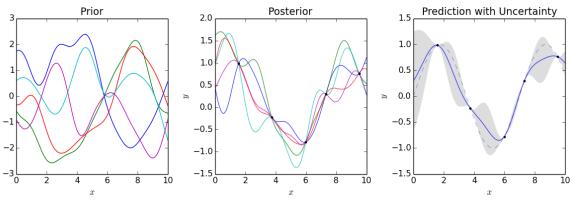
Gaussian Process Interpolation for Uncertainty Estimation in Image Registration

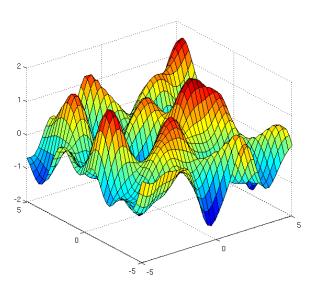


ECSE 626 - Project presentation



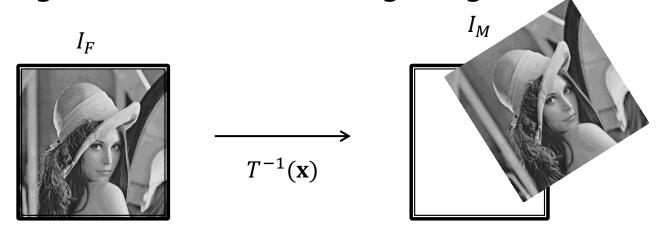
Guideline

- Image Registration
- Gaussian process Interpolation
- Method
- Preliminary Results



Registration

• What T align the fixed and moving image?



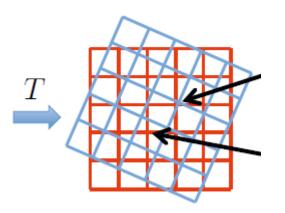
- After random initialization of a tested $T_t(\mathbf{x})$
- What is the best T_t that maximizes similarity S of I_F and $T_t(I_M)$

$$\widehat{T} = \underset{T_t}{\operatorname{argmax}} \left(S(I_F, T_t(I_M)) \right)$$

- Major problem
 - Each image is divided into a grid
 - To compute $S(I_F(x), T_t(I_M(x)))$ comparison of pixel value at the same position x
 - Impossible to compare grid points of I_M and and I_F !



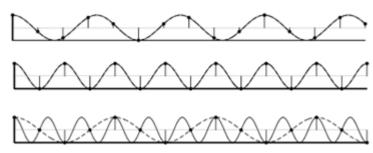




[1]

- Interpolation :
 - Construction of the continuous version of a discrete signal
 - Convolution with a kernel through all the observations
 - Interpolator with Nyquist frequency [2]

fe > fs/2



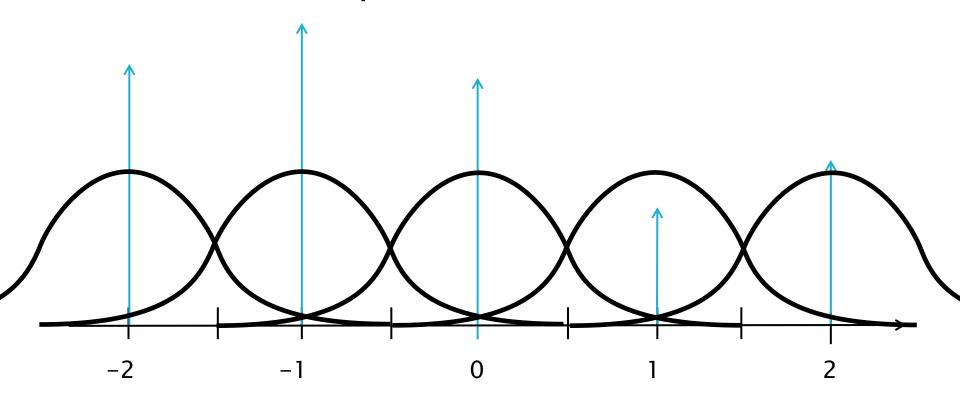
https://commons.wikimedia.org/ wiki/File:Nyquist_Aliasing.svg

 Example of aliased image (too low image resolution for the details)

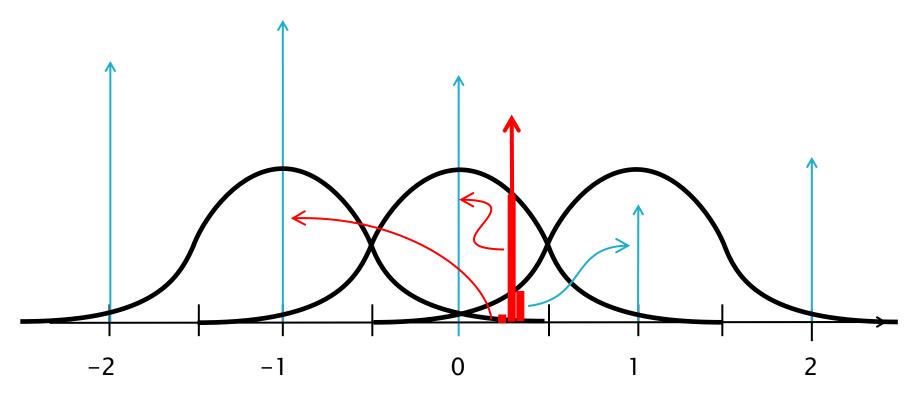


https://commons.wikimedia.org/wiki/ File:Nyquist_Aliasi http://forum.hardware.fr/hfr/VideoSo n/Traitement-Video/unik-artefactsvideos-sujet_142007_1.htm ng.svg

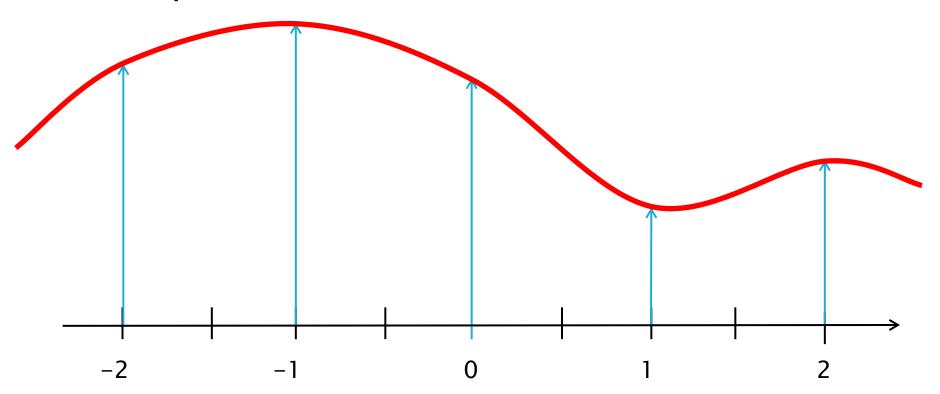
Quadratic interpolation



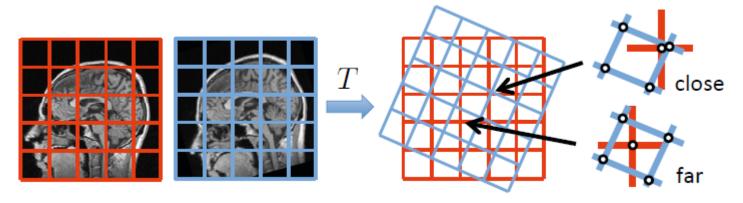
• Resampling of x = 0.3



Interpolated values



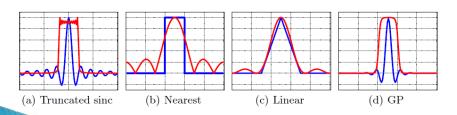
- Drawback of all the approaches
 - Difficult because interpolation error varies among grid points



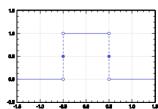
How to model the interpolation uncertainty?

Gaussian Process Interpolation

- Gaussian process
 - $\mathcal{GP}(m,k)$: Stochastic process defined by mean function m(x) and covariance function k(x,x') [3]
 - Also called « Kriging » (used in geostatistic) [4]
- Why Gaussian Process interpolator
 - Because it estimate uncertainty and is closed to the optimal interpolator!



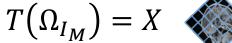




Method: Bayesian Regression

- Fixed grid of image $I_F: X^*$
- Grid of image $I_M: \Omega_{I_M} =>$



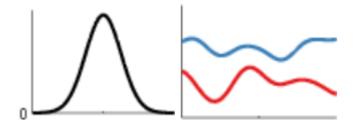




- Assumptions
 - $\mathcal{GP}(0,k)$ prior over resampled image I_M^*
 - Gaussian noise $\varepsilon = \mathcal{N}(0, \sigma_{I_M}^2)$ on measurements I_M
- Posterior of resampled values I_M^*
 - $p(I_{M}^{*}|I_{M}, X, X^{*}) = \mathcal{N}(\mu_{I_{M}^{*}}, \Sigma_{I_{M}}^{*})$ $\mu_{I_M^*} = k(X, X^*) \cdot [k(X, X) + \sigma_{I_M}^2 \mathbf{I}]^{-1} \cdot I_M$ $\Sigma_{I_M}^* = k(X^*, X^*) - k(X, X^*) \cdot \left[k(X, X) + \sigma_{I_M}^2 \mathbf{I} \right]^{-1} \cdot k(X, X^*)$

Method: Bayesian Regression

- Choice of covariance function k(x, x')
 - The most important choice of \mathcal{GP} !
 - Gaussian kernel : $k(x, x') = \exp(-\frac{\|x x'\|^2}{2l^2})$
 - Because it captures the neighbours relation
 - Parametrized by the length l



http://people.seas.harvard.e du/~dduvenaud/cookbook/

Method: Similarity measure

Generative model instead of MAP

$$p(I_F, I_M, I_M^*; T, \sigma_{I_M}, \sigma_{I_F}, l) = p(I_M^* \big| I_M; T, \sigma_{I_M}, l) \cdot p(I_F | I_M^*)$$
 Previous posterior Likelihood

• After marginalization over I_M^*

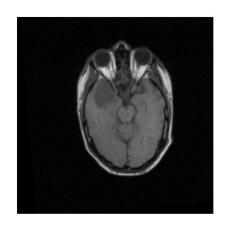
•
$$\hat{T} = \underset{T}{\operatorname{argmax}} \left[\log \left(p(I_F, I_M; T, \sigma_{I_M}, \sigma_{I_F}, l) \right) \right]$$

$$\log\left((2\pi)^{-\frac{k}{2}}|\Sigma|^{-\frac{1}{2}}\right) - \frac{1}{2}\left(I_F - \mu_{I_M^*}\right)^t \Sigma^{-1}\left(I_F - \mu_{I_M^*}\right)$$

$$\Sigma = \Sigma_{I_M}^* + \sigma_{I_M}^2$$

Data

- MRI-T1 3D volume from RIRE dataset [5]
- Downsampling of one slice in one direction by 5
- Random T for moving image



slice no3



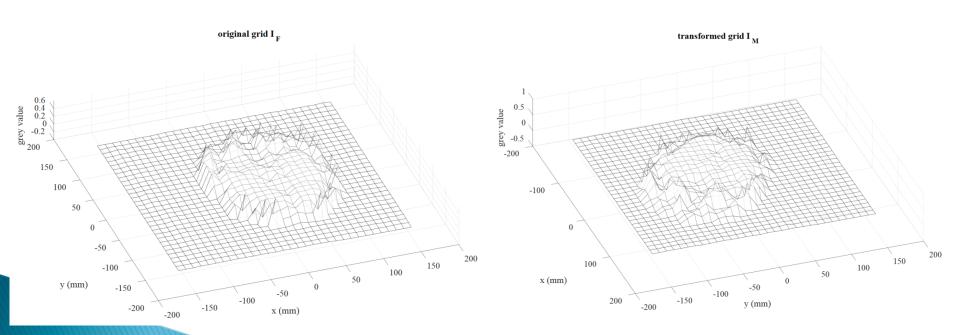
downsampled in x direction



im transformed by 0 0 -126.0484°

Data

- $[32 \times 32]$ grid for fixed image : X
- \circ [32 × 32] grid for moving image : Ω_{I_M}



- Interpolation results
 - \circ With lengthscale l=6,25 and noise $\sigma_{I_M}=0,1$



transformed Moving image

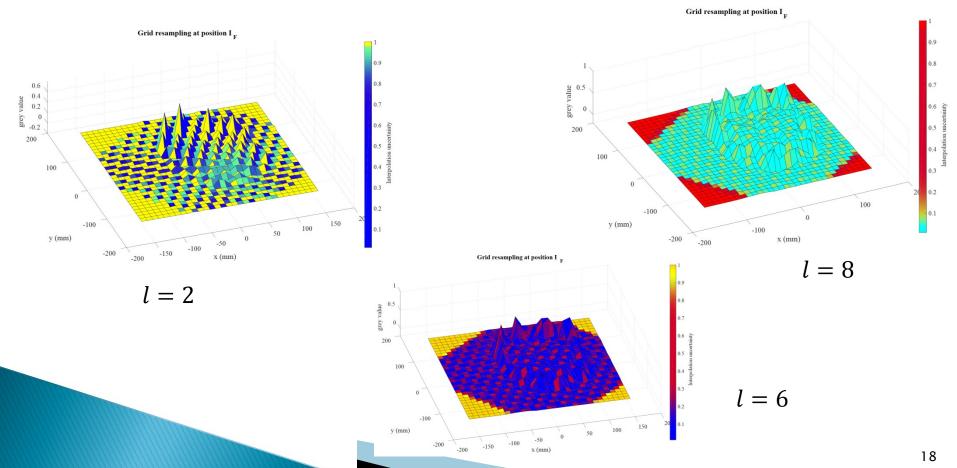


Interpolated values

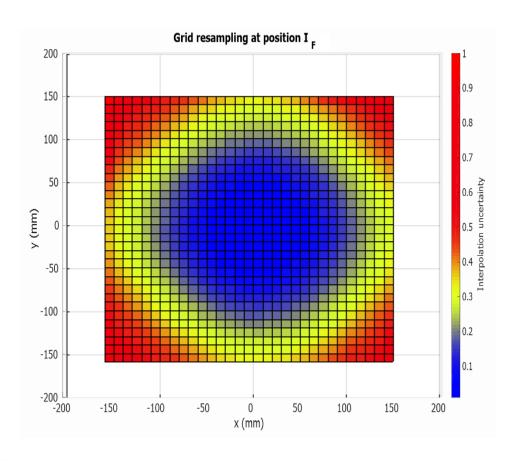


Fixed image

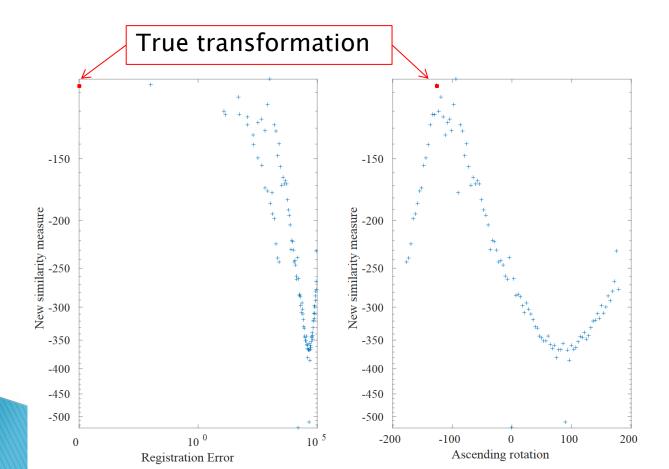
- Interpolation results
 - Influence of l: smoothness 1 and uncertainty 1



Influence of rotation



- Cost function
 - $^{\circ}$ Test with $T_{\chi}=0$; $T_{y}=0$; $T_{ heta_{z}}=-106^{\circ}$



Future work

- Still work to do...
 - \circ Best parameter l by maximization of BIC criteria
 - Qualitative comparison of interpolation methods
 - Quantitative comparison of interpolation (NN, cubic, spline) with X-corr and \mathcal{GP} similarity measure

Conclusion

Advantages

- Compact and easy adjustable
- Accurate with measure of uncertainty
- \circ \mathcal{GP} is a growing field

Drawbacks

- Complexity
- High memory requirement
- Covariance $\Sigma_{I_M}^*$ sensible to noise
- Instability because of high dimensionnality

References

- ▶ [1] Wachinger, Christian, et al. "Gaussian process interpolation for uncertainty estimation in image registration." *Medical Image Computing and Computer-Assisted Intervention-MICCAI 2014*. Springer International Publishing, 2014. 267–274.
- [2] Lehmann, Thomas M., Claudia Gönner, and Klaus Spitzer. "Survey: Interpolation methods in medical image processing." *Medical Imaging*, *IEEE Transactions on* 18.11 (1999): 1049-1075.
- [3] Rasmussen, Carl Edward. "Gaussian processes for machine learning." (2006).
- [4] Van Beers, Wim, and Jack PC Kleijnen. "Kriging interpolation in simulation: a survey." *Simulation Conference, 2004. Proceedings of the 2004 Winter.* Vol. 1. IEEE, 2004.
- ▶ [5] Fitzpatrick, J. Michael, Jay B. West, and Calvin R. Maurer Jr. "Predicting error in rigid-body point-based registration." *Medical Imaging, IEEE Transactions on* 17.5 (1998): 694–702.

Discussion



Annexe: Matrix computation on *Matlab*

```
% define the coordinates
% along x and y
x=[-3:1:3];
                                        y = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 \\ -3 & -2 & -1 & 0 & 1 & 2 \end{bmatrix}
y=[-3:1:2];
% define the coordinates
% along the x-y plane
[xx,yy]=meshgrid(x,y)
xx =
                                           yy =
```