PARALLEL PROGRAM DESIGN

Course “Parallel Computing”

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A methodological approach in multiple stages.
The PCAM Approach

Partitioning.
- Decompose computation and data.
- Exhibit opportunities for parallelism by creating many small tasks.

Communication.
- Analyze data dependencies.
- Determine structure of communication and coordination.

Agglomeration.
- Combine tasks to bigger tasks.
- Improve performance of execution on real computers.

Mapping.
- Assign tasks to processors.
- Maximize utilization and minimize communication.
Partitioning

Expose opportunities for parallelism.

- Construct fine-grained decomposition of problem.
  - Domain/data decomposition:
    - Partition data, associate computation to data.
  - Functional/task decomposition:
    - Partition computation, associate data to computation.

- Complementary approaches.
  - Should be both considered.
  - Can lead to alternative algorithms.
  - Can be applied to different parts of problem.

- Avoid replication of computation or data.
  - May be introduced later to reduce communication overhead and to increase the granularity of tasks.
Domain Decomposition

Focus on the decomposition of the data.

- Divide data into small pieces and associate computation.
  - If computation requires several, associate to “main” piece.
  - Communication is required for access to the other pieces.
- Resulting tasks should be of roughly the same size.
  - Otherwise load balancing may become difficult.
- Prefer finer decomposition over coarse ones.
  - Small tasks may be agglomerated in later stage.

Typical for problems with large central data structures.
Functional Decomposition

Focus on the decomposition of the computation.

- Decompose according to the algorithmic structure.
  - Independent computational blocks.
  - Independent loop iterations.
  - Independent (recursive) function invocations.
- Determine data requirements of each task.
  - If requirements overlap, communication is required.

Typical for problems without central data structures.
Partitioning Design Checklist

- Is number of tasks large enough?
  - Order of magnitude larger than processor number.
  - Keeps flexibility for further stages.

- Does number of tasks scale with problem size?
  - Larger problems can be solved with more processors.

- Are the tasks of comparable size?
  - Otherwise load balancing may become difficult.

- Are redundant computations and data avoided?
  - Otherwise scalability may suffer.

- Have alternative partitions been considered?
  - Try both domain and functional decomposition.

Do we have sufficient concurrency?
Communication

Specify flow of information between tasks.

- Describe communication structure by “channels”.
  - Connections between those tasks that produce data and those that consume them.
  - Typically easy to determine for functional decomposition from data flow between tasks.
  - May be complex to determine for domain decomposition due to data dependencies.

- Analyze the usage of channels.
  - Number and sizes of messages flowing through channels.
  - Temporal relationship/dependencies between messages flowing through different channels.

Also a healthy exercise for shared memory programs.
Types of Communication

■ Local versus global:
  □ Communication with a small set of tasks (“neighbors”) or with many other tasks.

■ Structured versus unstructured:
  □ Communication forms a regular structure (tree, grid, . . .) or an arbitrary graph.

■ Static versus dynamic:
  □ Identity of communication partners is known in advance and does not change or depends on runtime data and may vary.

■ Synchronous versus asynchronous:
  □ Producers and consumers cooperate in data transfer or consumer may acquire data without producer cooperation.
Local Communication

Example: Jacobi finite differences method.

\[ X_{i,j}^{t+1} = \frac{1}{8} \left( 4X_{i,j}^t + X_{i-1,j}^t + X_{i+1,j}^t + X_{i,j-1}^t + X_{i,j+1}^t \right) \]

for \( t=0 \) to \( T-1 \) do
  send \( X(i,j) \) to each neighbor
  receive \( X(i-1,j), X(i+1,j), X(i,j-1), X(i,j+1) \) from neighbors
  update \( X(i,j) \)
end
Global Communication

Example: parallel reduction operation.

\[ S = \sum_{i=0}^{n} X_i \]

- **Centralized algorithm:**
  - Single task becomes bottleneck of communication and computation.

- **Sequential algorithm:**
  - Additions are performed one after each other.
Global Communication

Example: parallel reduction operation.

\[ \sum_{i=j}^{n} X_i = X_j + \sum_{i=j+1}^{n} X_i \]

- Decentralized algorithm:
  - Communication/computation are distributed among tasks.
- But still a sequential algorithm.
Global Communication

Example: parallel reduction operation.

\[\sum_{i=j}^{j+k} X_i = \left( \sum_{i=j}^{j+\lceil k/2 \rceil} X_i \right) + \left( \sum_{i=j+\lceil k/2 \rceil+1}^{j+k} X_i \right)\]

- **Decentralized and parallel algorithm:**
  - Up to \(k/2\) additions can be performed in parallel.
Unstructured/Dynamic Communication

Example: finite element method.

- Mesh of points representing a physical object.
  - Simulation of, e.g., the impact of force on the object.
  - Shape of the mesh is modified by the impact.
- Domain decomposition.
  - Unstructured communication: mesh is irregular.
  - Dynamic communication: mesh changes.
Asynchronous Communication

Example: management of a shared data structure.

- A set of “data tasks” manages a shared data structure.
- Data structure is distributed among tasks.
- A set of “computing tasks” produce and consume data.
- Exchange of messages between computing tasks and data tasks for reading and writing the data structure.

Consumption of data decoupled from their production.
Communication Design Checklist

- Do all tasks perform the same amount of communication?
- Does each task communicate only with a few neighbors?
- Can the communication operations proceed concurrently?
- Can the computation operations proceed concurrently?

Do we have the potential for scalability?
Agglomeration

In the previous phases we have developed a parallel algorithm.

- Algorithm not efficiently executable.
  - Large number of small tasks.
  - Large amount of communication.

- Combine tasks to larger tasks.
  - Increase the granularity of tasks.
    - Granularity: the ratio of computation to communication.
  - Still retain design flexibility.
    - Sufficiently many tasks for scalability and mapping flexibility.

- Reduce engineering costs.
  - Avoid effort of parallelization where it does not pay off.
Increasing Granularity: Surface to Volume

- **Before:** granularity $1/4 = 0.25$.
  - 1 local computation operation.
  - 4 data items sent.
- **After:** granularity $16/16 = 1$.
  - 16 local computation operations.
  - 16 data items sent.

**Surface to Volume Effect**

- Typical for domain decomposition.
- Communication proportional to “surface” of subdomain.
- Computation proportional to “volume” of subdomain.
- Surface grows slower than volume.
  - Square: $S/V = 4a/a^2 = 4/a$.

Decreasing surface-to-volume ratio increases granularity.
Increasing Granularity: Replicating Computation

Communication may be decreased by replicating computation.

Example: two algorithms computing a global sum in \( N \) tasks.

\[
\begin{align*}
\text{Time } & 2(N - 1) \text{ resp. } 2 \log_2 N \text{ for performing } N - 1 \text{ additions.}
\end{align*}
\]
Increasing Granularity: Replicating Computation

A replicating algorithm computing a global sum in $N$ tasks.

Time $\log_2 N$ for performing $N \log N$ additions.
Increasing Granularity: Avoiding Communication

Agglomerate tasks that cannot execute concurrently.

Only $N$ agglomerated tasks are needed.
Retaining Design Flexibility

Do not “over-agglomerate”.

- Goal is not a fixed number of tasks.
  - Task number should grow with problem and machine size.
  - Algorithm should remain scalable.
- Goal is not one task per processor.
  - There should be still multiple tasks per processor.
  - If one task is blocked, another one may execute and keep the processor busy.

Agglomeration should not “hardwire” the algorithm to a fixed problem and machine size.
Reducing Engineering Costs

- Try to avoid extensive code changes.
  - One partitioning/agglomeration may be much more difficult to implement than another.
- Try to avoid extensive data structure changes.
  - Conversions from/to data structures given by the context of the parallel application may be cumbersome.

Consider also the costs of development in relation to the expected performance gains.
Agglomeration Design Checklist

- Has communication been reduced (granularity increased)?
- Does computation replication outweigh its costs?
- Does data replication not limit scalability?
- Have tasks still similar sizes?
- Is there still sufficient concurrency?
- Does the number of tasks still scale with problem size?
- Can task number be reduced without limiting flexibility?
- Are the engineering costs reasonable?

Do we have sufficient execution efficiency?
Mapping

We need a strategy for mapping tasks to processors (cores).

- Only a problem for systems with distributed memory or shared memory with non-uniform memory access.
  - On multi-core processors and SMP systems, the automatic placement of tasks to cores by the OS suffices.
- Conflicting goals:
  - Place tasks that are able to execute concurrently on different processors.
  - Place tasks that communicate frequently on the same processor.

The mapping problem is NP-complete, so we can in general only hope for good heuristics.
Types of Mapping

- **Static mappings:**
  - A fixed number of permanent tasks is mapped at program start to processors; this mapping does not change.

- **Load balancing algorithms:**
  - The assignment of permanent tasks to processors is adapted at runtime to keep processors equally busy.

- **Task scheduling algorithms:**
  - Many short-living tasks are created at runtime; a scheduler maps tasks to processors where they run until termination.

Static mapping is usually only sufficient for domain decomposition with structured communication.
Load Balancing: Recursive Bisection

Recursively divide domain into partitions with equal costs.

- **Recursive coordinate bisection:**
  - Recursively cut multi-dimensional grid at longest dimension.
- **Unbalanced recursive bisection:**
  - Choose among partitions the one with lowest aspect ratio.
- **Recursive graph bisection:**
  - Decompose graph according to distance from extremities.
Load Balancing: Local Algorithms

Compare load with that neighbor processors; transfer load if difference gets too big.

Use only local information and that of neighbor processors.
Load Balancing: Probabilistic/Cyclic Mapping

- **Probabilistic mapping:**
  - Map tasks to randomly selected processors.
  - If task number is much larger than processor number, every processor receives about the same amount of computation.
  - Generally leads to high communication.

- **Cyclic mapping:**
  - Map tasks to processors in a cyclic (scattered) mapping.
  - Each of \( P \) processors receives every \( P \)-th task in turn.
  - Similar to probabilistic mapping but more regular structure.
Task Scheduling

Maintain pool of tasks to which all new tasks are added.

- Manager/workers scheme:
  - Manager controls pool; idle workers ask manager for tasks.

- Hierarchical manager/worker scheme:
  - Subsets of workers with own submanagers and subpools.
  - Submanagers interact with manager (and each other).

- Decentralized schemes:
  - Each worker maintains its own task pool.
  - Idle workers request tasks from other workers.

Termination detection may become an issue.
Mapping Design Checklist

- If considering a program where tasks are only created at startup, have you also considered task scheduling?
- If considering task scheduling, have you also considered a program where tasks are only created at startup?
- If considering load-balancing, have you evaluated simpler alternatives such as probabilistic or cyclic mappings?
- If considering probabilistic or cyclic mappings, have you verified that task number is large enough to balance load?
- If considering task scheduling, have you verified that the manager does not become a bottleneck?

Do we have sufficient processor utilization?
General Recommendations

- Be sure to parallelize the actual hotspots of a program.
  - First you must understand where computation time is spent.
- Consider alternatives.
  - Do not just implement the first scheme that comes to mind.
- Remember scalability.
  - You may get more cores available than originally thought.
- But also consider the coding effort.
  - A simple solution may be sufficient as a starting point.
- And do not forget the application context.
  - The parallel code must be integrated into a bigger system.

Ultimately, determining the most efficient parallelization strategy for a given problem may require multiple iterations of performance debugging and optimizing/rewriting the code.