Knowledge driven segmentation

In the following, we will detail how the statistical distribution (@1) can be used to enhance level set basd segmentation process.

To this end, we formulate level set segmentation as a probelm of Bayesian inference, where the segmentation is obtained by maximizing the donditional probability

$$\mathcal{P}(\phi|I) = \frac{\mathcal{P}(I|\phi)(\mathcal{P}(\phi)}{\mathcal{P}(I)} \quad (23)$$

with respect to the level set funciton ϕ , given the input image I

For a given image, this is equivalent to minimizing the negative log-likelihood which is given by a sum of two energies [2] :

$$E(\phi) = \frac{1}{\alpha} E_{cv}(\phi) + E_{shape}(\phi) \qquad (24)$$

with a positive weighting factor α and the shape energy

$$E_{shape}(\phi) = -\log \mathcal{P}(\phi) \qquad (25)$$

Minimizing the energy(24) generates a segmentation process which simultaneously aims at maximizing intensity homogeneity in the separated phases and a similarity of the evolving shape with respect to all the training shapes encoded through the statistical estimator(21)

gradient descent with respect to the embedding funtion amounts to the evolution:

$$\frac{\backslash\mathrm{part}\phi}{\backslash\mathrm{part}t} = -\frac{1}{\alpha}\frac{\backslash\mathrm{part}E_{cv}}{\backslash\mathrm{part}\phi} - \frac{\backslash\mathrm{part}E_{shape}}{\backslash\mathrm{part}\phi} \qquad (26)$$

Which decays exponentially with the distance from the training shape ϕ_i

The invariant shape gradient $\frac{\backslash\mathrm{part}}{\backslash\mathrm{part}\phi} d^2(H\phi, H\phi_i)$ is given by the expression (18) or (2) respectively