

INSTITUTE OF MICROELECTRONICS

NSSC - Exercise 3

Group 4

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Submission: December 15, 2019

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1 Conjugate Gradients Implementation

For symmetric positive definite matrices A, the A-norm of the error decreases monotonically with increasing iteration number.[1] One can observe this behaviour in our own implementation in Fig.2. In exact arithmetic, the residual should hit it's minimum after approximately n iterations, where n stands for the dimension of the solution vector x which is roughly 5500 in our case. This is as well shown in our plot in Fig.1. After 5500, the residual experiences no significant changes any more. After this point, the minimum is essentially reached. The oscillations that can be observed afterwards are results of the numerical discretization and finite resolution inherent to computer precision. In general, it can be assumed that the minimum point is not exactly represented in the floating point representation of the computer.

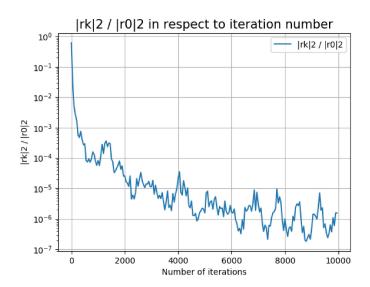


Figure 1: Normed residual of our implementation as a function of number of iterations

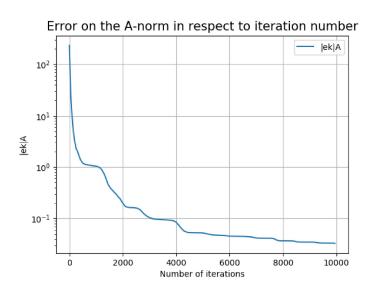


Figure 2: A-norm of the error as a function of number of iterations

Note that for readability reasons, we only plotted every 50^{th} value. Please take into account, that the existing data files will be overwritten once the program is executed and will therefore not deliver the same plots as below when called by the python script. However, a backup containing the data for a run with 10000 iterations is provided in the subfolder $./Abgabe_1/data_10000it/$.