Intensity-based Registration



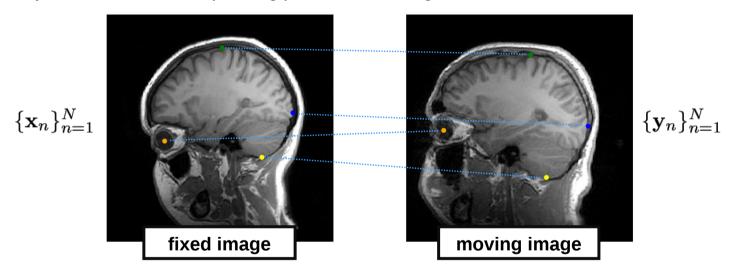
Medical Image Analysis

Koen Van Leemput

Fall 2023

Recall landmark-based registration

ightharpoonup Manually annotate N corresponding points in two images:



Register the images by minimizing the distance between matching point pairs:



$$E(\mathbf{w}) = \sum_{n=1}^{N} \|\mathbf{y}_n - \mathbf{y}(\mathbf{x}_n, \mathbf{w})\|^2$$

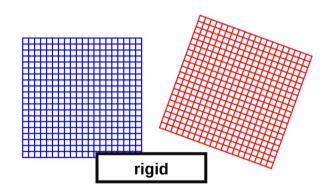
Spatial transformation model

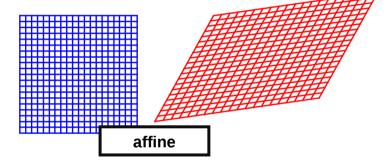
Spatial transformation models

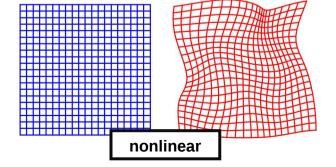
Spatial transformation y(x, w):

 \checkmark maps world positions \mathbf{x} in the fixed image to world positions \mathbf{y} in the moving image

controlled by parameters w

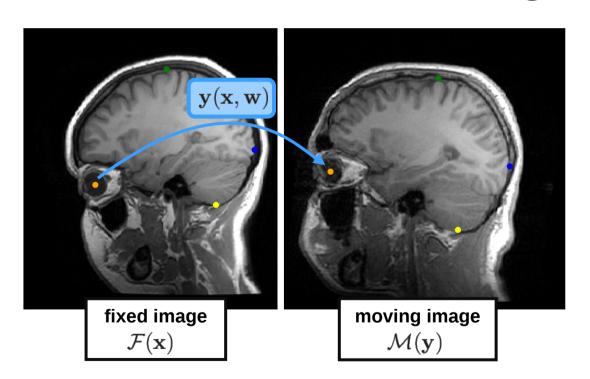


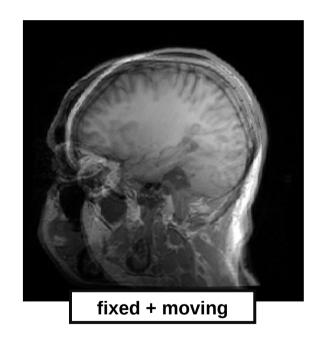






Landmark-based registration

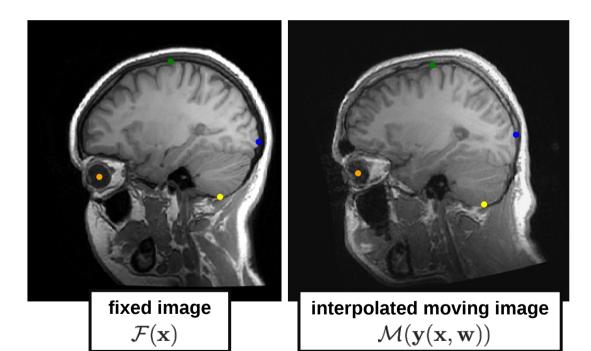


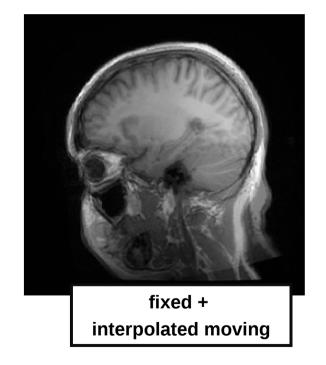




Before registration

Landmark-based registration

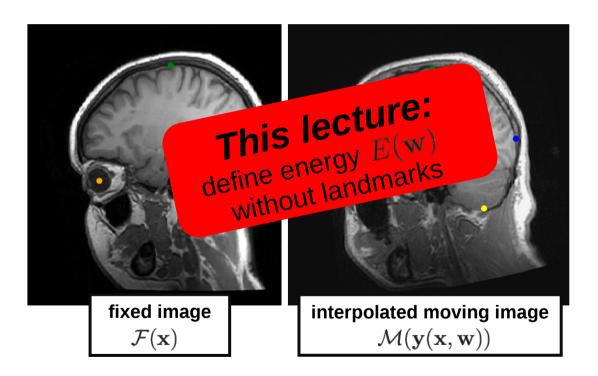


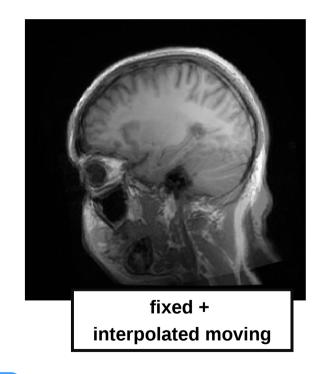




After registration

Landmark-based registration

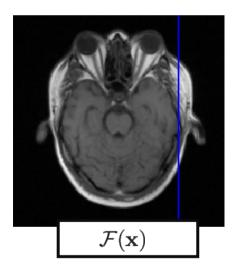


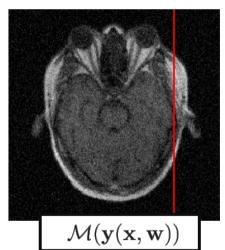


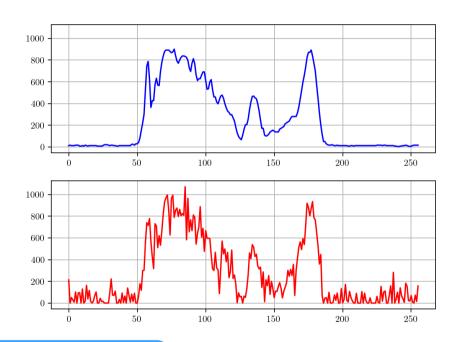


After registration

Images have similar intensity characteristics

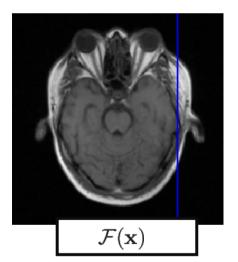


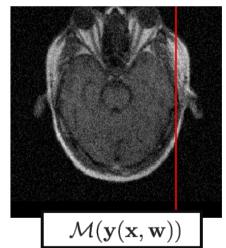


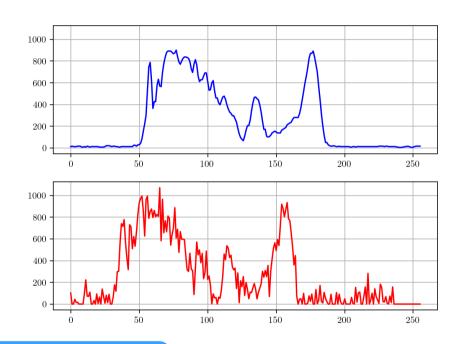




Images have similar intensity characteristics

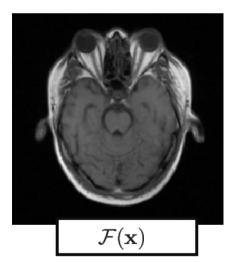


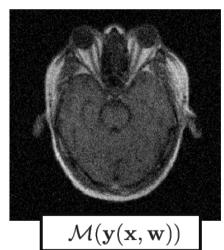


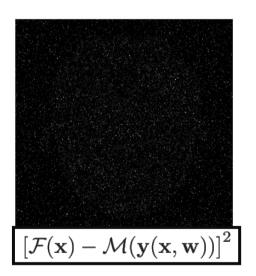




Images have similar intensity characteristics





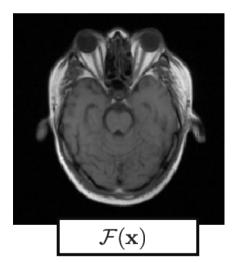


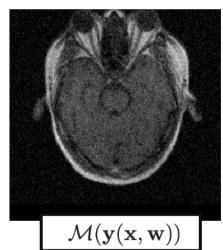
$$E(\mathbf{w}) = \sum_{n=1}^{N} \left[\mathcal{F}(\mathbf{x}_n) - \mathcal{M}(\mathbf{y}(\mathbf{x}_n, \mathbf{w})) \right]^2$$

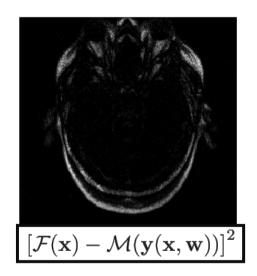
Aalto-yliopisto
Aalto-universitetet
Aalto University

sum over all voxels

Images have similar intensity characteristics

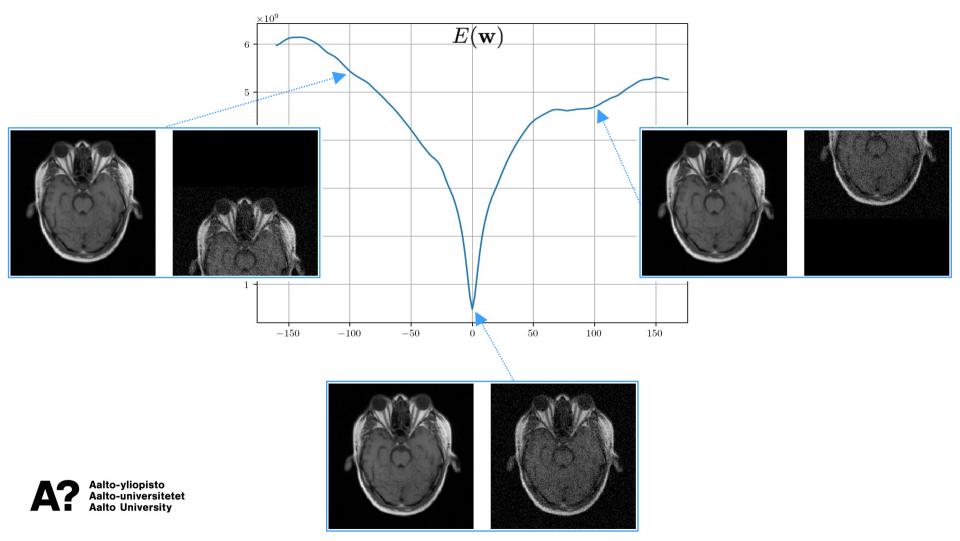




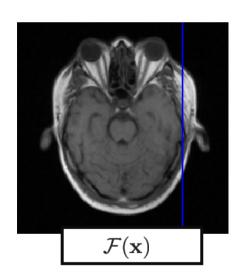


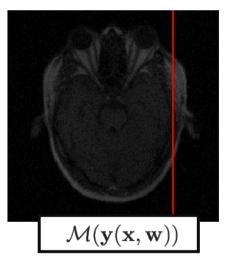


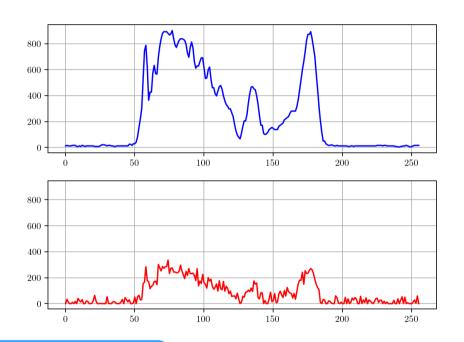
$$E(\mathbf{w}) = \sum_{n=1}^{N} \left[\mathcal{F}(\mathbf{x}_n) - \mathcal{M}(\mathbf{y}(\mathbf{x}_n, \mathbf{w})) \right]^2$$

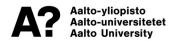


Same but images are scaled differently

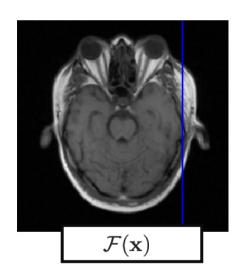


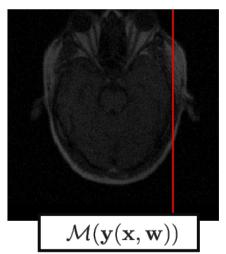


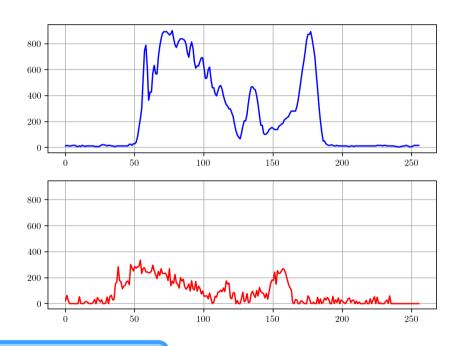


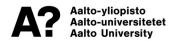


Same but images are scaled differently

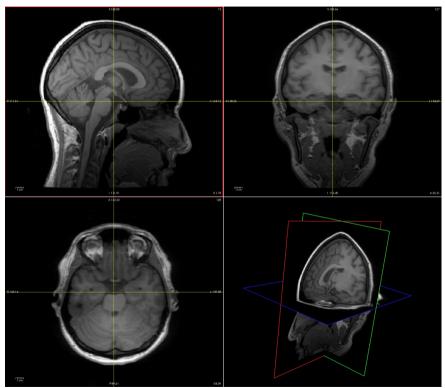




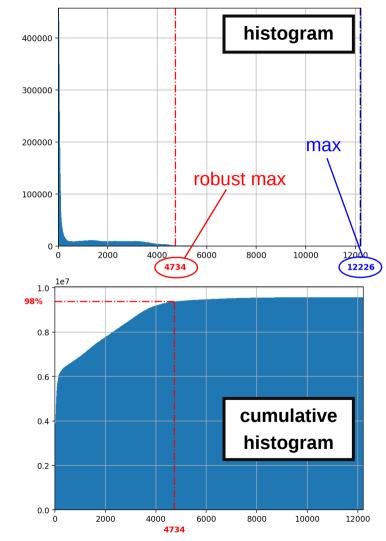




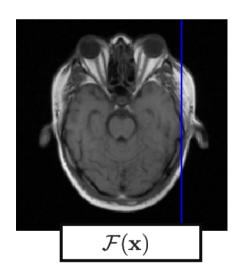
"Maximum" intensity

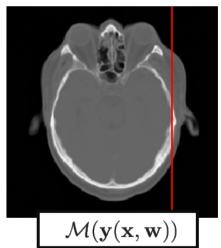


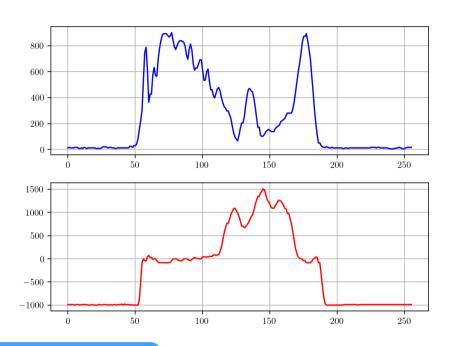




Images have different intensity characteristics

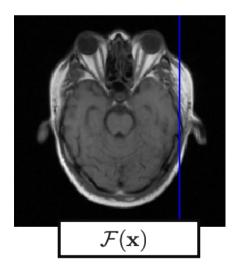


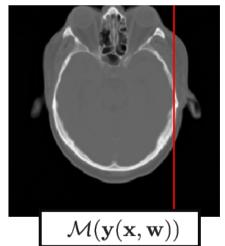


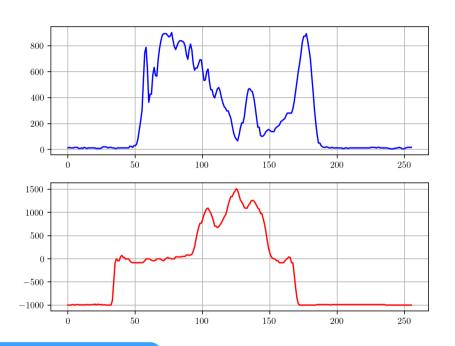




Images have different intensity characteristics

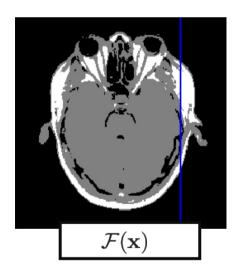


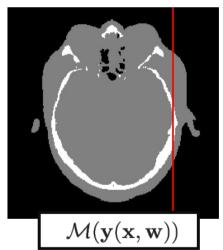


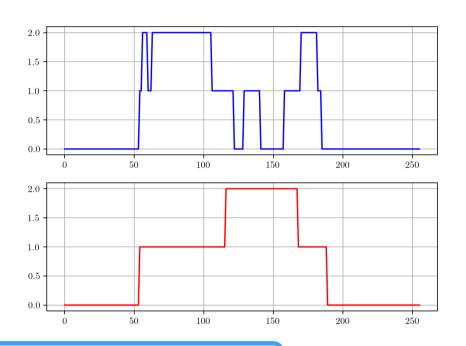


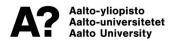


Images have different intensity characteristics



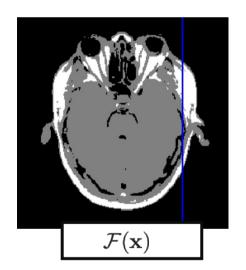


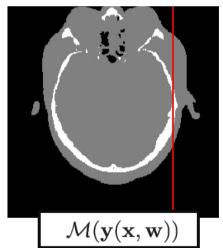


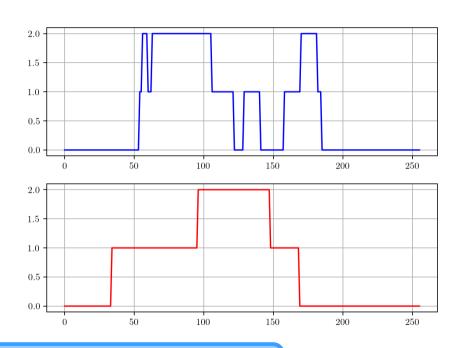


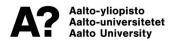
Easier task: what's a good energy function $E(\mathbf{w})$ now?

Images have different intensity characteristics

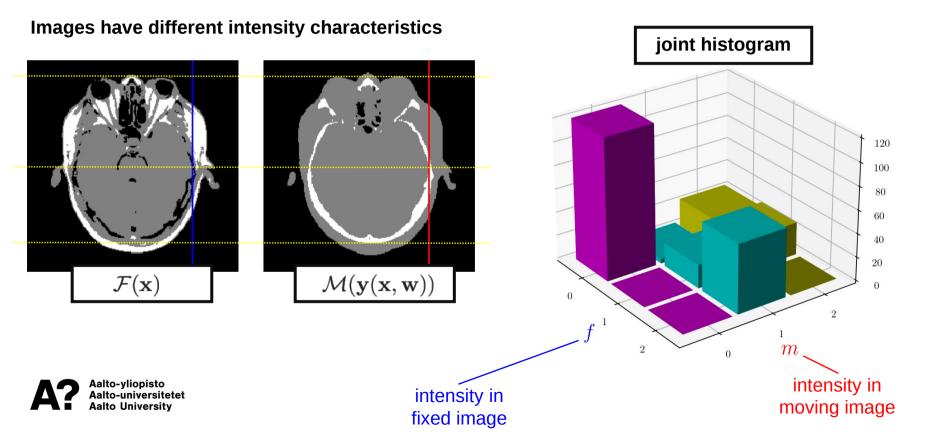


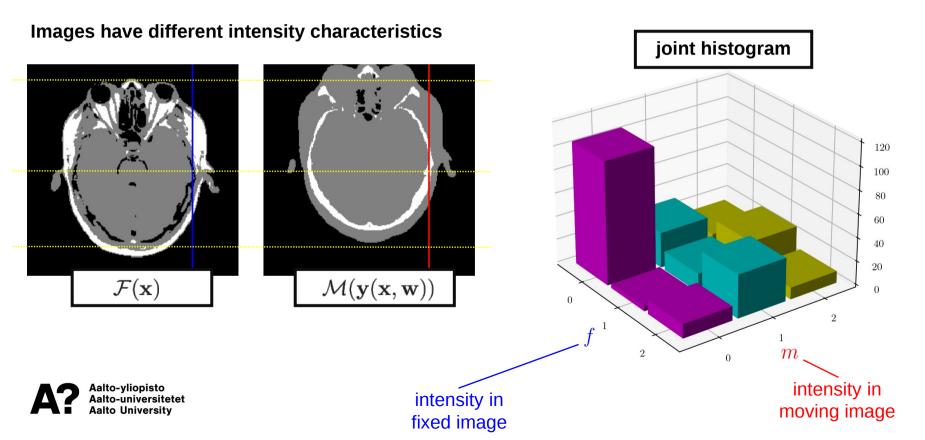




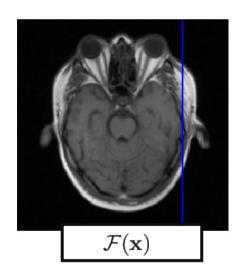


Easier task: what's a good energy function $E(\mathbf{w})$ now?

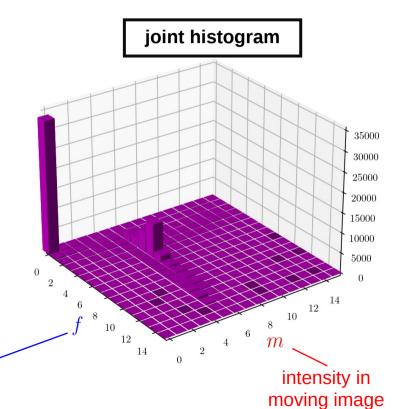




Images have different intensity characteristics



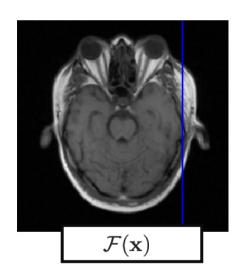


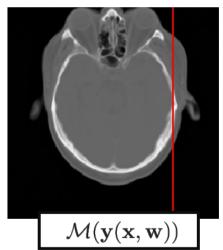


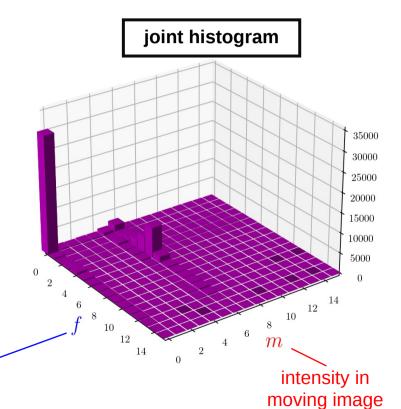


intensity in fixed image

Images have different intensity characteristics









intensity in fixed image

A bit of information theory...

Imagine that a coin is "rigged":

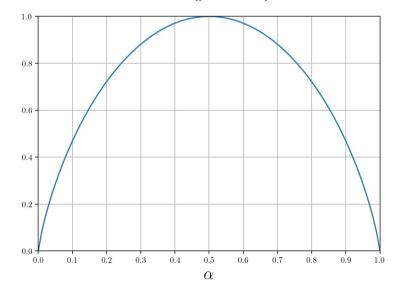
- $m{\prime}$ lands on heads with probability $0 \le \alpha \le 1$
- \checkmark I toss it <u>many</u> times, and the result is 11010001011111011101000101111101101000101...1

"heads"

✓ The minimum number of bits required to store/communicate this result is (per toss):

$$-\alpha \log_2(\alpha) - (1 - \alpha) \log_2(1 - \alpha)$$

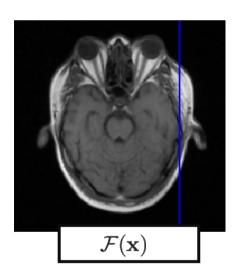
"entropy"

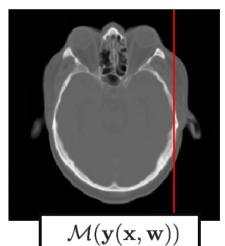


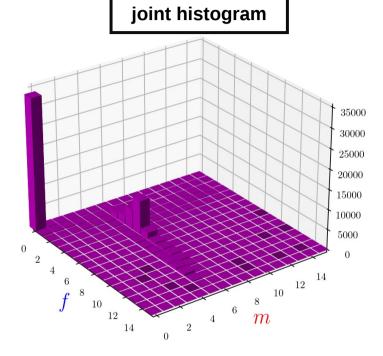
"tails"



Images have different intensity characteristics





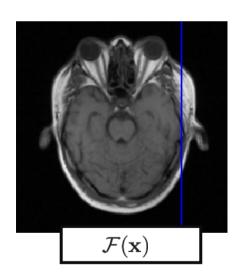


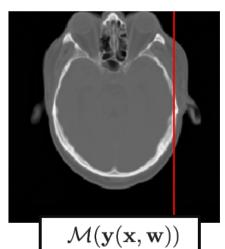


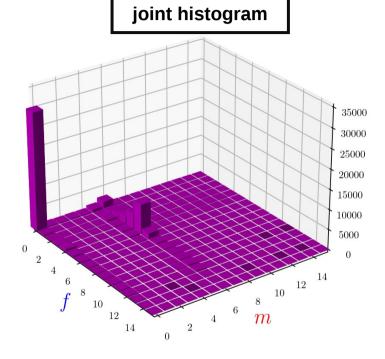
$$E(\mathbf{w}) = H_{F,M}$$
 where $H_{F,M} = -\sum_{f=1}^B \sum_{m=1}^B p_{f,m} \log(p_{f,m})$

__ normalized histogram counts

Images have different intensity characteristics

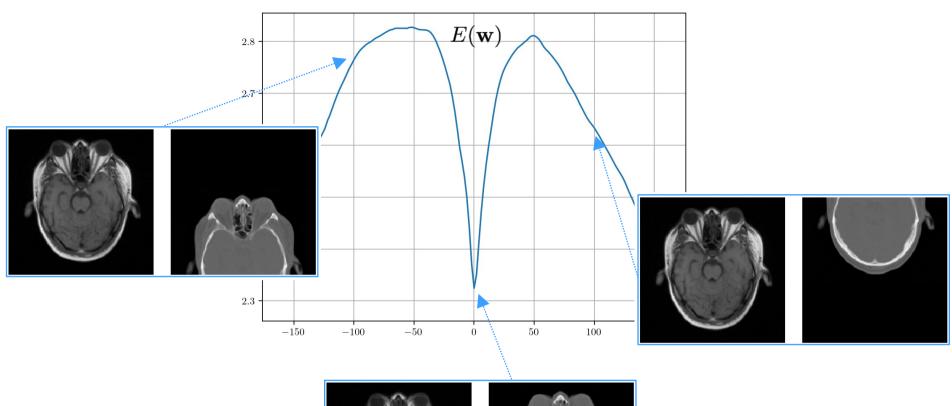




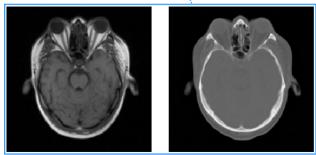




$$E(\mathbf{w}) = H_{F,M}$$
 where $H_{F,M} = -\sum_{f=1}^B \sum_{m=1}^B p_{f,m} \log(p_{f,m})$

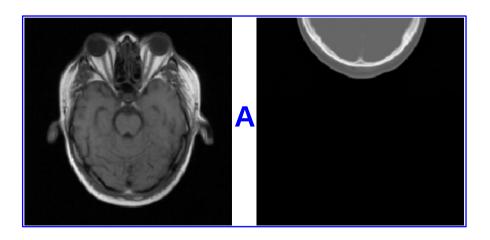


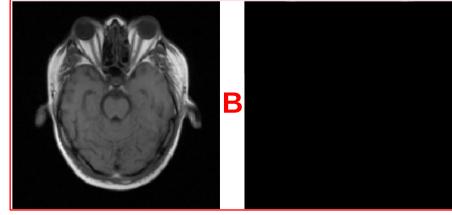




Diagnosing the problem

Question: which image pair takes more bits to encode?

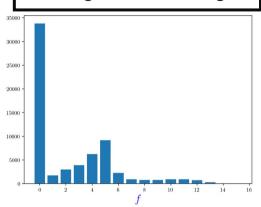






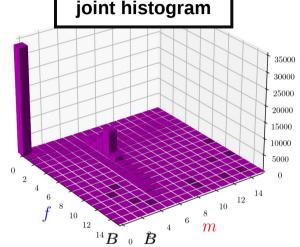
Solution

histogram fixed image



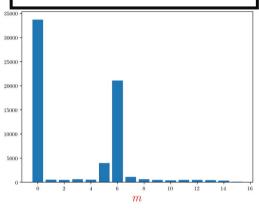
$$H_F = -\sum_{f=1}^B p_f \log(p_f)$$

joint histogram



$$H_F = -\sum_{f=1}^{D} p_f \log(p_f)$$
 $H_{F,M} = -\sum_{f=1}^{D} \sum_{m=1}^{D} p_{f,m} \log(p_{f,m})$ $H_M = -\sum_{m=1}^{D} p_m \log(p_m)$

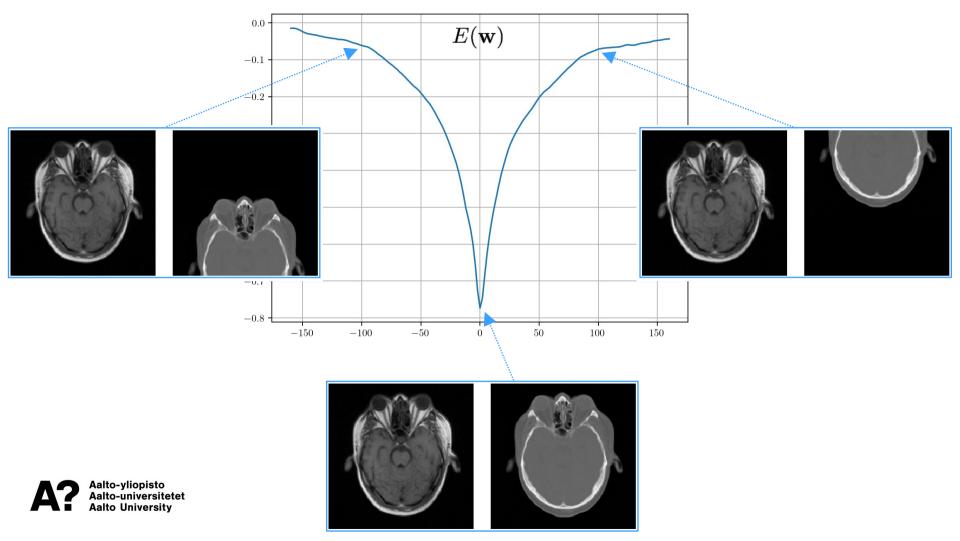
histogram moving image



$$H_M = -\sum_{m=1}^B p_m \log(p_m)$$



 $E(\mathbf{w}) = H_{F,M} - H_F - H_M$ (negative "mutual information")



Numerical optimization

Find transformation parameters \mathbf{w} that minimize $E(\mathbf{w})$

