Enhancing the performance of the simultaneous iterative reconstruction technique by adaptive relaxation factors

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In numerical reconstruction of tomographic data, one of the great benefits of algebraic methods is the possibility to include *a priori* information to constrain the calculation at each iterative cycle, as e.g. in discrete tomography [1]. One the other hand huge computational effort is needed, which requires effective algorithms. Nowadays, the simultaneous iterative reconstruction technique (SIRT) is often employed [2, 3, 4], of which the relaxation parameter λ is central feature. It controls the fraction by which a correction is applied to the intermediate solution of a given iteration cycle. However, the proper choice of λ decides on the stability of the algorithm, since values that are too large will not lead to convergence. Though Herman und Lent [3] have given detailed instructions how to choose the relaxation factor, more recent literature generally advises to take it as constant [5, 6]. But choosing λ in such a heuristic way is unsatisfactory as a proper choice depends on the individual properties of the data (e.g. noise [4], number of projections etc.).

There are suggestions in the literature to adapt the relaxation factor to the iteration process [7, 3, 8]. Bissessur und Peyton [8] proposed to increase λ by a factor (to be chosen beforehand) as long as the process stays stable and to decrease it by another factor as soon as instability is observed. As this strategy leads to an exponential increase of $\lambda$the reconstruction is very likely to become temporally unstable. Therefore, it might be better to have a more gentle, e.g. linear, increase of the relaxation factor. In the present work the convergence behavior of SIRT will be tested, too, for the case that is increased by adding (or subtracting, respectively) a certain value (in the following named BP SIRT with addition of the in/decrementing factors/sumands).

The strategies described above have the disadvantage that they adapt to the reconstruction only if it becomes unstable and then re-adjust λ in a heuristic manner. However, a more advanced route can be found, if one recalls that the SIRT algorithm aims at minimizing the difference between experimental and the calculated projections. Reaching this aim can be enforced by recalculating λ at each iteration cycle such, that the norm of the residual of the subsequent cycle is minimized. As this strategy does not rely on any input parameters it can be regarded as a truly adaptive SIRT (ASIRT).

For testing, four data sets have been used in comparison: a Shepp-Logan phantom (512$\times$512 pixels, 181 projections, 1° steps, no noise, [9]); a HAADF STEM tilt series of Ru-Se catalyst particles on carbon black (FEI Tecnai F20, 200 kV, 1024$\times$1024 pixels, -74° – +74°, 2° steps, [10]); ZLF TEM tilt series on a similar sample (Zeiss LIBRA 200 FE, 200 kV, 1536$\times$1536 pixel, -72° – +72°, 1° steps, [11]); magnetite crystals in bacteria (LIBRA 200 FE, 2048$\times$2048 pixel, -65° – +62, 1° steps, [12]).

The flavors of SIRT described here have been implemented on a GPU and a qualitative comparison of the results is shown in Fig. 1 (a quantitative comparison will be published elsewhere [13]). It can be observed that the contrast of the images after 15 iteration cycles is best in case of ASIRT, followed by ordinary SIRT. Compared to ordinary SIRT, ASIRT reaches a given level of the residual norm up to 300 % faster which regains the additional computational efforts for ASIRT. But not only the speed of convergence is higher also the final residual norm is the lowest reached. However, the most important advantage is that it is no longer necessary to find a proper relaxation factor by trial and error before starting the reconstruction process.

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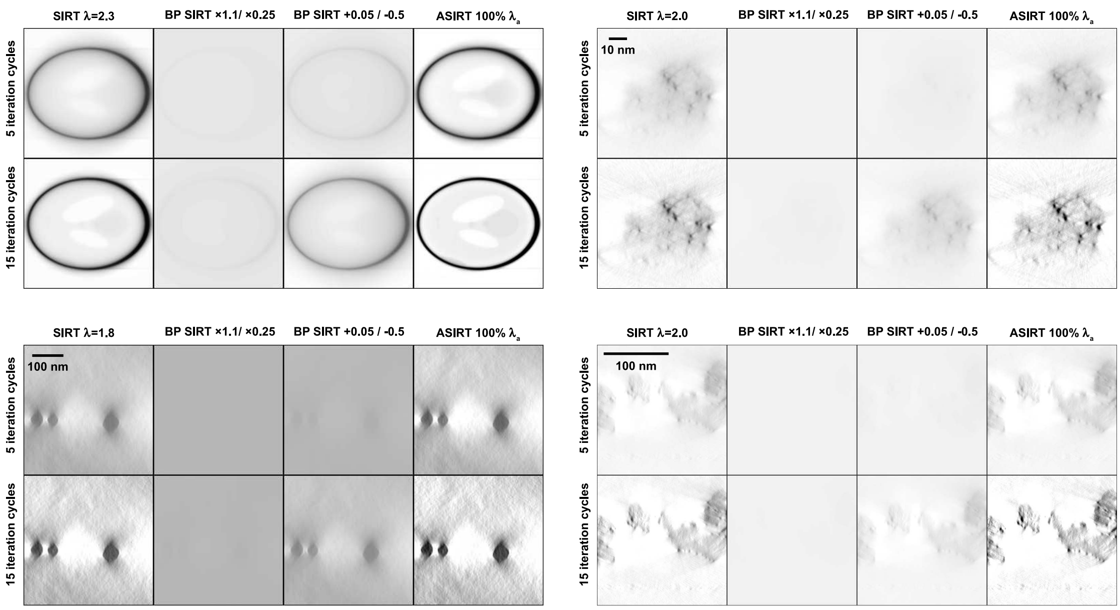

Figure 1. Qualitative comparison of the different reconstruction approaches for four example data sets. For each set the central part (to make structural details better visible) of a reconstructed slice is shown after 5 and 15 iteration cycles of the four SIRT variants. The eight images for each set are reproduced using the same look up table. Only in the case of the phantom a gamma value of 3 has been used to make the interior of the model skull better discernible. After 15 iteration cycles, ASIRT calculations reach the best contrast for all examples.

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