Appendix 2: Optical Flow Method (OFM) for Tracking 3D Tagged MR Images

Optical flow is a method (OFM) for tracking the motion in an image sequence using intensity gradients imbedded in the image. This approach is robust for tracking cardiac motion in tagged images because of the image intensity gradient provided by the tags. The OFM used in this study is a coarse-to-fine motion estimation technique that is performed in a multi-step procedure. It first estimates a global parametric transformation (translation and rotation) between two images and then, using the global transformation as an initialization, proceeds to an estimation of the local flow (displacement) vector for each point between the two images. The tagged multi-phase images were sequentially pair-wise compared to compute the flow field and vector integrated was performed to calculate the overall local displacement from which the strain tensor was calculated.

Tagged image analysis required pre-processing using a 3D Laplacian filter to eliminate the local image intensity offset and to enhance the edges, making alignment more sensitive to structure as opposed to just intensity [1,2,3]. Within each estimate stage, the image was decimated to create a pyramid of coarse-to-fine resolution levels to improve large displacement tracking. The 3D voxel velocity *u(r)* was then computed for each adjacent pair of images (*L*) by minimizing the sum of the square difference (SSD) between the pair ($L_i\,(t)$, $L_i(t+1)$). The SSD at each voxel is given by:

$$E*\left(\{u\}\right) = \sum\left(L_i\left(r,t\right) - L_i\left(r+u\left(r\right),t+1\right)\right)^2 \quad (1)$$

Where L_i is the Laplacian pyramid image intensity; *i* is the pyramid level; *r* is the 3D spatial location; *u(r)* is voxel velocity.

The minimization of Equation (1) with respect to *u* is an iterative process. Incremental change in velocity is computed between iteration using the Gauss-Newton optimization technique. The error due to incremental change in velocity for the kth iteration is given by:

$$
\begin{aligned}
&E(\{\partial \mathbf{u}\}) = \sum_{\mathbf{x}} (\Delta L_i + (\nabla L_i) \cdot \partial \mathbf{u}(\mathbf{x}))^2 \\
&\Delta L_i = L_i(\mathbf{x}, t) - L_i(\mathbf{x} + \mathbf{u}_k(\mathbf{x}), t+1) \qquad (2) \\
&\mathbf{u}_k \ = \text{ current estimate of flow field} \\
&\nabla L_i = \text{spatial gradient of intensity}
\end{aligned}
$$

For global estimates of motion, the region of interest (ROI) is the entire image, whereas for local estimates, the inspection window is a 3 × 3 region around each pixel. Spatial gradients are computed from forward and backward differences (+/- half the window width) and then averaged. The incremental estimate ∂u is computed and added to the current estimate u_k to obtain a new estimate u_{k+1}. This process is repeated for a fixed number of iterations or until there is convergence, which is tested using the SSD. When there is no reduction in the SSD, the process moves to the next pyramid level. This is performed sequentially, in coarse to fine order, through each level of the pyramid and provides an initial estimate for the succeeding level [4].

References:

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