

# OPT++

## A Toolkit for Nonlinear Optimization

Juan Meza

High Performance Computing Research  
Lawrence Berkeley National Laboratory

<http://crd.lbl.gov/~meza>

# Outline

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- ❖ Introduction
- ❖ Classes of Optimization Solvers
- ❖ Setting up a Problem and Algorithm
- ❖ Example 1: Unconstrained Optimization
- ❖ Example 2: Constrained Optimization
- ❖ Parallel optimization techniques
- ❖ Example application
- ❖ Summary

# Introduction

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- ❖ OPT++ is an open source toolkit for general nonlinear optimization problems
- ❖ Original development started in 1992 at Sandia National Labs/CA
- ❖ Major contributors
  - Juan Meza, LBNL
  - Ricardo Oliva, LBNL
  - Patty Hough, SNL/CA
  - Pam Williams, SNL/CA

# OPT++ USERS



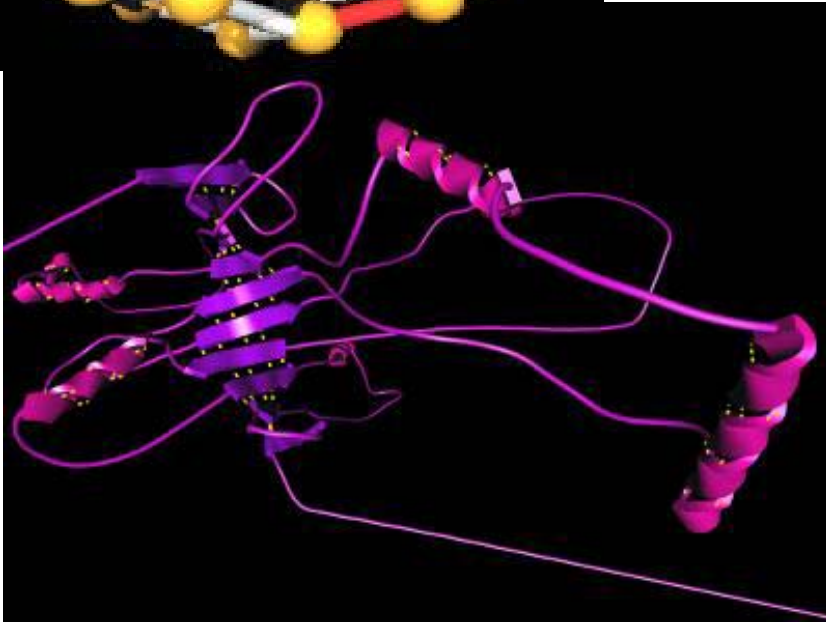
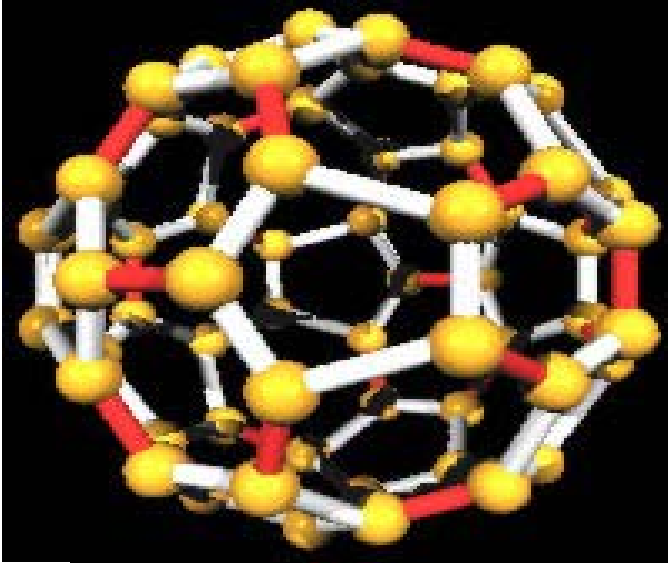
Total = 338

Other (Country not identified) = 120

As of April, 2003

5<sup>th</sup> International Congress on Industrial and Applied Mathematics, Sydney, Australia, July 7-11, 2003

# Application targets



- ❖ Predict properties of nanostructures and/or design nanostructures with desired properties
- ❖ Create secondary structures: obtain predictions of  $\alpha$ -helices and  $\beta$ -sheets.
- ❖ Configuration of T174 generated using ProteinShop

<http://graphics.cs.ucdavis.edu/~okreylos/ResDev/ProtoShop/index.html>

# General Optimization Problem

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$$\min_{x \in \mathbb{R}^n} f(x),$$

Objective function

$$s.t. \quad h(x) = 0,$$

Equality constraints

$$g(x) \geq 0$$

Inequality constraints

$$L = f(x) + y^T h(x) - w^T g(x)$$

# Classes of Optimization Problems

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- ❖ Unconstrained optimization
- ❖ Bound constrained optimization
  - Only upper and lower bounds
  - Sometimes called “box” constraints
- ❖ General nonlinearly constrained optimization
  - Equality and inequality constraints
  - Usually nonlinear
- ❖ Some special case classes (not currently handled in OPT++)
  - Linear programming (function and constraints linear)
  - Quadratic programming (quadratic function, linear constraints)

# OPT++ Philosophy

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- ❖ Problem should be defined in terms the user understands
  - *Do I have second derivatives available? and not*
  - *Is my objective function twice continuously differentiable?*
- ❖ Solution methods should be easily interchangeable
  - Once the problem is setup, methods should be easy to interchange so that the user can compare algorithms
- ❖ Common components of algorithms should be interchangeable
  - Algorithm developers should be able to re-use common components from other algorithms, for example line searches, step computations, etc.



# Classes of Problems in OPT++

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## ❖ Four major classes of problems available

- *NLF0(ndim, fcn, init\_fcn, constraint)*
  - Basic nonlinear function, no derivative information available
- *NLF1(ndim, fcn, init\_fcn, constraint)*
  - Nonlinear function, first derivative information available
- *FDNLF1(ndim, fcn, init\_fcn, constraint)*
  - Nonlinear function, first derivative information approximated
- *NLF2(ndim, fcn, init\_fcn, constraint)*
  - Nonlinear function, first and second derivative information available

# Classes of Solvers in OPT++

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## ❖ Direct search

- No derivative information required

## ❖ Conjugate Gradient

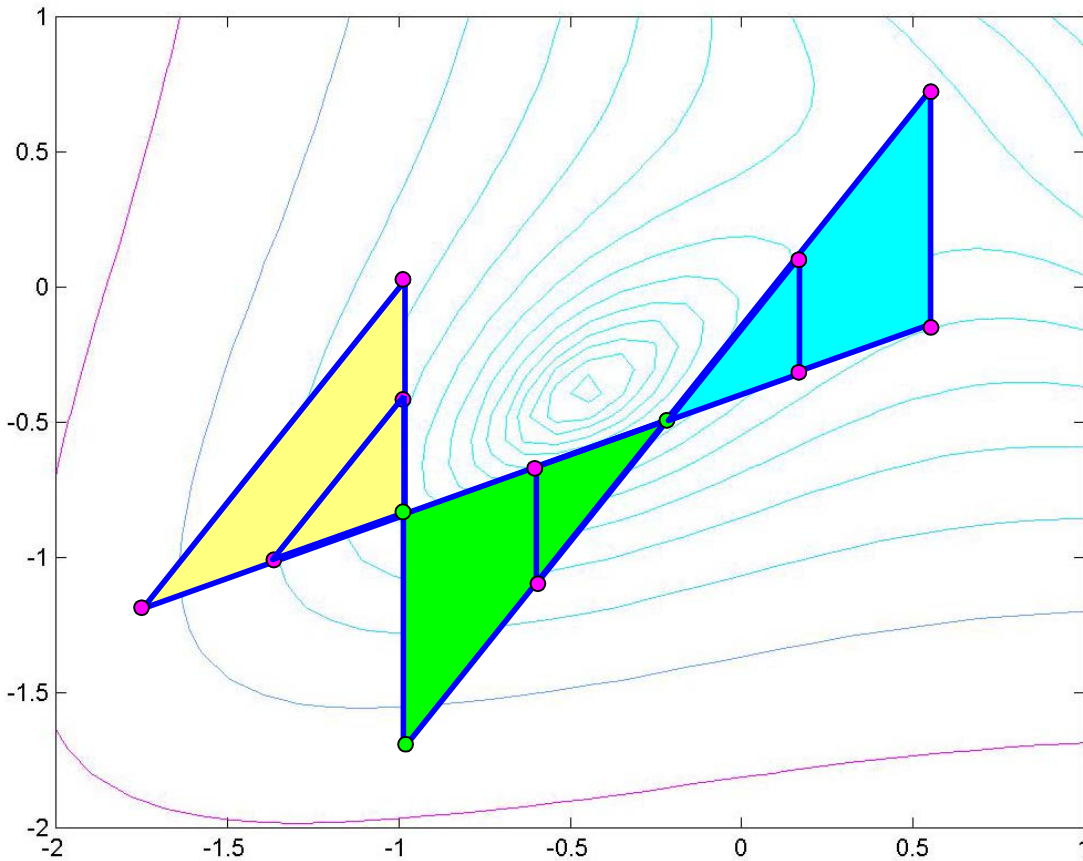
- Derivative information may be available but doesn't use quadratic information

## ❖ Newton-type methods

- Algorithm attempts to use/approximate quadratic information
- Newton
- Finite-Difference Newton
- Quasi-Newton
- NIPS

# Quick tour of some of the algorithms

# Pattern search



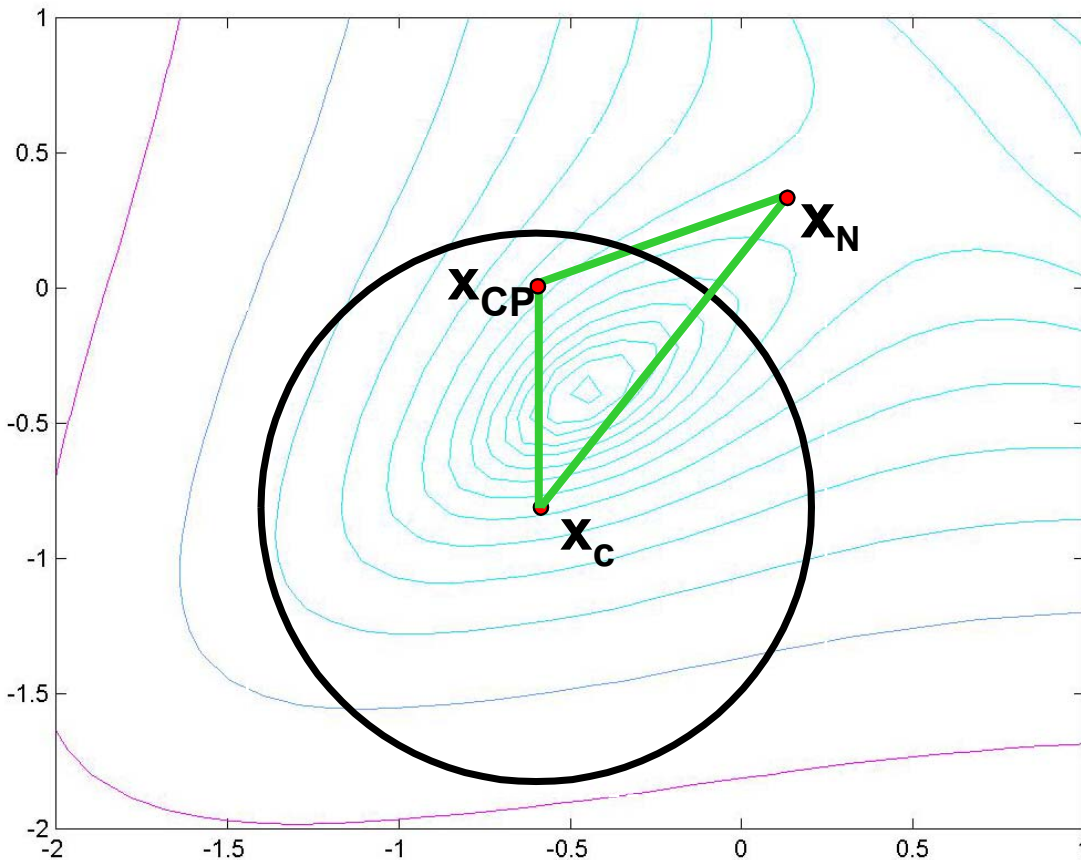
- ❖ Can handle noisy functions
- ❖ Do not require derivative information
- ❖ Inherently parallel
- ❖ Convergence can be painfully slow

# Conjugate Gradient Methods

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- ❖ Two major classes
- ❖ Standard nonlinear conjugate gradient
  - Two different types of line searches
- ❖ Limited Memory BFGS
  - Unconstrained version available
  - Bound constrained version under development

# Newton-type Methods



- ❖ Fast convergence properties
- ❖ Good global convergence properties
- ❖ Inherently serial
- ❖ Difficulties with noisy functions

# NIPS: Nonlinear Interior Point Solver

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- ❖ Interior point method
- ❖ Based on Newton's method for a particular system of equations (perturbed KKT equations, slack variable form)
- ❖ Can handle general nonlinear constraints
- ❖ Can handle strict feasibility

$$F(\mu) = \begin{bmatrix} \nabla f(x) + \nabla h(x)y - \nabla g(x)w \\ w - z \\ h(x) \\ g(x) - s \\ ZSe - \mu e \end{bmatrix} = 0$$

# Constraints

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## ❖ Constraint types

- `BoundConstraint(numconstraints, lower, upper)`
- `LinearInequality(A, rhs, stdFlag)`
- `NonLinearInequality(nlprob, rhs, numconstraints, stdFlag)`
- `LinearEquation(A, rhs)`
- `NonLinearEquation(nlprob, rhs, numconstraints)`

## ❖ The whole shebang

- `CompoundConstraint(constraints)`



# Algorithm Choices Depend on Problem

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	NLF0	FDNLF1	NLF1	NLF2
OptPDS	X	X	X	X
OptCG		X	X	X
OptLBFGS		X	X	X
OptQNewton		X	X	X
OptBCQNewton		X	X	X
OptFDNewton		X	X	X
OptFDNIPS		X	X	X
OptNewton				X
OptBCNewton				X
OptNIPS				X

# Bare bones example: unconstrained optimization

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```
void init_rosen_x0(int ndim, ColumnVector& x);  
void rosen(int ndim, const ColumnVector& x, double& fx, int& result);  
  
int main() {  
    int ndim = 2;  
    FDNLF1 nlp(ndim, rosen, init_rosen_x0);  
    nlp.initFcn();  
    OptQNewton objfcn(&nlp);  
    objfcn.setSearchStrategy(TrustRegion);  
    objfcn.setMaxFeval(200);  
    objfcn.setFcnTol(1.e-4);  
    objfcn.optimize();  
}
```

# Example 2: Constrained optimization

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$$\min (x_1 - x_2)^2 + (1/9)(x_1 + x_2 - 10)^2 + (x_3 - 5)^2$$

*s.t.*

$$x_1^2 + x_2^2 + x_3^2 \leq 48,$$

$$-4.5 \leq x_1 \leq 4.5,$$

$$-4.5 \leq x_2 \leq 4.5,$$

$$-5.0 \leq x_3 \leq 5.0$$

# Constrained optimization: Step 1

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Defining the bound constraints:

$$-4.5 \leq x_1 \leq 4.5,$$

$$-4.5 \leq x_2 \leq 4.5,$$

$$-5.0 \leq x_3 \leq 5.0$$

```
int ndim = 3;
```

```
ColumnVector lower(ndim), upper(ndim);
```

```
lower << -4.5 << -4.5 << -5.0;
```

```
upper << 4.5 << 4.5 << 5.0 ;
```

```
Constraint bc = new BoundConstraint(ndim, lower, upper);
```

# Constrained optimization: Step 2

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Defining the nonlinear inequality constraint:

$$x_1^2 + x_2^2 + x_3^2 \leq 48$$

```
NLP* chs65 = new NLP(new NLF2(ndim, 1, ineq, init_hs65_x0));
```

```
Constraint nleqn = new NonLinearInequality(chs65);
```

Collecting both constraints into one constraint object :

```
CompoundConstraint* constraints =  
    new CompoundConstraint(nleqn, bc);
```

# Constrained optimization: Step 3

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Defining and initializing the nonlinear problem:

```
NLF2 nips(ndim, hs65, init_hs65_x0, constraints);  
nips.initFcn();
```

Defining the Optimization object and optimizing it!

```
OptNIPS optobj(&nips);  
optobj.optimize();
```

# Parallel Optimization

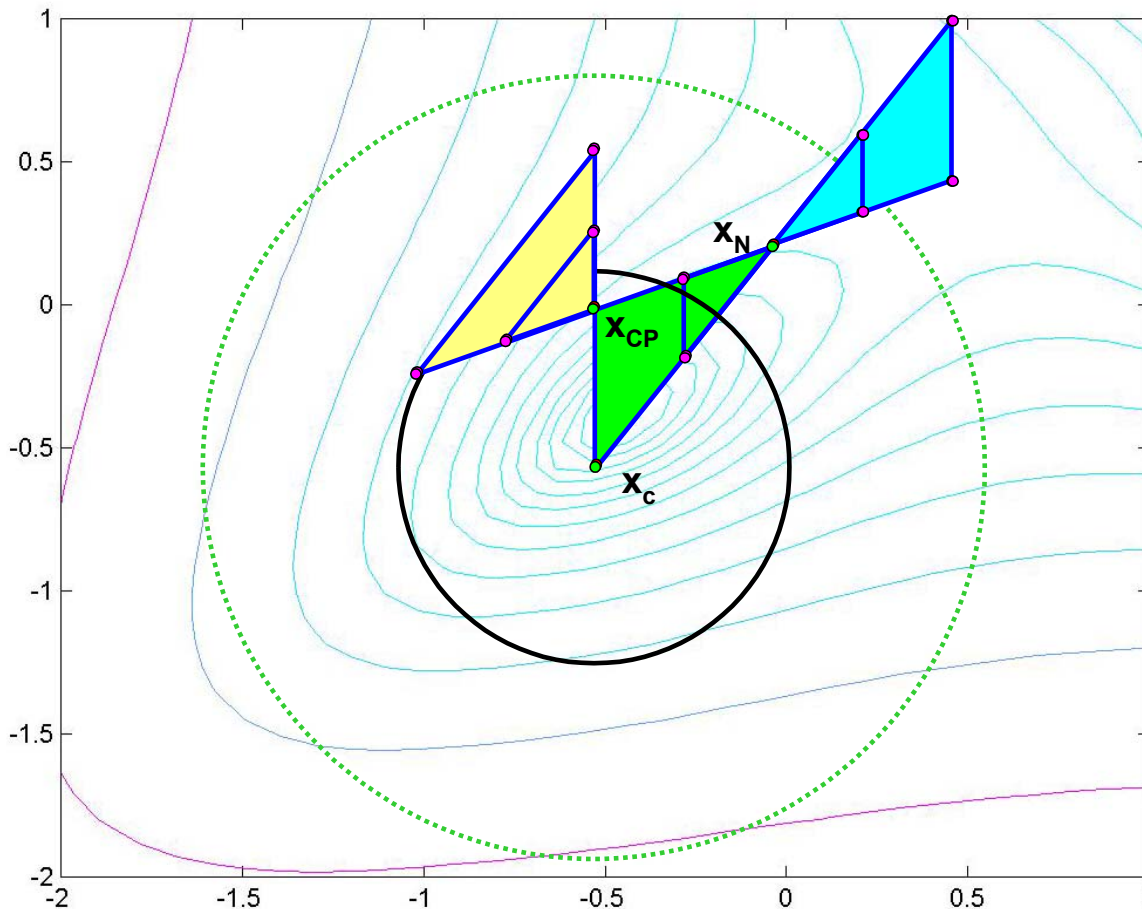
# Schnabel (1995) Identified Three Levels for Introducing Parallelism Into Optimization

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- ❖ Parallelize evaluation of function/gradient/constraints
  - May or may not be easy to implement
- ❖ Parallelize linear algebra
  - Really only useful if the optimization problem is large-scale
- ❖ Parallelize optimization algorithm at a high level
  - Multiple function evaluations in parallel

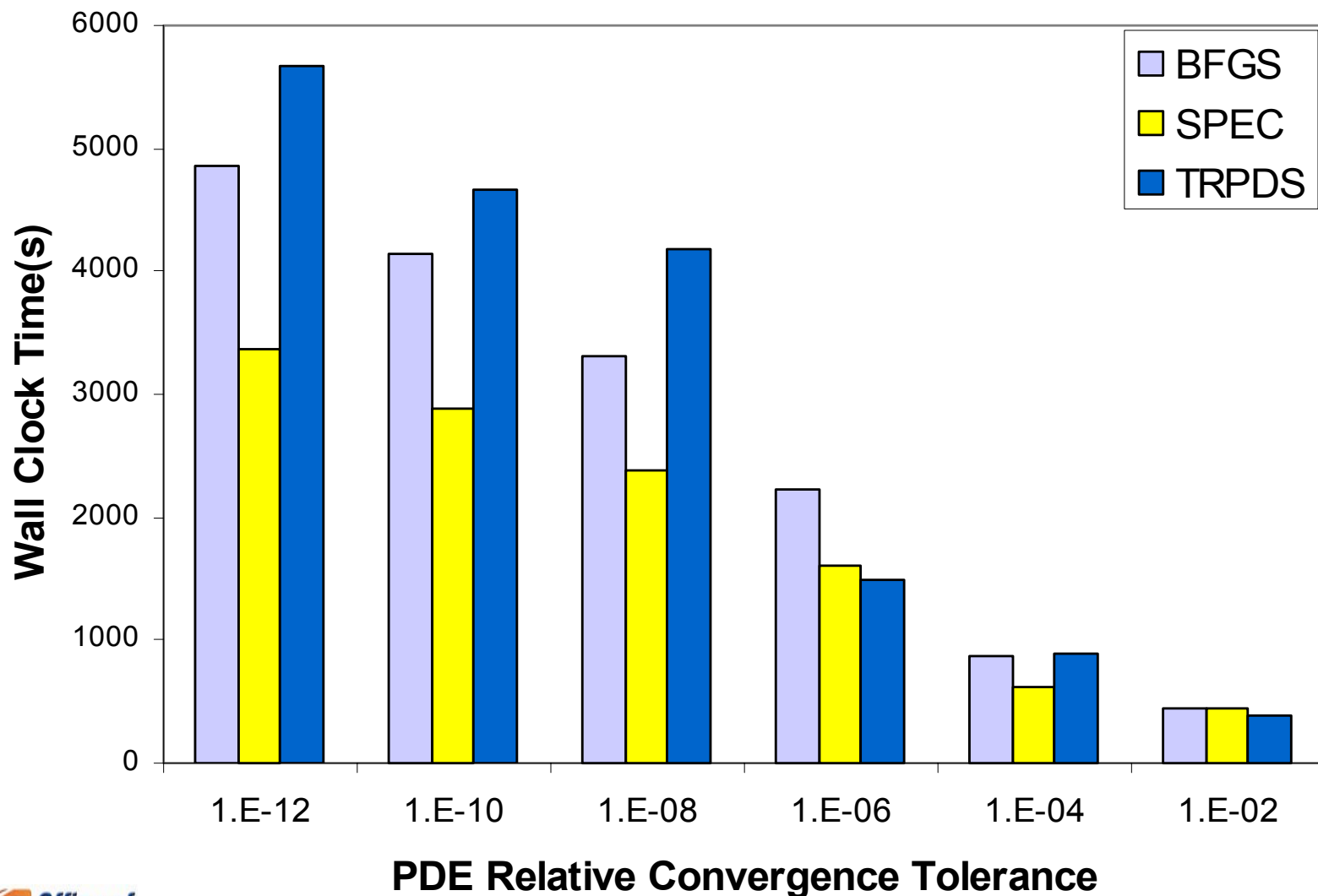


# Trust Region + PDS



- ❖ Fast convergence properties of Newton method
- ❖ Good global convergence properties of trust region approach
- ❖ Inherent parallelism of PDS
- ❖ Ability to handle noisy functions

# Comparison of TRPDS with other approaches



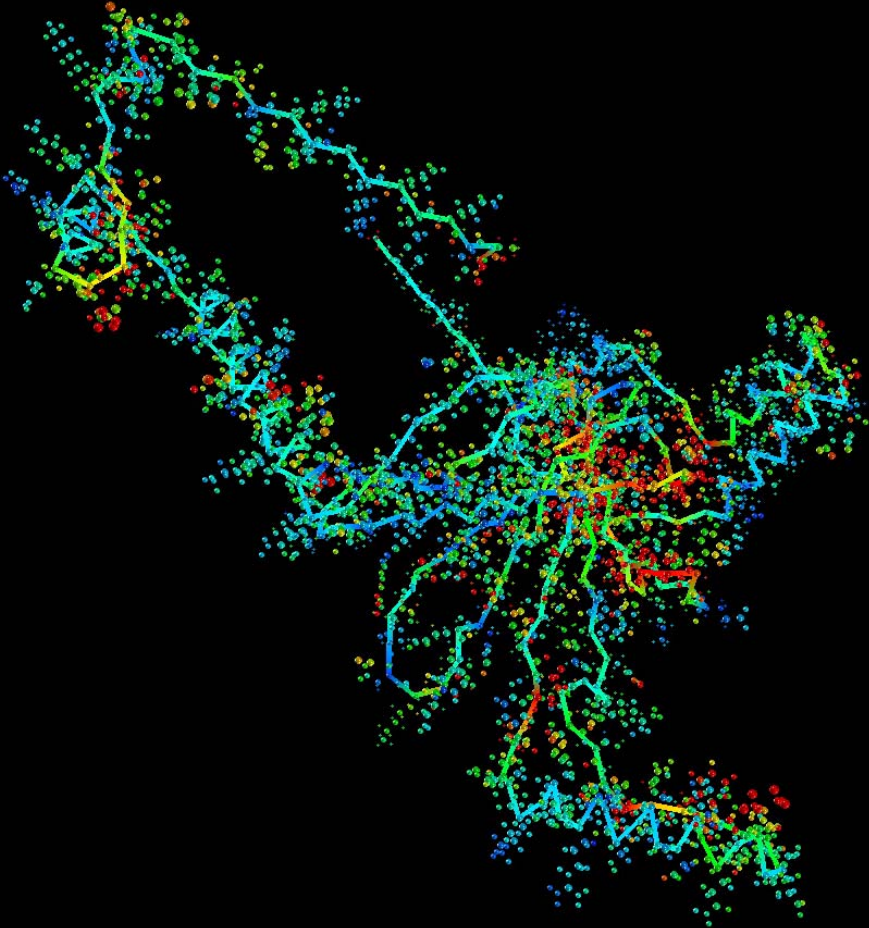
# Application: Protein Folding

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```
void init_X0(int ndim, ColumnVector& x);  
void eval_energy(int ndim, const ColumnVector& x, double& fx, int&  
    result);  
int main() {  
    PDB pdb("t162.pdb"); // loads pdb file  
    int ndim = 3 * pdb.NumAtoms();  
    FDNLF1 nlp(ndim, eval_energy, init_X0);  
    nlp.initFcn();  
    OptLBFGS optobj(&nlp);  
    optobj.setMaxFeval(10000);  
    optobj.setFcnTol(1.e-6);  
    optobj.optimize();  
}
```

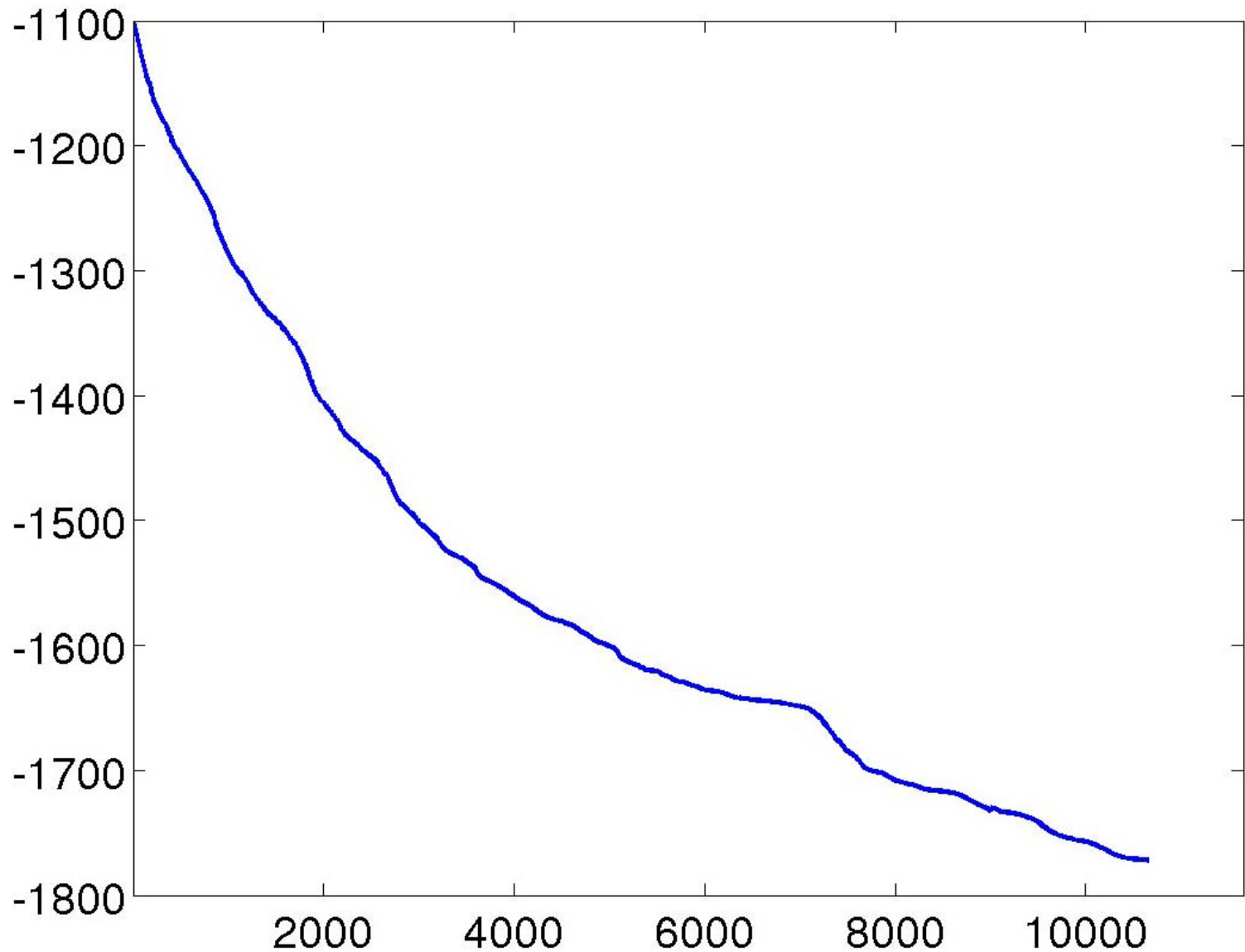
# Energy Minimization Using LBFGS

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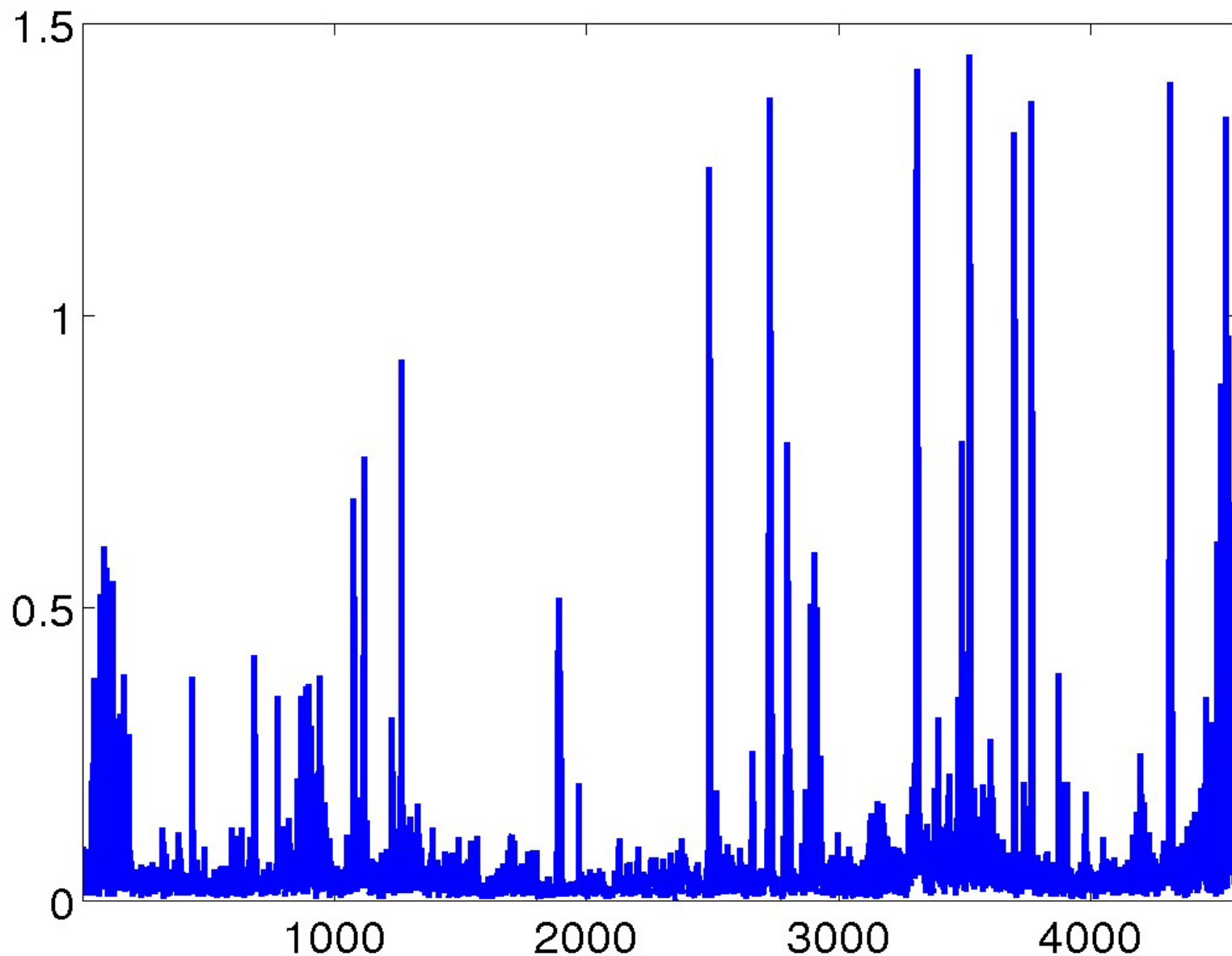


- ❖  $N=13728$  (4576 Atoms)
- ❖ Energy Function: AMBER
- ❖ LBFGS with  $M=15$
- ❖ 11656 iterations, 11887 function evaluations
- ❖ Stop on  $f$  tolerance with  $ftol=1e-6$
- ❖ Each function eval:  $\sim 5\text{sec}$

# Energy vs. LBFGS iterations

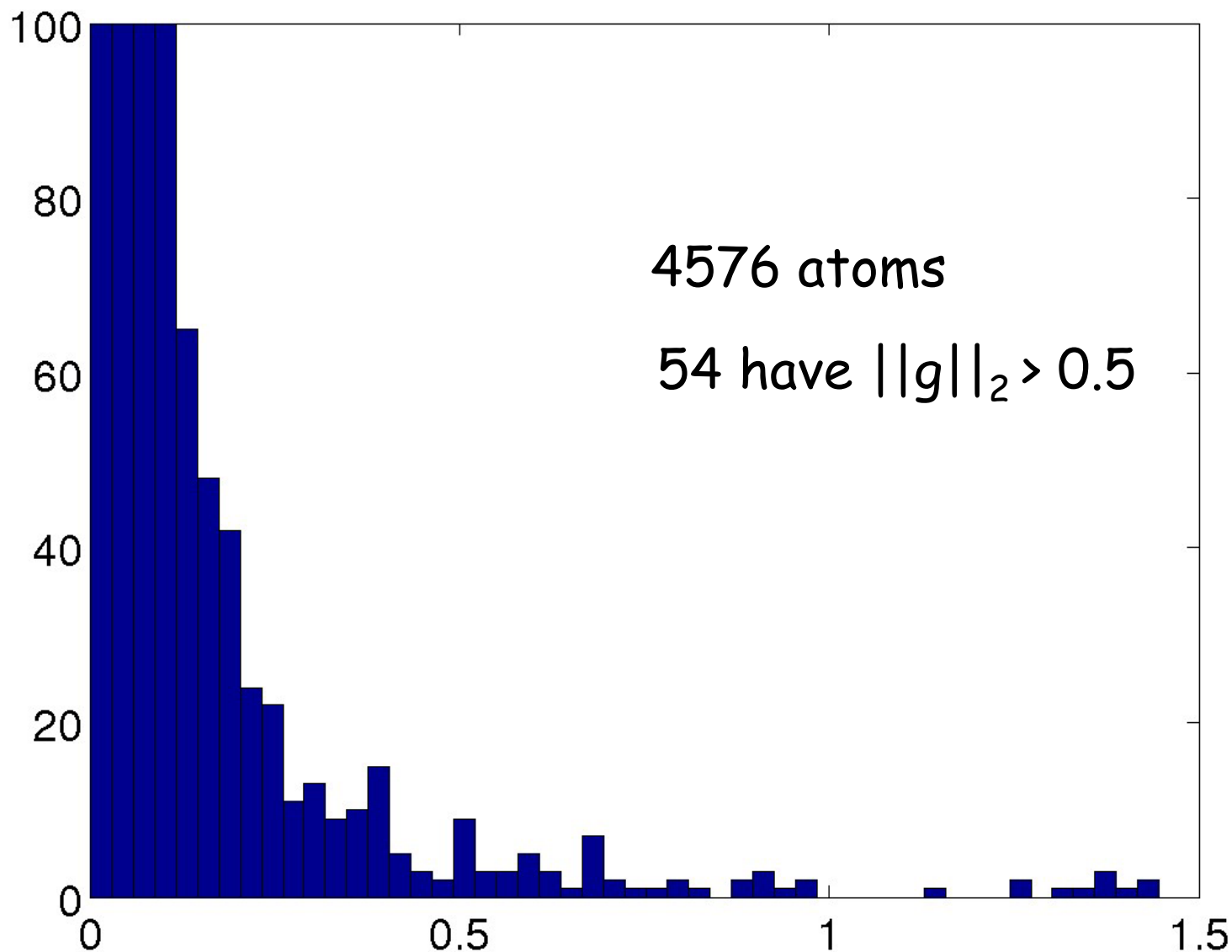


# Norm of *gradient* for each atom



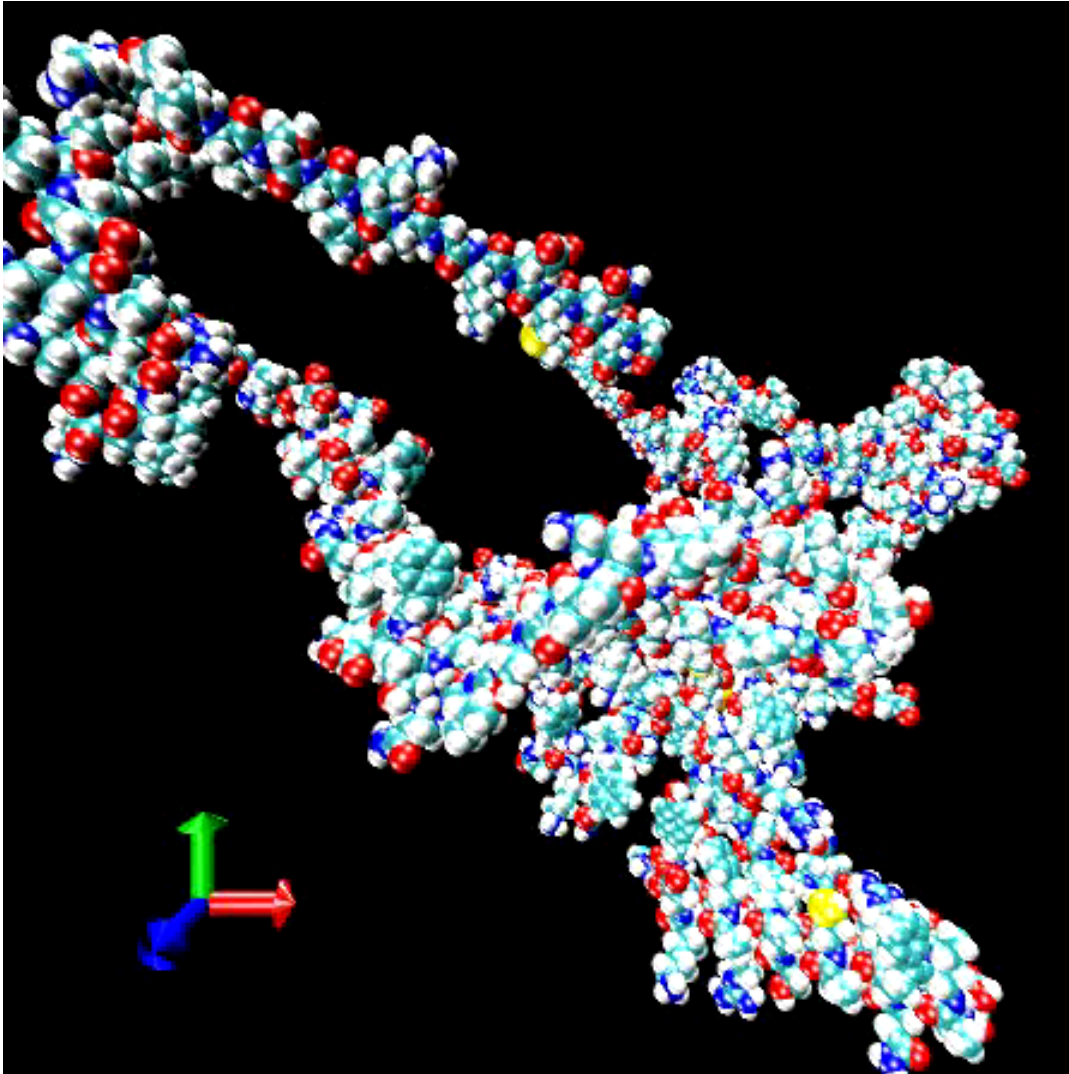
5<sup>th</sup> International Congress on Industrial and Applied Mathematics, Sydney, Australia, July 7-11, 2005

# Distribution of $\| \text{gradient} \|$ by atom





# Protein T162 (from CASP5)



- ❖ Initial configuration created using ProteinShop (S. Crivelli)
- ❖ Energy minimization computed using OPT++/LBFGS
- ❖ Final RMSD change: 3.9 (avg)
- ❖ Total simulation took approximately 32 hours on a 1.7GHz machine with 512 RAM



# Summary

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- ❖ OPT++ can handle many types of nonlinear optimization problems
- ❖ The toolkit can be used to compare the effectiveness of several algorithms on the same problem easily
- ❖ The user needs to provide only functions for the objective function and the constraints
  - If additional information is available it can be easily incorporated
- ❖ The code is open source and available at either
  - <http://www.nersc.gov/~meza/projects/opt++>
  - <http://csmr.ca.sandia.gov/opt++>

# References

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## ❖ Other links

- <http://sal.kachinatech.com/B/3/index.shtml>
- <http://www-neos.mcs.anl.gov/neos>
- <http://www.mcs.anl.gov/tao>
- <http://endo.sandia.gov/DAKOTA/index.html>

## ❖ Books/Papers

- Dennis and Schnabel, *Numerical Methods for Unconstrained Optimization and Nonlinear Equations*, Prentice-Hall, 1983
- Gill, Murray, Wright, *Practical Optimization*, Academic Press, 1981
- El-Bakry, Tapia, Tsuchiya, Zhang, *On the Formulation and Theory of the Newton Interior-Point Method for Nonlinear Programming*, JOTA, Vol. 89, No.3, pp.507-541, 1996
- More' and Wright, *Optimization Software Guide*, SIAM, 1993

# OPT++ Users around the world



Total = 235

Other (Country not identified) = 34