Sparse QR Factorizations in multicore sauce

Alfredo Buttari, CNRS-IRIT Toulouse MUMPS Users Group Meeting, April 2010



Multifrontal QR, introduction

The Multifrontal QR method builds upon the equivalence between the R factor and the Cholesky factor of $A^T A$

From $A^T A = LL^T$ to A = QR

Under the assumption that A is a <u>Strong Hall</u> matrix, L and R have exactly the same structure.

A **Multifrontal** method can be used relying on the elimination/assembly tree generated for the Cholesky factorization of $A^{T}A$

Multifrontal QR

- I. Analysis: symbolic computations to reduce fill-in, compute elimination tree, symbolic factorization, estimates etc.
- 2. Factorization: compute the Q and R factors
- 3. Solve: use Q and R to compute the solution of a problem (e.g. $min_x ||Ax b||_2$)

2. Factorization: compute the Q and R factors



- the tree is processed bottom-up
- a dense frontal matrix is associated to each node
- at each node:
 - I. Assembly: the contribution blocks from the children nodes are assembled into the frontal matrix
 - 2. Factorization: the frontal matrix is factorized (fully or partially)

Different approaches can be used for front factorization:



Option 2 (Strategy 3 in Puglisi's thesis) is the winner.

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- I. contribution blocks are simply appended at the bottom of the father front
- a row permutation must be computed to restore a staircase structure



Multifrontal QR, parallelism



Parallelism

As for the Cholesky, LU, LDL^{T} multifrontal method, two levels of parallelism can be exploited:

- Tree Parallelism: fronts associated to nodes in different branches are independent and can, thus, be factorized in parallel
- Front Parallelism: if the size of a front is big enough, the front can be factorized in parallel

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Parallelism: classical approach



What's wrong with this approach? A complete separation of the two levels of parallelism which causes

- potentially strong load unbalance
- heavy synchronizations due to the sequential nature of some operations (assembly)
- sub-optimal exploitation of the concurrency in the multifrontal
 method
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Parallelism: classical approach

Node parallelism grows towards the root



Tree parallelism grows towards the leaves

fine-grained, data-flow parallel approach

- fine granularity: tasks are not defined as operations on fronts but as operations on portions of fronts defined by a 1-D partitioning
- data flow parallelism: tasks are scheduled dynamically based on the dependencies between them

Both node and tree parallelism are handled the same way at any level of the tree.

Fine-granularity is achieved through a 1-D block partitioning of fronts and the definition of five elementary operations:

- I. activate(front): the activation of a front corresponds to a full determination of its (staircase) structure and allocation of the needed memory areas
- 2. panel(bcol): QR factorization (Level2 BLAS) of a column
- update(bcol): update of a column in the trailing submatrix wrt to a panel
- 4. assemble (bcol): assembly of a column of the contribution block into the father
- clean(front): cleanup the front in order to release all the memory areas that are no more needed



How do we handle all this complexity?

Data-flow programming model [Silc et al. 97]

An instruction is said to be executable when all the input operands that are necessary for its execution are available to it. The instruction for which this condition is satisfied is said to be fired. The effect of Firing an instruction is the consumption of its input values and generation of output values.



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- Firing rule #2: a column can be updated wrt a panel if it is up to date wrt all previous panels





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- Firing rule #3: a node can be activated only if all of its children are already active
- Firing rule #4: a column can be assembled into the father, if it is up-to-date wrt all the preceding panels and the father is active
- Firing rule #5: a column can be factorized if it is fully assembled regardless of the status of the rest of the front



Data-flow programming model [Silc et al. 97]

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Parallelism: scheduling

```
exec_loop .
do
   call get_task()
   select case(task_type)
   case (0)
      exit
   case (1)
      call do_activate(...)
   case(2)
      call do_panel(...)
   case (3)
      call do_update(...)
   case (4)
      call do_assemble(...)
   case (5)
      call do clean(...)
   end select
end do
```

Data-flow programming model [Silc et al. 97]

Due to the above rule the model is asynchronous. It is also self-scheduling since instruction sequencing is constrained only by data dependencies.

Parallelism: scheduling



Parallelism: results



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Parallelism: results



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Parallelism: results



QR-MUMPS

QR-MUMPS: keywords

QR, least-squares, multifrontal, hybrid parallelism, asynchronous, rank-revealing, Fortran, free, open-source

The idea to develop QR-MUMPS stems from:

- the experience accumulated in MUMPS (by Patrick, Jean-Yves and Abdou)
- the enthusiasm (and time) of young researchers (Alfredo, Bora)
- a solid base in the work done by Chiara
- the RTRA project

Done!

COLAMD Ordering, Symbolic Factorization, OpenMP factorization, Singletons Detection, Amalgamation, Fortran 95/2003 software infrastructure, stackless memory management, multiple precisions

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TODO

Solution, Rank Revealing, MPI tree parallelism, MPI front parallelism, reorder tree, front-to-processor mapping, memory consumption minimization, more ordering methods, splitting, in-place assembly flops/memory estimates, matlab interface,out-of-core, numerical preprocessing, C interface, blocking optimality, low-rank approximations, 2-D OpenMP parallelism, memory affinity, scheduling policies, parallel

analysis, partial QR, incomplete QR

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```
do
    write(*,'(" Questions?")')
```

```
if (question) then
     if(have_answer) then
        call give_answer()
     else
        call pretend_the_question_is_ill_posed()
     end if
  else
     write(*,'(" Thank you!")')
     exit
  end if
end do
```

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