Ultrasound Transmission Tomography Using Algebraic Reconstruction Techniques

Igor Peterlík, Radovan Jiřík

UBMI FEKT VUT Brno

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The problem

- having large overdetermined linear system Ax = b, find a solution minimising ||Ax - b||
- the matrix is sparse, however the number of equation can be large (hundreds of thousand)

The Methods

- classical approach:
 - Least Mean Squares
 - Minimisation Techniques
- alternative: Kaczmarz Method

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- · the solution is a point in the space
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- the classical Kaczmarz method does not converge every time to the least square solution
- extension: in each outer iteration, first the right-hand side vector is corrected
- the correction is performed as orthogonal projection of the initial RHS onto the columns



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Original vs. Extended



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Further Improvement

Regularisation Technique

- usual technique for "smoothing" the solution
- special square matrix added to the system
- directly incorporated into the Kaczmarz method (adding m equations)





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The Idea

- both the original and extended method are strictly sequential, since the computation in inner k-th iteration depends on the (k - 1)-th inner iteration
- the straight forward possibility is to partition the matrix into blocks, which are then processed separately (in parallel)
- partitioning is static and regular

Partitioning

- the original KM: the matrix is partitioned into row blocks, the inner iterations are performed separately in each block
- the extended KM:
 - 1st phase: column partitioning
 - 2st phase: row partitioning

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Partitioned Original KM

Partitioned Kaczmarz



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Partitioned Extended KM

Partitioned Extended Kaczmarz



Measurements

Data

- the experiments were performed on both synthetic (127400 eq.) and phantom data (81000 eq)
- since the partitioning modifies the inner data-dependency inside the method, accuracy and convergence were analysed as well

Accuracy

- the accuracy was measured by the residual r = ||Ax b|| which proved to be experimentally equivalent to the image difference $\Delta(a, b) = \sqrt{\sum_{m} \sum_{n} [a_{ref}(m, n) - a(m, n)]^2}.$
- the stopping criterium is given by relative residual $r^{(k)}/r^{(k-1)}$

Convergence

• the relation between the number of the outer iterations and the number of partitions

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Number of partitions versus the residual



partitioning improves the accuracy of the original Kaczmarz method

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Number of Iterations vs. Partitioning



Analysis

- the convergence depends on the number of the partitions
- original method: for 2,4,8,16 the convergence get better, for larger number of the partitions, increasing number of the outer iteration
- extended method: only for 2 is better, for larger number of the partitions get still worse

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Parallel Efficiency of Original Method



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Conclusion

- comparison of the original and the extended version: the extended do better job
- partitioning scheme makes sense for the original method:
 - phantom data: max 15× speed-up with 16 blocks (on 16 CPUs)
 - synthetic data: max $28 \times$ speed-up with 16 blocks (on 16 CPUs)
- not too much for the extended:
 - phantom data: max 2.3× speed-up with 4 blocks (on 4 CPUs)
 - synthetic data: max 2.6× speed-up with 4 blocks (on 4 CPUs)
- when the accuracy of the original method is sufficient, then the parallelisation can be applied with this method

Future Work

- larger set of equations (including the reflected signals)
- relaxation and regularisation extensions

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