A convergent least-squares regularized blind deconvolution approach

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Keywords. Blind deconvolution, Regularization, Least squares problems, Optimization methods.

Image deconvolution is an extremely prolific field in the community of mathematicians working on inverse problems and optimization methods. Most of the resulting works deal with the well-posed discrete problem in which the blurring matrix is assumed to be known and the goal is to find a good approximation of the unknown image by contrasting the high ill-conditioning due to the compactness of the continuous operator. However, in many real applications the blurring matrix is not completely known due to a lack of information on the acquisition model and/or to external agents which corrupt the measured image (atmospheric turbulence, thermal blooming, ...). This situation is known as blind deconvolution and is a very actual field and a much more challenging problem than the image deconvolution one, due to the strongly ill-posedness caused by the non-uniqueness of the solution. Most strategies to approach this problem are based on a simultaneous alternating recovery of both the image approximation and the point spread function (PSF) of the acquisition system.

The aim of this work is to present a new and efficient optimization method for the solution of blind deconvolution problems with data corrupted by Gaussian noise, which can be reformulated as a constrained minimization problem whose unknowns are the point spread function (PSF) of the acquisition system and the true image. Since we assume the noise corrupting the measured data to have a Gaussian nature, the objective function we consider is the weighted sum of the least squares fit-to-data discrepancy and possible regularization terms accounting for specific features to be preserved in both the image and the PSF. The solution of the corresponding minimization problem is addressed by means of a proximal alternating linearized minimization algorithm, in which the updating procedure is made up of one step of a gradient projection method along the arc and the choice of the parameter identifying the steplength in the descent direction is performed automatically by exploiting the optimality conditions of the problem.

In particular, the starting point of this work is a proximal alternating method (PALM) recently proposed by Bolte et al. [1] for a more general class of nonconvex and nonsmooth minimization problems, in which the parameters defining
the method are fixed by using the Lipschitz constants of the partial gradients of the least-squares plus regularizations part of the objective function. Convergence of the resulting sequence to a stationary point is ensured by the Kurdyka-Lojasiewicz property [2-4]. Unfortunately, the choice of the algorithm parameters equal to the Lipschitz constants often lead to very small steps, with a result of a very slow convergence of the related sequence toward the critical point. This weak point exhibited by PALM algorithm gives space for improvements.

In this work we exploit the possibility to select parameters larger than the Lipschitz constants of the partial gradients in order to achieve a faster convergence of the method to the critical point. Moreover, for the specific case of blind deconvolution, we extend the convergence results proved in [1] and propose a backtracking procedure to automatically select the algorithm parameters based on a measure of the optimality condition violation. Several numerical experiments with different images, PSFs and combinations of regularization terms validate the effectiveness of the proposed iterative method and show that the new variation of the method strongly reduces the number of iterations required by the PALM algorithm, and provides comparable results with respect to other state-of-the-art methods, leaving also space for further improvements.

References