



Faster MPSoC Task Mapping via Symmetry Reduction

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DRESDEN concept





WISSENSCHAFTSRAT



1. Inspirations





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- 2. Problem Statement



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- 3. Symmetry Reduction



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- 4. Representing and Extracting Symmetries



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- 7. Further Research





• Original idea: [Goens et al., 2017]



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- Theoretical foundations: [Holt, 2005] and [East et al., 2019]



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- Theoretical foundations: [Holt, 2005] and [East et al., 2019]
- Important optimizations: [Donaldson and Miller, 2009]







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Want to intelligently map tasks to processing elements





Want to intelligently map tasks to processing elements

Best choice depends on underlying optimality criteria





- Want to intelligently map tasks to processing elements
- Best choice depends on underlying optimality criteria
- Need to perform costly simulation!



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- Generate promising mappings based on previous simulations
- \blacksquare \rightarrow Traverse search space "intelligently"



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 - Partition search space by (partial) symmetry
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- \blacksquare \rightarrow Traverse search space "intelligently"
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 - $\blacksquare \rightarrow$ "Collapse" search space
- Both approaches can be combined!





(a)











(a)









Representing Symmetries: Automorphism Groups





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Representing Partial Symmetries: Partial Automorphism Inverse Monoids





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- Determine Automorphism Group *G*:
 - Transform into "equivalent" vertex colored graph
 - Use nauty [McKay and Piperno, 2014]
- Determine Partial Automorphism Inverse Monoid *M*:
 - Construct search tree of possible generators
 - Prune certain subtrees
 - Not efficient enough in practice







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$$\{(1\ 2), (3\ 4)\} \Rightarrow {\mathsf{Base:}\ [1,3]\atop\mathsf{Strong Generating Set:}\ \{(1\ 2), (3\ 4)\}}$$



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- Orbits partition search space
- Reduce search space to set of canonical orbit representatives



$$G = \langle \{ (1 \ 2 \ 3 \ 4), (2 \ 4) \} \rangle$$




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Determining all orbits usually too costly



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- Iteratively determine and hash canonical representatives
- 1: **procedure** ORBIT_IDENTIFIER(*t*, reprs)
- 2: repr \leftarrow TMOR(t)
- 3:
- 4: **if** repr \notin reprs **then**
- 5: Append repr to reprs
- 6: end if
- 7:
- 8: **return** index of repr in reprs
- 9: end procedure



The TMOR Problem II: Finding Canonical Orbit Representatives

First approach: explicit orbit enumeration

```
1: procedure TMOR_ORBIT(t, G = \langle S \rangle)
        orbit \leftarrow \{\}
 2:
 3:
        while orbit is changing do
 4:
             for t' \in \text{orbit}, g in S do
 5:
                 orbit \leftarrow orbit \cup \{g(t')\}
 6:
             end for
 7:
 8:
        end while
 9:
         return min(orbit)
10:
```

11: end procedure



The TMOR Problem II: Finding Canonical Orbit Representatives

Second approach: group enumeration

1: procedure TMOR_ITERATE(t, G)

```
2: repr \leftarrow t
```

```
3:
```

```
4: for g \in G do
```

5: **if**
$$g(t) < \operatorname{repr}$$
 then

6: repr
$$\leftarrow g(t)$$

- 7: end if
- 8: end for

9:

- 10: return repr
- 11: end procedure



The TMOR Problem II: Finding Canonical Orbit Representatives

- Third approach: local search
- 1: procedure TMOR_LOCAL_SEARCH($t, G = \langle S \rangle$)

```
2: repr \leftarrow t
```

```
3:
```

4: while repr is changing do

```
5: \operatorname{repr} \leftarrow \min(\{g(\operatorname{repr}) \mid g \in S\})
```

- 6: end while
- 7:
- 8: return repr
- 9: end procedure



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- Separable architectures: *direct products* $G = G_1 \times G_2$, $|G| = |G_1| \cdot |G_2| \cdots |G_n|$
- Hierarchical architectures: wreath products $G = G_{\text{proto}} \wr G_{\text{super}}, |G| = |G_{\text{proto}}|^{\text{deg}(G_{\text{super}})} \cdot |G_{\text{super}}|$



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- Solve TMOR problem separately for components
- Decomposition specified by user or detected automatically
- Idea based on [Donaldson and Miller, 2009]



Experiments run for: Exynos



Experiments run for: Exynos , Parallella





Experiments run for: Exynos , Parallella , HAEC





Experiments run for: Exynos , Parallella , HAEC , Kalray





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CHAIRFOR COMPILER CONSTRUCTION

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Performance of orbit enumeration depends strongly on k



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Lessons learned:

- Performance of orbit enumeration depends strongly on k
- Local search can be fast and accurate
- Decomposition can be very powerful
- mpsym outperforms GAP



Heuristic local search



- Heuristic local search
- Partial Automorphism discovery



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- Partial Automorphism discovery
- Inverse Monoid enumeration



- Heuristic local search
- Partial Automorphism discovery
- Inverse Monoid enumeration
- \blacksquare Interfacing GAP and C++





Thank you for your attention!


References



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