On Image Quality Assessment for Deep Learning in Medical Imaging

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Image quality assessment (IQA)

- **Full reference (FR)**
- **No reference (NR)**
- **Reduced reference (RR)**

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  Evaluation of newly developed algorithms
  - $\rightarrow$ compression
  - $\rightarrow$ reconstruction
- **No reference (NR)**
  Real-time quality control for subsequent usage
  - $\rightarrow$ analysis
  - $\rightarrow$ diagnosis
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Most common IQA measures are developed for natural images - medical images usually have different properties and special aims.

Motivation

The mean squared error (MSE) of a given image $I \in \mathbb{R}^{m \times n}$ und its reference $G \in \mathbb{R}^{m \times n}$ is given by

$$MSE(I, G) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (I_{i,j} - G_{i,j})^2.$$

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Example:

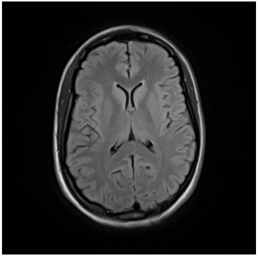
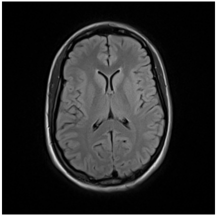
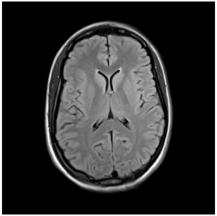


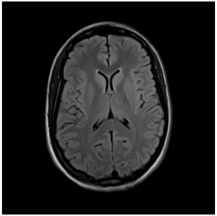
Figure: My brain MRI



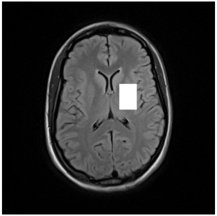
(a) Reference I



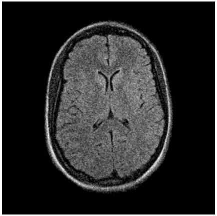
(b) Contrast



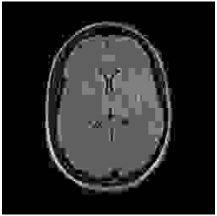
(c) Luminance



(d) Hole

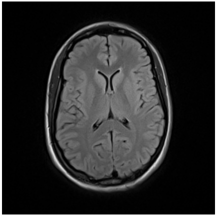


(e) Gaussian noise



(f) Jpeg

Figure: MSE is 0.0055 for all images (b) - (f) compared to (a).



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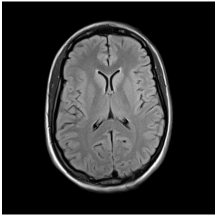
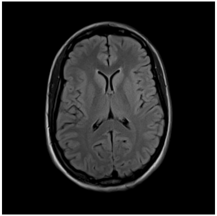


(b) PSNR: 22.5



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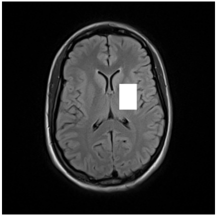

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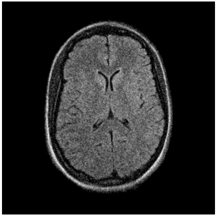

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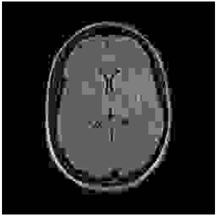
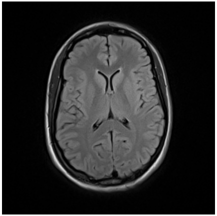


(f) PSNR: 22.5

B. Girod. Psychovisual aspects of image processing: *What's wrong with mean squared error?* Proceedings of the Seventh Workshop on Multidimensional Signal Processing,1991.



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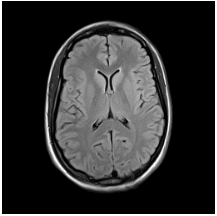
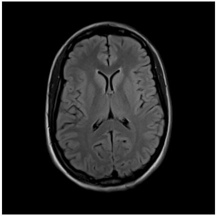
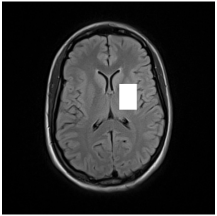


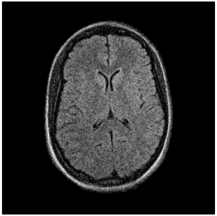
(b) SSIM[1]: 0.97



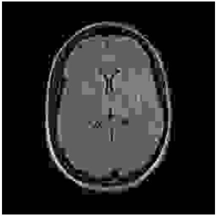
(c) SSIM: 0.87



(d) SSIM: 0.98



(e) SSIM: 0.64



(f) SSIM: 0.67

[1] Wang, Bovik, Sheikh, Simoncelli: *Image quality assessment: From Error Visibility to Structural Similarity*, IEEE Transactions on image processing, 2004

Outline

Problems

- Common measures not developed for medical imaging
- Specific medical measures not transferable

$\rightarrow$ Gap between ML and medical community

Longterm Goal

Development of an IQA toolbox that is

- suitable for diverse medical images
- adaptable for specific tasks
- standardized for common medical tasks

Future research

Approach based on Gabor theory (joint work with M. Dörfler)
Development of a Gabor parameter framework for IQA that

- closes gaps between 2-dim Gabor theory and applications
- use frequency representations to improve common IQA
- study parameter choices in Gabor filter banks

M. Dörfler and E. Matusiak: *Nonstationary Gabor frames - approximately dual frames and reconstruction errors*, Adv. Comput. Math., 2015

B., Llorden, Sanchez - Ferrero, Hoge, Ehler, Westin : *Orthogonal projections for image quality analyses applied to MRI*, Proceedings in Applied Mathematics and Mechanics, 2021

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For some first experiments enhancing structural information...

→ talk to me in the break, and/or

→ find my poster at WiMIUA tomorrow :)

Thanks for your attention!

2-dim Gabor representation

Let $f \in L^2(\mathbb{R}^2)$ represent an image that is mapped from position-domain to its frequency-domain representation $\hat{f}$ by a 2-dim Fourier transform:

$$\hat{f}(\xi) = \int_{x \in \mathbb{R}^2} f(x) e^{-2\pi i x \cdot \xi} dx, \quad (1)$$

where $x \cdot \xi$ denotes the usual dot-product in $\mathbb{R}^2$.

A Gabor filter can be formulated via the following operators:

- Modulation by $\omega \in \mathbb{R}^2$: $[M_\omega g](x) = g(x) e^{2\pi i x \cdot \omega}$
- Translation by $z \in \mathbb{R}^2$: $[T_z g](x) = g(x - z)$
- Rotation by $\theta \in [0, 2\pi]$:

$$[R_\theta g](x) = g \begin{pmatrix} x_1 \cos\theta + x_2 \sin\theta \\ -x_1 \sin\theta + x_2 \cos\theta \end{pmatrix}$$

Parameter spaces

We consider here a 3-dim parameter space, i.e.

$$\Lambda_K^c = \mathbb{Z}_{N_2} \times \mathbb{Z}_{N_1} \times \mathbb{Z}_K,$$

where the shift-parameters are implicit in the convolution of the modulated and rotated windows

$$\mathscr{G}^{\theta,\omega} = \{g_{\theta,\omega} = M_\omega R_\theta g, (\omega,\theta) \in \Lambda_K^c\}.$$

Convolutions with the image f yields $\#\omega \cdot \#\theta$ filtered images:

$$\begin{aligned}(f * g_{\theta,\omega})(x_1,x_2) :=& \{f * g_{\theta_j,\omega_i})(x_1,x_2)\}_{j,i} \\ =& \{\int_{\hat{x_1}}\int_{\hat{x_2}} f(x_1,y_1) \cdot \overline{g_{\theta_k,\omega_l}}(x_1-\hat{x_1}, x_2-\hat{x_2}) d\hat{x_1} d\hat{x_2}\}_{k,l}.\end{aligned}$$

Common choice of 2-dim Gabor filters in applications

A continuous 2-dim Gabor filter g with Gaussian window can be written as

$$g_{\theta,\omega}(x_1,x_2) = \frac{\omega^2}{\pi\sigma_1\sigma_2}\ e^{-\omega^2\left(\frac{(x_1\cos\theta+x_2\sin\theta)^2}{\sigma_1^2}+\frac{(-x_1\sin\theta+x_2\cos\theta)^2}{\sigma_2^2}\right)} e^{2\pi i\omega(x_1\cos\theta+x_2\sin\theta)},$$

for some chosen frequency ω, orientation θ and σ_1, σ_2 correspond to the spatial widths of the filter.

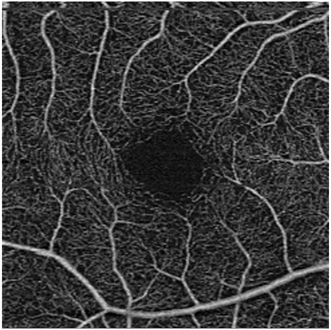
B. S. Manjunath and W. Y. Ma: *Texture features for browsing and retrieval of image data*, IEEE Transactions on Pattern Analysis and Machine Intelligence, 18(8):837–84, 1996

The representation of $g_{\theta,\omega}(x_1,x_2)$ in the frequency domain is

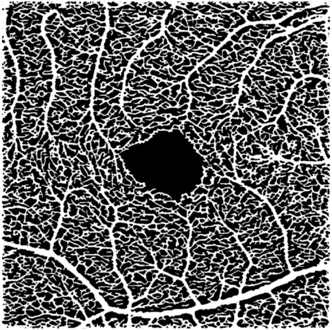
$$\mathscr{F}\left(g_{\theta,\omega}\right)(v_1,v_2) = e^{-\frac{\pi^2}{\omega^2}\left(\sigma_x^2(v_1\cos\theta+v_2\sin\theta-\omega)^2+\sigma_y^2(-v_1\sin\theta+v_2\cos\theta)^2\right)}.$$

Example Gabor representations OCTA

Segmentation of blood vessels in OCTA en-face images



(a) En-face OCTA image



(b) Segmentation

B., Goldbach, Gerendas, Schmidt-Erfurth, Ehler: *Blood vessel segmentation in en-face OCTA images: a frequency based method*, accepted to appear in SPIE Medical Imaging Proceedings, 2022.

B., Ehler, Bogunovic, Waldstein, Philip, Schmidt-Erfurth, Gerendas: *Supervised learning and dimension reduction techniques for quantification of retinal fluid in optical coherence tomography images*, Eye, Springer Nature (2017).