

# Fast CSD

Problem is to minimise per iteration:

$$F(f_n) = \|Mf_n - s\|^2 + \lambda \|H_{n-1}f_n\|^2$$

Where  $M$  maps current FOD SH coefficients  $f_n$  to DW signals  $s$ , and  $H_{n-1}$  maps FOD SH coefficients  $f_n$  to amplitudes along set of negative directions identified in previous iteration (i.e. the matrix formed by the rows of  $H$  for which  $Hf_{n-1} < 0$ , where  $H$  maps FOD to amplitude along a dense set of (300) directions.

Solve by differentiating and setting to zero:

$$\begin{aligned} \Rightarrow \frac{\partial F}{\partial f_n} &= 2M^T(Mf_n - s) + 2\lambda H_{n-1}^T H_{n-1}f_n = 0 \\ (M^T M + \lambda H_{n-1}^T H_{n-1})f_n &= M^T s \end{aligned}$$

Define  $Q = M^T M + \lambda H_{n-1}^T H_{n-1}$ , which by construction is a square positive-definite symmetric matrix of size  $n_{SH} \times n_{SH}$ . If needed, positive definiteness can be enforced with a small minimum norm regulariser (helps a lot with poorly conditioned direction sets and/or super-resolution):

$$Q = M^T M + \lambda H_{n-1}^T H_{n-1} + \mu I$$

Solve using Cholesky decomposition:

$$Q = LL^T$$

where  $L$  is lower triangular. Then problem can be solved by back-substitution:

$$Ly = M^T s$$

$$L^T f_n = y$$

To speeds things up further, form  $P = M^T M + \mu I$ , and update to form  $Q$  by rank-n update with  $H_{n-1}$ . Form  $M^T s$  initially, and re-use over iterations since it doesn't change. Algorithm then looks like:

- form  $P = M^T M + \mu I$
- for each voxel:
  - form  $z = M^T s$
  - estimate  $f_0$  by solving  $Pf_0 = z$  (note in practice I use a simplified  $l_{max} = 4$  solution here, but I'm not sure it makes a great deal of difference what the initial FOD actually is).
  - then iterate until no change in rows of  $H$  used in  $H_n$ :
    - form  $H_{n-1}$  given  $f_{n-1}$
    - form  $Q = P + \lambda H_{n-1}^T H_{n-1}$  by rank-n update
    - solve  $Qf_n = z$  using Cholesky decomposition



