Dual-Modality Imaging

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Calendar of seminars

Sept. 19 Physical Basis of Magnetic Resonance Imaging

spin under a magnetic field, RF pulses, Bloch equations

Sept.27 Sequences and Reconstruction in MRI

K-space, aliasing, sequences

Oct. 18 Positron Emission Tomography: an introduction

general introduction, attenuation correction, level set methods

- Nov. 8 Kinetics of the Tracer in PET compartment model for ¹⁸FdG
- Nov. 21 Dual-Modality Imaging

The challenges of PET/MR

PET/MRI is a new, arising hybrid-imaging technology that incorporates MRI morphological imaging and PET functional imaging.

At the moment 3 companies declare availability of their $\mathsf{PET}/\mathsf{MRI}$ imaging devices:

- PHILIPS
- SIEMENS
- GE

Introduction Reconstruction in PET/RM Experimental results



Consider the linear system Ax = b, with b projection (PET) data and x the image to reconstruct Maximum Likelihood Expectation Maximization (MLEM) is based on a probabilistic argument (the noise is assumed to be Poissonian).

$$L(x) = P(b|x) = \prod_{i=1}^{l_p} \frac{(b_i^*)^{b_i}}{b_i!} e^{-b_i^*}$$

where $b^* = Ax$ is the exact sinogram, i.e. the projection of the exact solution x. Equivalently, it maximizes

$$I(x) = \log(L(x)) = \sum_{i=1}^{lp} - (Ax)_i + b_i \log(Ax)_i$$

Kuhn-Tucker conditions are then:

$$x_j \frac{\partial I(x)}{\partial x_j} = 0 \text{ if } x_j > 0$$

 $\frac{\partial I(x)}{\partial x_j} \le 0 \text{ if } x_j = 0$

From the first equation (the second is always satisfied) we get

$$0 = x_j \frac{\partial I(x)}{\partial x_j} = x_j \left(-\sum_{i'=1}^{l_p} a_{i',j} + \sum_{i=1}^{l_p} \frac{a_{i,j}b_i}{\sum_{j'=1}^{N^2} a_{i,j'}x_{j'}} \right)$$

this leads to the iterative scheme:

$$x_j \leftarrow \frac{x_j}{\sum\limits_{i'=1}^{l_p} a_{i',j}} \sum\limits_{i=1}^{l_p} \frac{a_{i,j}b_i}{\sum\limits_{j'=1}^{N^2} a_{i,j'}x_{j'}}$$

If we write the scheme in a vectorial and multi-step form

1 $b^f := Ax^{(k)}$ 2 $b^q := b./b^f$ (punctual division)

$$3 x^b = A^T b^q$$

4 s_j = ∑_i a_{i,j}
5 x^(k+1) = x^(k). * x^b./s (product and division are made elementwise)

The goal of a reconstruction iterative scheme is to minimize the distance D(b, Ax). For instance the least-squares method proposes to minimize the euclidean distance

$$D_1(b,Ax) = \sum_i \left(\sum_j a_{i,j}x_j - b_j\right)^2.$$

Note that using this distance leads to the normal equations.

The Bayesian methods are similar, but they add an extra penalty term D_2 to the objective function

$$J_{\beta}(x) = D_1(b, Ax) + \beta D_2(x)$$

with the constant $\beta \ge 0$ set up by the user. Sometimes D_2 can be the distance between the current image and a prior image model p. In this case the objective function is

$$J_{\beta}(x) = D_1(b, Ax) + \beta D_2(x, p).$$

The cross-entropy or Kullback-Leiber distance is defined as it follows

$$S(u,v) = \sum_i u_i \log(u_i/v_i) - u_i + v_i.$$

Note that minimizing S(b, Ax) is equivalent to minimizing the log-likelihood function I(x) described above. So we minimize

$$J_{\beta}(x) = S(b, Ax) + \beta S(x, p).$$

Minimizing this function leads to the iterative scheme:

$$x_j \leftarrow \frac{x_j}{\sum_{i'} a_{i',j}} \left[\sum_i \frac{a_{i,j} b_i}{\sum_{j'} a_{i,j'} x_{j'}} - \beta \log(x_j/p_j) \right]$$

This scheme is called MXE1 and converges provided the non-negativity Kuhn-Tucker conditions

$$\sum_{i} \frac{a_{i,j}b_i}{\sum_{j'} a_{i,j'}x_{j'}} > \beta \log(x_j/p_j)$$

so for β too large this condition is violated.

Another iterative scheme for solving the optimization problem is

$$x_j \leftarrow p_j \exp\left[-\frac{1}{\beta}\left(\sum_i a_{i,j} - \sum_i \frac{a_{i,j}b_j}{\sum_{j'} a_{i,j'}x_{j'}}\right)\right]$$

this scheme is called MXE2. MXE2 satisfies the non-negativity constraint for all $\beta > 0$.

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Essential bibliography





Catana C., Drzezga A., Heiss W.-D., Rosen B.R. , *PET/MRI for Neurologic Applications*, J Nucl Med 2012

Hofmann M., Pichler B., Schlkopf B., Beyer T. Towards quantitative PET/MRI: a review of MR-based attenuation correction techniques, Eur J Nucl Med Mol Imaging, 2009

Schulz V., Torres-Espallardo I., Krombach G. A. et al. Automatic, three-segment, MR-based attenuation correction for whole-body PET/MR data, Eur J Nucl Med Mol Imaging 2011