Diverse imaging with sparsity priors

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Compressed imaging methods are usually directed toward recovery from undersampled data. However, sparsity priors are also applicable when there are plenty of samples, but the signal is buried under extreme noise and low- or band-pass filtering. In such cases, diversity, i.e. capturing multiple images and combining, often results in better overall reconstruction quality. Fluorescence microscopy methods such as 3Phase, HiLo, etc. fall under this category. Here, for the first time to my knowledge, I propose a general approach for combining the diverse images while exploiting a sparsity prior.

Let \( f \) and \( g_j \) (\( j = 1, \ldots, N \)) denote the object and \( N \) measurements, respectively. We assume a linear forward model for the \( j \)-th measurement as \( g_j = H_j f_j \), where \( H_j \) is the forward operator. The object estimate \( \hat{f} \) is obtained as

\[
\hat{f} = \arg\min_{f} \Psi(\hat{f}), \quad \text{where} \quad \Psi(\hat{f}) = \sum_j w_j \| g_j - H_j \hat{f}_j \|^2 + \epsilon \Phi(\hat{f}),
\]

\( \| . \|^2 \) is the \( L_2 \) norm, \( w_j \) is a weight term expressing our confidence in the \( j \)-th measurement, \( \epsilon \) is a regularization parameter, and \( \Phi(\hat{f}) \) is the regularizer function.

Below are simulated examples of an original object (top left) imaged with severe blur (mid- and low-NA at top center and right, respectively) and noise (SNR=30dB). The bottom row shows the compressive reconstructions from the mid (left) and low (center) NA, respectively. In the bottom right, the diverse compressive reconstruction, according to (1) with \( w_1 = w_2 = 1 \) and \( \Phi(\hat{f}) \) as the total variation (TV) operator, shows better behavior in the regions of smooth gradient (around the face.)

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