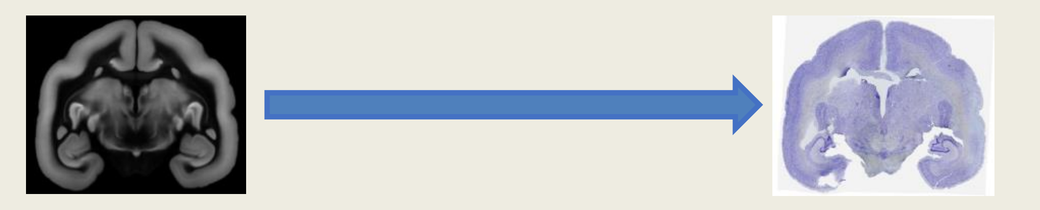


Select the image pairs where registration works for training



Backlit-to-template training set



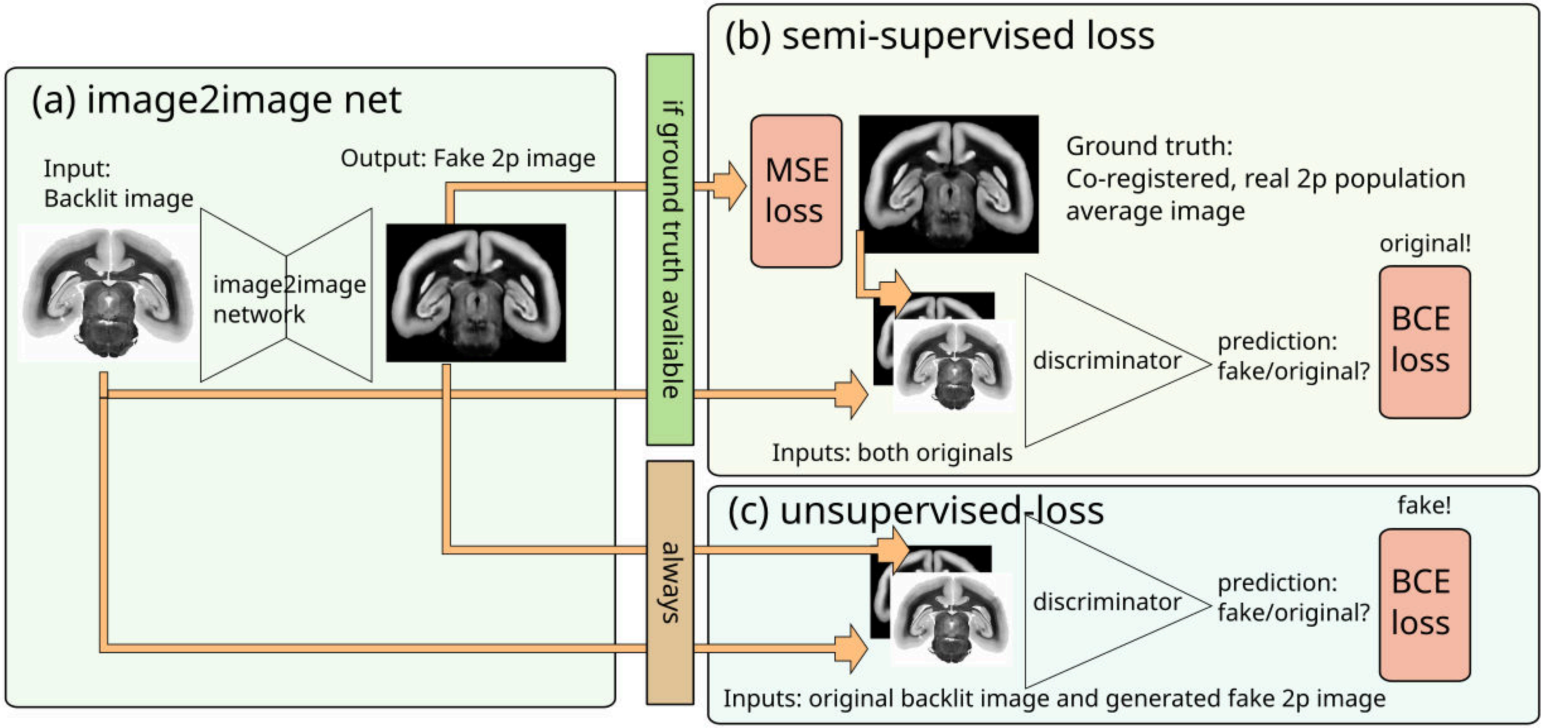
Nissl-to-template training set

For both classes Backlit and Nissl, we created two datasets:

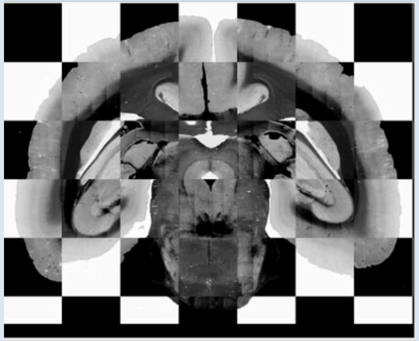
1. **Paired training set**: a training set for supervised training. Pairs of correctly matched slices from 10 brains (about 5000)
2. **Unpaired training set**: a training set for unsupervised training: Niss/Backlit images from 25 brains.

We use an average 2P-template as target image instead of the individual 2P-images to iron out the influence of individual features like tissue damage, acquisition artifacts or image post-processing artifacts.

Training



Example



before

after

a) For the image-to-image translation, we used a U-Net (Ronneberger et al. 2015)

b) For paired images, we used both a "local", pixel-wise loss (MSE) and a "global" loss (A discriminator network).

c) For unpaired Nissl/Backlit images, we only use the discriminator

Our architecture and training is inspired by DCGAN*. Our code can be found here: https://bitbucket.org/skibbe/midl2021_henrik

*Radford et al. Unsupervised Representation Learning With Deep Convolutional Generative Adversarial Networks, 2015