Optimization methods for phase estimation in differential-interference-contrast (DIC) microscopy
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The DIC image is formed by the interference of two orthogonally polarized beams that have a lateral displacement (called shear) and are phase shifted relatively one to each other. The resulting image has a 3D high contrast appearance, which can be enhanced by introducing a uniform phase difference between the beams (called bias).

Model: The DIC image formation is described by the polychromatic rotational-diversity model [1,2]

\[ (\eta_{k,\lambda_j})_j = \left( (h_{k,\lambda_j} \otimes e^{-i\phi/(\lambda_j)}) \right)^2 + (\eta_{k,\lambda_j})_j, \quad k = 1, \ldots, K; \ell = 1, 2, 3; j \in \chi \]

- \( k \) is the index of the rotation of the specimen w.r.t. the horizontal axis, \( \ell \) is the index denoting one of the RGB channels and \( j = (\mu, \nu) \) is a 2D-index varying in the set \( \chi = \{1, \ldots, M\} \times \{1, \ldots, P\} \)
- \( \lambda_j \) is the \( \ell \)-th observation wavelength
- \( h_{k,\lambda_j} \in \mathbb{R}^{MP} \) is the \( \ell \)-th component of the \( k \)-th observed image \( \alpha_k = (h_{k,\lambda_j}, h_{k,\lambda_j}, h_{k,\lambda_j}) \in \mathbb{R}^{MP \times 3} \)
- \( e^{-i\phi/(\lambda_j)} \in \mathbb{C}^{MP} \) is the unknown phase vector and \( e^{-i\phi/(\lambda_j)} \) is defined by \( (e^{-i\phi/(\lambda_j)})_j = e^{-i\phi/(\lambda_j)} \)
- \( \eta_{k,\lambda_j} \in \mathbb{C}^{MP} \) is the discretization of the continuous DIC Point Spread Function
- \( \eta_{k,\lambda_j} \in \mathbb{R}^{MP} \) is the noise corrupting the data, \( \eta_{k,\lambda_j} \sim \mathcal{N}(0, \sigma^2_{k,\lambda_j}) \).

Problem: given the rotationally diverse images \( \alpha_1, \ldots, \alpha_K \), retrieve the phase vector \( \phi \) by solving

\[
\min_{\phi \in \mathbb{R}^{MP}} J(\phi) \equiv J_0(\phi) + J_{TV}(\phi),
\]

- \( J_0(\phi) = \sum_{k=1}^{K} \sum_{j \in \chi} \left( (h_{k,j} - (h_{k,j} \otimes e^{-i\phi/(\lambda_j)})_j^2 \right) \) is the nonconvex least-squares term
- \( J_{TV}(\phi) = \mu \sum_{j \in \chi} (\mathbb{D}^j)^2 + (\mathbb{D}^j)^2 + \sigma^2 \) is the total variation (TV) functional, where \( \mu > 0 \) is the regularization parameter and \( \delta \geq 0 \) is the smoothing parameter (\( \delta = 0 \to \) standard TV).

Convergence and numerical results

Convergence: Any limit point of Algorithm 1 and 2 is stationary for problem (P). Since \( J \) satisfies the Kurdyka-Lojasiewicz property, Algorithm 1 converges to a limit point; the same result can be proved for Algorithm 2 when the proximal point is computed exactly [4].

Results: for both objects, cone (top row) and cross (bottom row), \( K = 2 \) DIC images have been generated.

The parameters of the methods have been tuned as follows: \( \rho = 0.5, \omega = 10^{-4}, m = 4, \alpha_{min} = 10^{-5}, \alpha_{max} = 10^{2}, \tau = 10^{2} - 1, \phi(0) = 0 \).

The methods are compared with the Polak-Ribiere conjugate gradient method equipped with the strong Wolfe conditions (PR-SW) and a linesearch based on polynomial approximation (PR-PA) [1].

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