🛔 THE DEPARTMENT OF BIOMEDICAL ENGINEERING

Getting More Image Quality with Less Data in X-Ray CT

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 Image Volume
 Projection Data

 Discrete-Discrete
 Image Volume
 Image Volume

 Parameterization
 Image Volume
 Image Volume







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How to deal with unequal measurement noise (Simple Estimation Problem)

3 Random Variables Different std dev ($\sigma_1, \sigma_2, \sigma_3$)

Best way to estimate µ?





Maximum Likelihood Estimation for CT
Log transformed data case (e.g.
$$l = -\log\left[\frac{y}{l_0}\right]$$
)
 $\bar{l}(\mu) = A\mu$ $P_{l_1} = \frac{1}{\sqrt{2\pi a_1^2}} \exp\left(-\frac{1}{2a_1^2}(l_1-\bar{l}(\mu))^3\right)$
Likelihood-based Objective $\log L(y;\mu) = -\frac{y_1H}{2}\log(2\pi a_1^2) - \frac{y_1H}{2a_1^2}(l_1-|A\mu|)^3$
 $\cong -[l - A\mu]^T D\left\{\frac{1}{a_1^2}\right\}[l - A\mu] = -||l - A\mu||_{2^{-1}}^2$
Solve for μ $\hat{\mu} = \arg\max\log L(y;\mu) = \left[A^T D\left\{\frac{1}{a_1^2}\right\}A\right]^{-1} A^T D\left\{\frac{1}{a_1^2}\right\}l$



Statistical methods weigh important of individual data points BUT noise control requires additional information

Additional Information through Regularization

Integrating information via a change in the objective function

 $\hat{\mu} = \operatorname{argmax} \log L(y; \mu) - \beta R(\mu)$ Penalized-Likelihood Estimation

Choices of regularization $R(\mu)$

Local smoothness Edge-preservation Prior images Patches/dictionaries/learned regularization



Regularization of Local Image Properties









Regularization using Prior Images







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Slewerdsen, J. W. Stayman, 'dPIRPLE: A joint estimation framework for deformable registration and penalized-likelihood CT image reconstruction using prior images," Physics in Medicine and Biology, 59(17) 4799-826 (September 2014). PMID:





Regularization using Patches/Dictionaries

General/learned knowledge of image features Need a dictionary of features/patches Sparse representations, linear combinations of few patches Objective Function $\{\hat{\mu}, \hat{\lambda}\} = \arg\max \log L(y; \mu)$ $-\beta \left(\sum_{n} \left\| \mathbf{E}_{p} \mu - \mathbf{D} \lambda_{p} \right\|_{2}^{2} + \sum_{n} \nu_{p} \left\| \lambda_{p} \right\|_{0} \right)$ $\mathbf{D}\lambda_r$ $\mathbf{E}_{p}\mu$ 11 10.0 D STEL 1 88 N NOR ed from: Q Xu, H Yu, X Mou, L Zhang, J Hsieh, G Wang, "Low ag 31(9) September 2012



Additional Information in the Forward Model

$\bar{y}(\mu) = I_0 \exp(-\mathbf{A}\mu)$

Forward model has many simplifications in physics... Model ignores Scatter Spectral effects Focal spot blur Detector blur

Object model may have constraints Nonnegativity Known element/components in the field-of-view

Modeling Known Components in the Object

Implants Susceptible to metal artifacts Strongest near the device Region-of-interest is near implant



Include a component model in explicitly in the object model $\mu(\mu_{anatomy},\lambda) = \mathbf{D}\{\mathbf{W}(\lambda)m\}\mu_{anatomy} + \mathbf{W}(\lambda)\mu_{implant}$







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Improving the Physical Model (Focal Spot Blur)



Supposed Physical Modeling (Focal Spot)

CT Reconstruction Summary

Advanced Reconstruction Aims

Dose reduction, improved image quality

CT Forward Model Nonlinear, but often linearized Measurement statistics are important (SNR varies widely) Advanced physical modeling permits image quality improvements

- CT Regularization Strategies Standard smoothness and edge-preservation Use of prior images (e.g., sequential studies) Generalized dictionary methods including machine learning
- Other Objective Function Modifications Additional constraints on the object (e.g., known components)

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