

#### THE POSSIBILITIES ARE INFINITE

## Parallelization of the Molecular Orbital Program MOS-F

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## Plan of talk

 Introduction to MOS-F Parallelizing MOS-F Choice of eigensolver Performance evaluation on an IA32 cluster Conclusions

## Introduction to MOS-F

MOS–F is a semiempirical molecular orbital package for spectroscopy developed by A. Matsuura of Fujitsu Laboratories

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#### Main Features

- Semiempirical molecular orbital methods INDO/S, CNDO/S, CNDO/S2, CNDO/S3 and CNDO/2
- Calculations of
  - UV-visible spectrum
  - Electron density and dipole moment in excited states
  - Electron density and dipole moment difference between the ground and the excited state
  - Frequency-dependent polarizability ( $\alpha$ ), first hyperpolarizability ( $\beta$ ) and second hyperpolarizability ( $\gamma$ )
- Coordinate input from Gaussian Z-matrix or MOPAC internal coordinates
- WinMOPAC IO interface

## **Introduction to MOS-F: Computational limitations**



Two major components of the computational time for typical MOS-F calculations:

- Determination of all eigenvalues and eigenvectors of a real symmetric matrix
- Matrix multiplication

*To perform MOS-F calculations efficiently: Optimized eigensolver and matrix multiplication routines are required* 

- Large memory requirements: ~ n<sup>2</sup>
  (*n* is number of basis functions)
- Calculations restricted to relatively small molecules (currently  $n \le 5,000$ )
- *n* must be tens of thousands to develop new materials or pharmaceutical products

#### For large systems: Data distribution is needed

Computational profile of crambin, *n*=1,622

Matrix multiplication: 62.4% Eigensolver: 37.1%

Computational profile of poly-azomethyne, n=807

Eigensolver: 85.8%

## **Introduction to MOS-F: Computational limitations**



**Required Memory** 

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## **Parallelization approaches**

Two different approaches to parallelizing MOS-F:

Introduce parallelism through a set of localized code changes, with ScaLAPACK eigensolvers and matrix multiplication being used (LP-MOS-F)

- simple implementation
- high single-processor performance
- but, substantial memory requirements

#### Overall data distribution approach (DD-MOS-F)

 memory usage is reduced significantly
 both computational work and memory scale with number of processors



Required Memory for Crambin (n=1622) with DD-MOS-F



## **Choice of eigensolver: LAPACK**

#### Eigensolvers used in the testing procedure

Name	Matrix storage	Algorithm
MOS-F eigensolver (EISPACK)	Packed	Rational QL + inverse iteration
DSY(P)EV	Full (Packed)	Implicitly shifted QR
DSY(P)EVX	Full (Packed)	Implicitly shifted QR or bisection + inverse iteration
DSY(P)EVD	Full (Packed)	Divide and conquer (DC)
DSYEVR	Full	Relatively robust representations (RRR)

Use of packed storage results in large increase in CPU time over full storage

*Two LAPACK eigensolvers RRR and DC show consistently better performance than the original MOS-F code* 

**Comparative performance of LAPACK solvers** 



Input matrix: 4225 x 4225 Machine environment: 733 MHz Pentium III

## **Choice of eigensolver: ScaLAPACK**

#### Parallel eigensolvers used in the testing procedure

Name	Matrix storage	Algorithm
PDSYEV	Full	Implicitly shifted QR
PDSYEVX	Full	Bisection + inverse iteration
PDSYEVD	Full	Divide and conquer (DC)

The parallel QR eigensolver PDSYEV is not competitive in terms of parallel performance with the other parallel eigensolvers

There is little to choose between PDSYEVX and PDSYEVD on the basis of wall time performance

#### Parallel performance of ScaLAPACK eigensolvers



Input Matrix: 4225 x 4225 Machine environment: A cluster of four dual-processor 733 MHz Pentium III nodes connected via Myrinet

## **Choice of eigensolver: ScaLAPACK**

- For inverse iteration methods, eigenvalues that are close in value are "clustered" onto the same processor
  - Orthogonalization of the set of eigenvectors corresponding to these eigenvalues can then be performed without communication
  - This can lead to load imbalance and hence poor parallel scaling
- Parallel performance of PDSYEVX is therefore sensitive to the choice of orthogonalization tolerance parameter ORFAC
- The choice of ORFAC to minimize clustering but at the same time retain acceptable accuracy is not trivial
- For this reason, divide and conquer methods are "safer"



Effect of Reothogonalisation on Scaling of PDSYEVX

## **Choice of eigensolver: Memory requirements**



The memory required for the fast parallel eigensolvers is much greater than for the current MOS-F code

**PDSYEVX**: Requires a fixed  $N^2$  array on each processor to ensure that orthogonalisation of eigenvectors is not limited by available workspace

**PDSYEVD:** Memory requirement is high but scales with increasing processor count due to completely distributed data

Our choice: Use DSYEVR (relatively robust representation) on a single node and PDSYEVD (divide and conquer) in parallel

## Parallelization approaches: Key features

Features	DD-MOS-F	LP-MOS-F
Requires separate source code	Yes	Νο
Standard mathematical libraries	BLAS, ScaLAPACK	BLAS, LAPACK, ScaLAPACK
Linear algebra routines used	PDSYEVD (block size=1)	DSYEVR, PDSYEVD DGEMM, PDGEMM
Data distribution	Overall	Local
Memory use compared with original MOS-F	Lower	Higher

 A block size of 1 is used in DD-MOS-F. This is compatible with the data distribution scheme used in the code, but is not optimal in terms of computational performance

 The optimal block size can be used in LP-MOS-F at the expense of higher memory usage (due to local data redistribution)

#### **Performance evaluation: Machine environment**

Front-end server Dual 2.4 GHz Pentium Xeon, 1 GB memory, 120 GB disk SCore parallel environment Intel and Portland Group compilers and DDT parallel debugger



#### Gigabit Ethernet switch

Compute nodes
 Dual 2.4 GHz Pentium
 Xeon with 2 GB memory

Myrinet 2000 interconnect

## **Performance evaluation: Benchmarks**

Jop	Formula	Number of Atoms	Number of Basis Functions	Method
crambin	$C_{202}H_{314}N_{55}O_{64}S_{6}$	641	1622	CNDO/S SCF

dof	Formula	Number of Atoms	Number of Basis Functions	Method
Poly- azomethyne (azm)	C <sub>153</sub> H <sub>111</sub> N <sub>21</sub>	285	807	CNDO/S CI (80,80)

#### **Performance evaluation: Serial performance**

LP-MOS-F outperforms DD-MOS-F on a single node due to the use of square rather than packed matrix storage combined with fast LAPACK and BLAS libraries



**Compiler**: pgf90 using *-fast -tp p7 –Mdalign* optimization LP-MOS-F uses **LAPACK 3.0** and **Intel MKL 5.2** for BLAS

#### **Performance evaluation: Parallel performance**

Parallel performance was measured on the IA32 cluster using different MPI implementations and interconnects:

- ✤ LAM 6.5.9
- MPICH 1.2.4
- MPICH 1.2.4 implemented under SCore 5.4.0 using Gigabit Ethernet network
- MPICH 1.2.4 implemented under SCore 5.4.0 using Myrinet 2000 network
- MPICH-GM 1.2.4..8a under GM 1.6

**PGI** compilers (pgf77, pgf90) with *-fast –tp p7 –Mdalign* optimization were used in all cases

## Performance evaluation using various MPI implementations

Parallel Scaling of DD-MOS-F. Poly-azomethyne



Performance evaluation: Parallel scaling of crambin benchmark

Crambin 14.00 12.00 **DD-MOS-F** Myrinet 10.00 **DD-MOS-F Ethernet** ---- DD-MOS-F LAM 8.00 6.00 -LP-MOS-F LAM 4.00 - Ideal 2.00

8

9

10 11 12

DD-MOS-F vs LP-MOS-F. Parallel Scaling.

Speed-up

0.00

2

3

5

Nodes

1

Performance evaluation: Parallel performance of crambin benchmark

#### DD-MOS-F vs LP-MOS-F. Parallel Performance. Crambin. SCore Myrinet



# Performance evaluation: Parallel scaling of poly-azomethyne benchmark

#### DD-MOS-F vs LP-MOS-F. Parallel Scaling. Poly-azomethyne



Performance evaluation: Parallel performance of poly-azomethyne benchmark

> DD-MOS-F vs LP-MOS-F. Parallel Performance. Poly-azomethyne. SCore Myrinet



# Performance evaluation: Communication costs



IA32 cluster, 8 nodes, SCore Myrinet

#### **Performance evaluation: Summary**

- The distributed-data version DD-MOS-F scales better than the locally parallelized LP-MOS-F code under all tested networks
- Poor scaling of LP-MOS-F is mainly caused by the need to redistribute data locally and by the limited scalability of the divideand-conquer eigensolver employed
- LP-MOS-F outperforms DD-MOS-F code for all benchmark jobs on any number of processors from the tested range
- Using Myrinet and Gigabit Ethernet under the SCore parallel environment provides good parallel performance
- ✤ In contrast, LAM-MPI and MPICH are not utilizing the low latency and high bandwidth of the Gigabit Ethernet network very well

## Conclusions

Two approaches to parallelizing the semiempirical code MOS-F were proposed

- Care must be taken in the choice of eigensolver to be used, as routines based on inverse iteration can scale very poorly under certain conditions
- The distributed-data parallel version of MOS-F has the advantage that memory usage and computational time scale with increasing number of processors and this will make calculations on molecules with thousands of atoms feasible
- ✤ The locally parallelized version is more efficient in computational time for small processor counts but requires more memory and scales poorly. This version would be useful for systems comprising of a moderate number of atoms
- The choice of MPI implementation is shown to have a dramatic effect on the parallel performance of MOS-F, with the "standard" LAM/MPI and MPICH performing poorly. In contrast, MPICH under the SCore parallel environment and MPICH-GM over Myrinet scale well

## **Further work**

 Combine the best features from LP-MOS-F and DD-MOS-F

- Use of LAPACK and BLAS with full matrix storage on a single processor if memory permits
- Use of ScaLAPACK with block size governed by available memory
  - For small systems, use the LP-MOS-F approach
  - For large systems, use the DD-MOS-F approach