

# Computational Material Science

## Part I

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# Aim of Part I

- Get familiar with the computational methodologies often used and properties often predicted in molecular- or cluster-based research.
- With the basic understanding acquired, hopefully, you will have the ability to read literature and conduct your own calculations when needed in research.

# Outline

- Potential energy surface: energy minimization and stationary point characterization
- Overview and comparison of methods
- Classical modeling: force field calculations (molecular mechanics; **MM**); solvation
- Quantum mechanical modeling (**QM**); qualitative molecular orbital analysis, various molecular orbital-based methods, calculation of chemical and physical properties
- Molecular dynamic (**MD**) and Monte Carlo (**MC**) calculations
- QM/MM

# Grading

- 15% -- take home assignments
- 15% -- oral presentation
- 20% -- final examination

## Useful Structure Database

CSD -- organic and metal-organic crystal structure database (350,000 compounds)

ICSD -- inorganic crystal structure database

CRYSTMET -- metals (alloys, intermetallics and minerals) structure database

--available at NCHC (NCHC: National Center for High-Performance Computing)

# Useful Books

- “Molecular Modelling: Principles and Applications”, 2nd Ed., A. R. Leach / Prentice Hall (2001)
- “Essentials of Computational Chemistry: Theory and Models”, C. J. Cramer / Wiley (2004)
- “Molecular Modeling Techniques in Material Sciences”, J.-R. Hill, L. Subramanian, and A. Maiti / Taylor & Francis (2005)
- “Molecular Modelling for Beginners”, A. Hinchliffe/Wiley (2003)
- “Encyclopedia of Computational Chemistry”, P. v. R. Schleyer, Ed. / Wiley (1998)

# Program Used

# Gaussian 03 GaussView

## Home:

<http://www.gaussian.com>

## Capability

[http://www.gaussian.com.g\\_brochures/g03\\_intro.htm](http://www.gaussian.com.g_brochures/g03_intro.htm)

## People

*Last update: 25 March 2006*

## Reflections on John Pople's Life and Legacy

## 1998 Nobel Prize Winner in Chemistry (with Walter Kohn).

## Current Gaussian Contributors:

Mike Frisch  
Gary Trucks  
John Montgomery  
Jim Cheeseman  
Thom Vreven  
Larry Cuffe  
Giovanni Scalmani  
Wei (David) Deng  
Marco Caricato  
Joanne Kurnik  
Jim Hess  
Jennifer Mercado  
Adria Carabetta  
Judy Pooley  
Monica Gindel  
Susan Ciemnienski  
Maria Temple  
Allex Townsend

Jim Hess  
Jennifer Mercado  
Adria Carabetta  
Judy Pooley  
Monica Gindel  
Susan Clemniewski  
Maria Temple  
Alley Townsend

Mike Robb  
Valerio Trigari  
Mike Bearpark  
**Odon Farkas**  
István Komárom

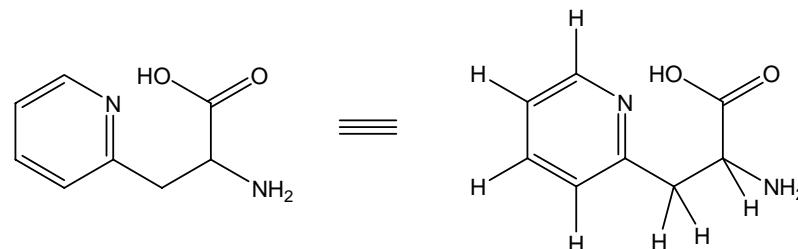
Carlo Adamo  
François Ogliaro

# Gaussian Citation

- Gaussian 03, Revision **C.02**, M. J. Frisch, G. W. Trucks, H. B. Schlegel, G. E. Scuseria, M. A. Robb, J. R. Cheeseman, J. A. Montgomery, Jr., T. Vreven, K. N. Kudin, J. C. Burant, J. M. Millam, S. S. Iyengar, J. Tomasi, V. Barone, B. Mennucci, M. Cossi, G. Scalmani, N. Rega, G. A. Petersson, H. Nakatsuji, M. Hada, M. Ehara, K. Toyota, R. Fukuda, J. Hasegawa, M. Ishida, T. Nakajima, Y. Honda, O. Kitao, H. Nakai, M. Klene, X. Li, J. E. Knox, H. P. Hratchian, J. B. Cross, V. Bakken, C. Adamo, J. Jaramillo, R. Gomperts, R. E. Stratmann, O. Yazyev, A. J. Austin, R. Cammi, C. Pomelli, J. W. Ochterski, P. Y. Ayala, K. Morokuma, G. A. Voth, P. Salvador, J. J. Dannenberg, V. G. Zakrzewski, S. Dapprich, A. D. Daniels, M. C. Strain, O. Farkas, D. K. Malick, A. D. Rabuck, K. Raghavachari, J. B. Foresman, J. V. Ortiz, Q. Cui, A. G. Baboul, S. Clifford, J. Cioslowski, B. B. Stefanov, G. Liu, A. Liashenko, P. Piskorz, I. Komaromi, R. L. Martin, D. J. Fox, T. Keith, M. A. Al-Laham, C. Y. Peng, A. Nanayakkara, M. Challacombe, P. M. W. Gill, B. Johnson, W. Chen, M. W. Wong, C. Gonzalez, and J. A. Pople, Gaussian, Inc., Wallingford CT, 2004.

# Chemical drawing

- H atoms next to C atoms are often omitted



- Three-dimensional effects



S-form

R-form

*Same molecular formula, different optical activity*

# Coordinate Systems

## ➤ Cartesian coordinates

C	0.0	0.0	0.0
O	0.0	1.22	0.0
H	0.94	-0.54	0.0
H	-0.94	-0.54	0.0

## ➤ Z-matrix coordinates

1	C						
2	C	1	1.54				
3	H	1	1.0	2	109.5		
4	H	2	1.0	1	109.5	3	180.0
5	H	1	1.0	2	109.5	4	60.0
6	H	2	1.0	1	109.5	5	-60.0
7	H	1	1.0	2	109.5	6	180.0
8	H	2	1.0	1	109.5	7	60.0

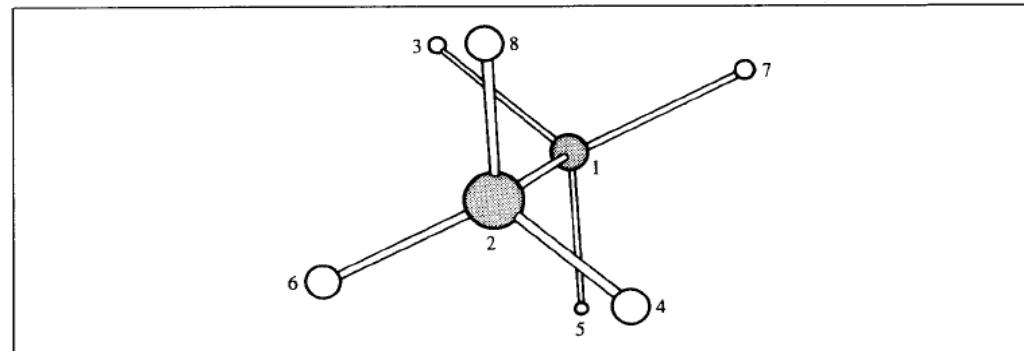


Fig. 1.1: The staggered conformation of ethane.

as follows:

# Goal of Modelling

- Develop an understanding of the relation between a material's properties and the underlying atomic structure
- A basic property: **Energy!**

# Potential Energy Surfaces

- Born-Oppenheimer approximation
  - The much smaller mass of the electrons make them adjust rapidly to any change in the nuclear positions: Enables the electronic and nuclear motions to be separated.
  - Consequently, the energy of a molecule in its ground electronic state can be considered a function of the nuclear coordinates only.

# Potential Energy Dependence on Nuclear Coordinates

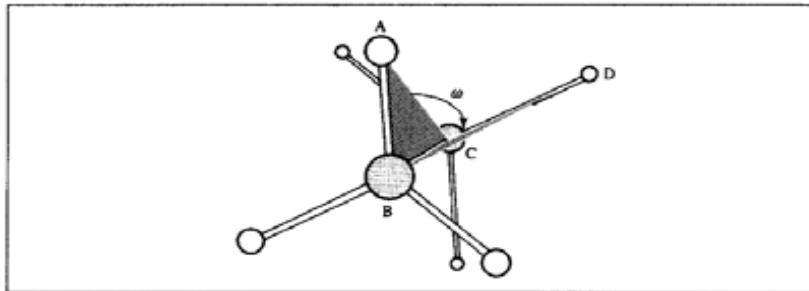


Fig. 1.2: A torsion angle  $A-B-C-D$  is defined as the angle between the planes  $A, B, C$  and  $B, C, D$ . A torsion angle can vary through  $360^\circ$  although the range  $-180^\circ$  to  $+180^\circ$  is most commonly used. We shall adopt the IUPAC definition of a torsion angle in which an eclipsed conformation corresponds to a torsion angle of  $0^\circ$  and a trans or anti conformation to a torsion angle of  $180^\circ$ . The reader should note that this may not correspond to some of the definitions used in the literature, where the trans arrangement is defined as a torsion angle of  $0^\circ$ . If one looks along the bond  $B-C$ , then the torsion angle is the angle through which it is necessary to rotate the bond  $AB$  in a clockwise sense in order to superimpose the two planes, as shown.

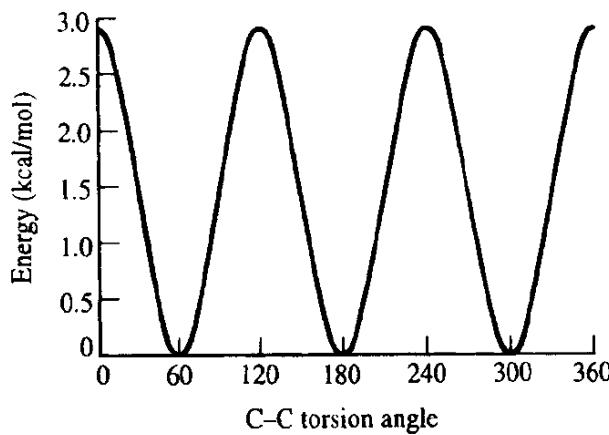
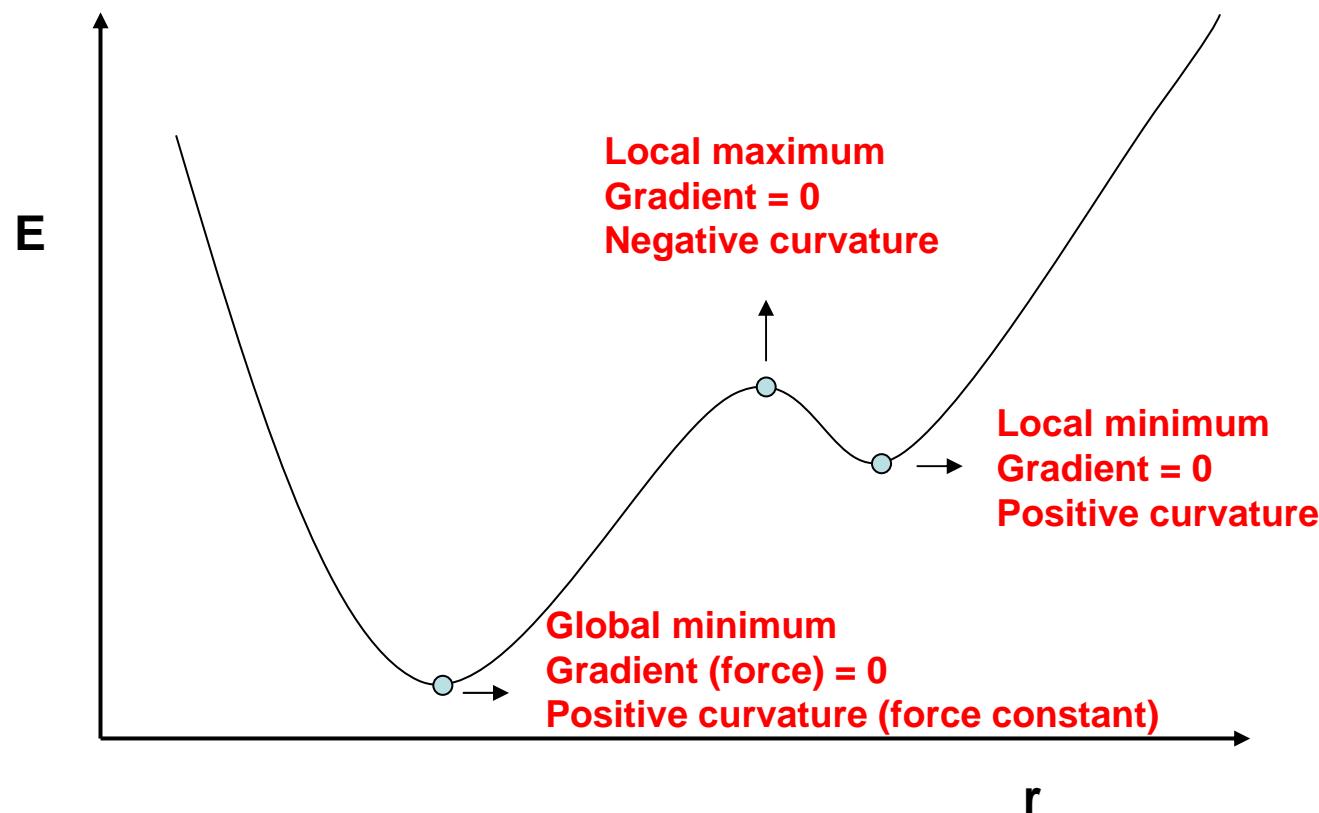


Fig. 1.3: Variation in energy with rotation of the carbon–carbon bond in ethane.

# Stationary Points (•) on Potential Energy Surface



# Characterization of Stationary Points

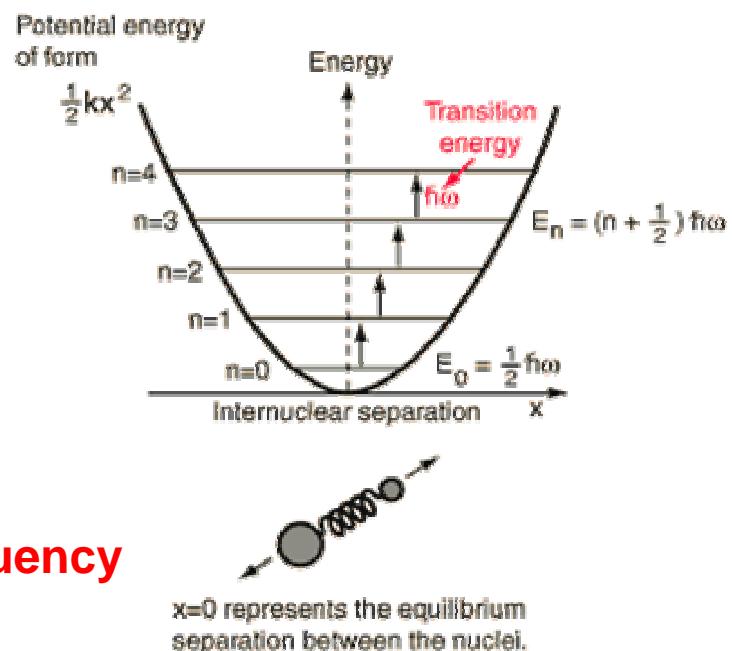
- An optimization procedure deemed “converged” when  $(\frac{\partial E}{\partial r}) \approx 0$
- Stationary points are further characterized by  $\frac{\partial^2 E}{\partial r^2}$  .

## Harmonic oscillator approximation of a diatomic molecule

$$\frac{\partial^2 E}{\partial r^2} = k$$

$$\omega = \frac{1}{2\pi} \sqrt{\frac{k}{\mu}}$$

If in a frequency analysis, imaginary frequency obtained  $\Rightarrow$  not at a local minimum



# Characterization of Stationary Points

2-D case

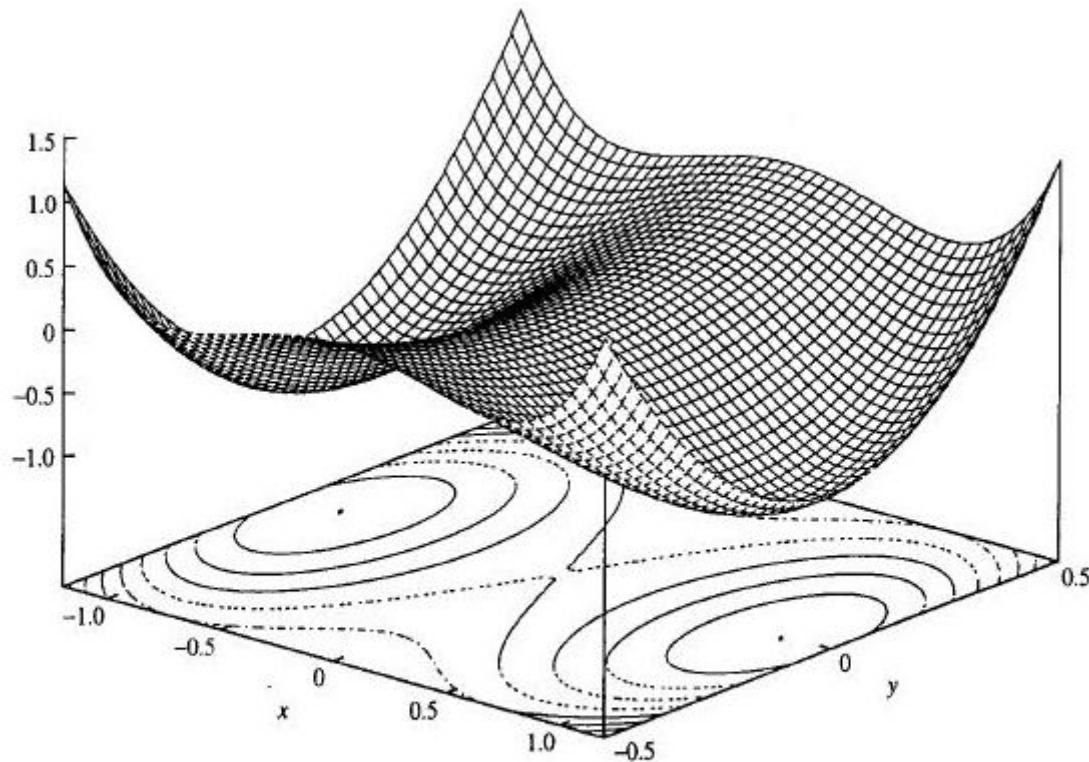


Fig. 4.24 The function  $f(x, y) = x^4 + 4x^2y^2 - 2x^2 + 2y^2$  has a saddle point at  $(0, 0)$  and minima at  $(1, 0)$  and  $(-1, 0)$ .

At points  $(1,0)$  and  $(-1,0)$   
eigenvalues of Hessian matrix  
(i.e. force constant matrix)  
all positive => minimum

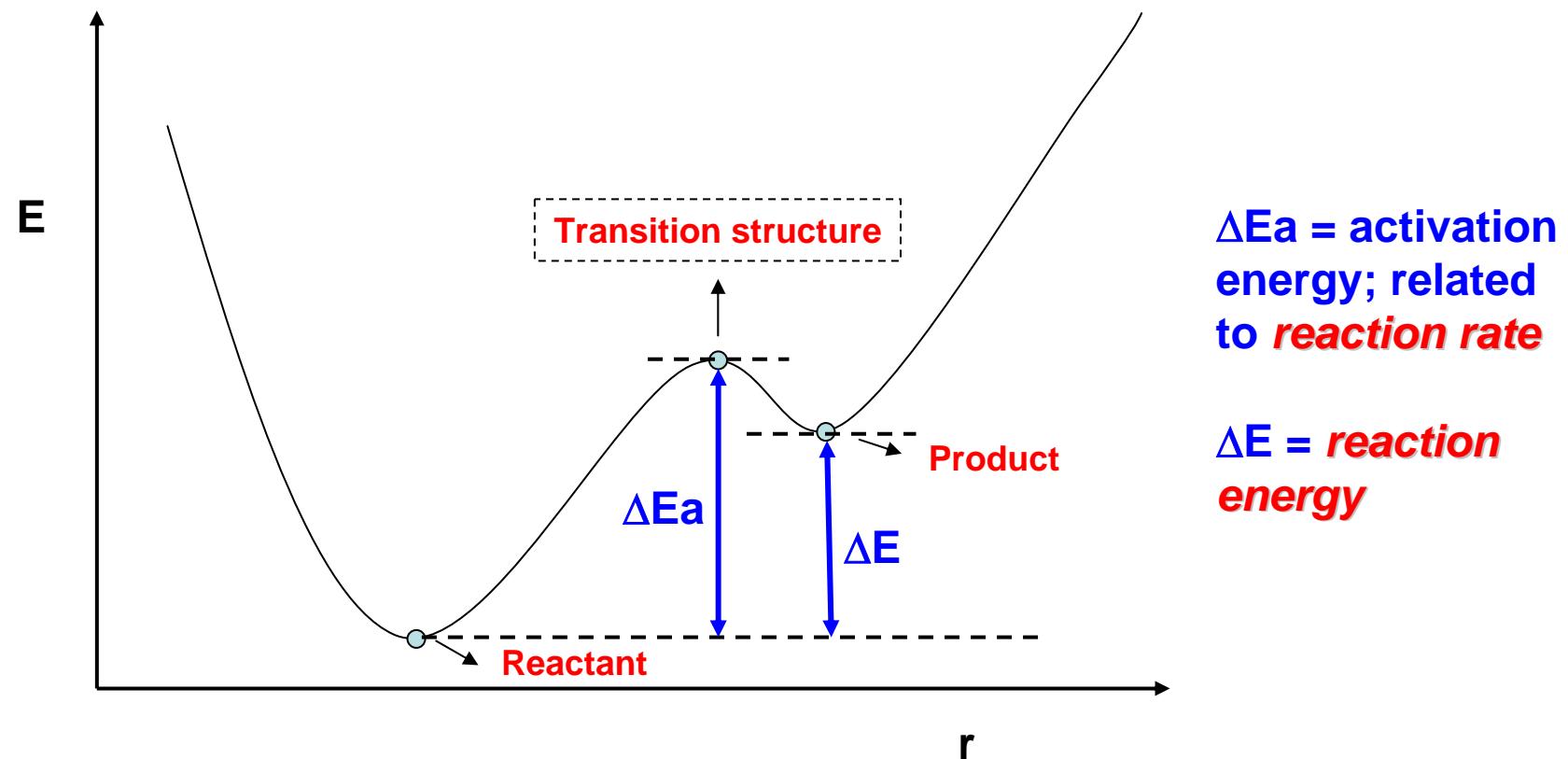
At point  $(0,0)$   
eigenvalue    eigenvector  
-4                     $(1,0)$   
+4                     $(0,1)$

=> maximum along x direction  
minimum along y direction

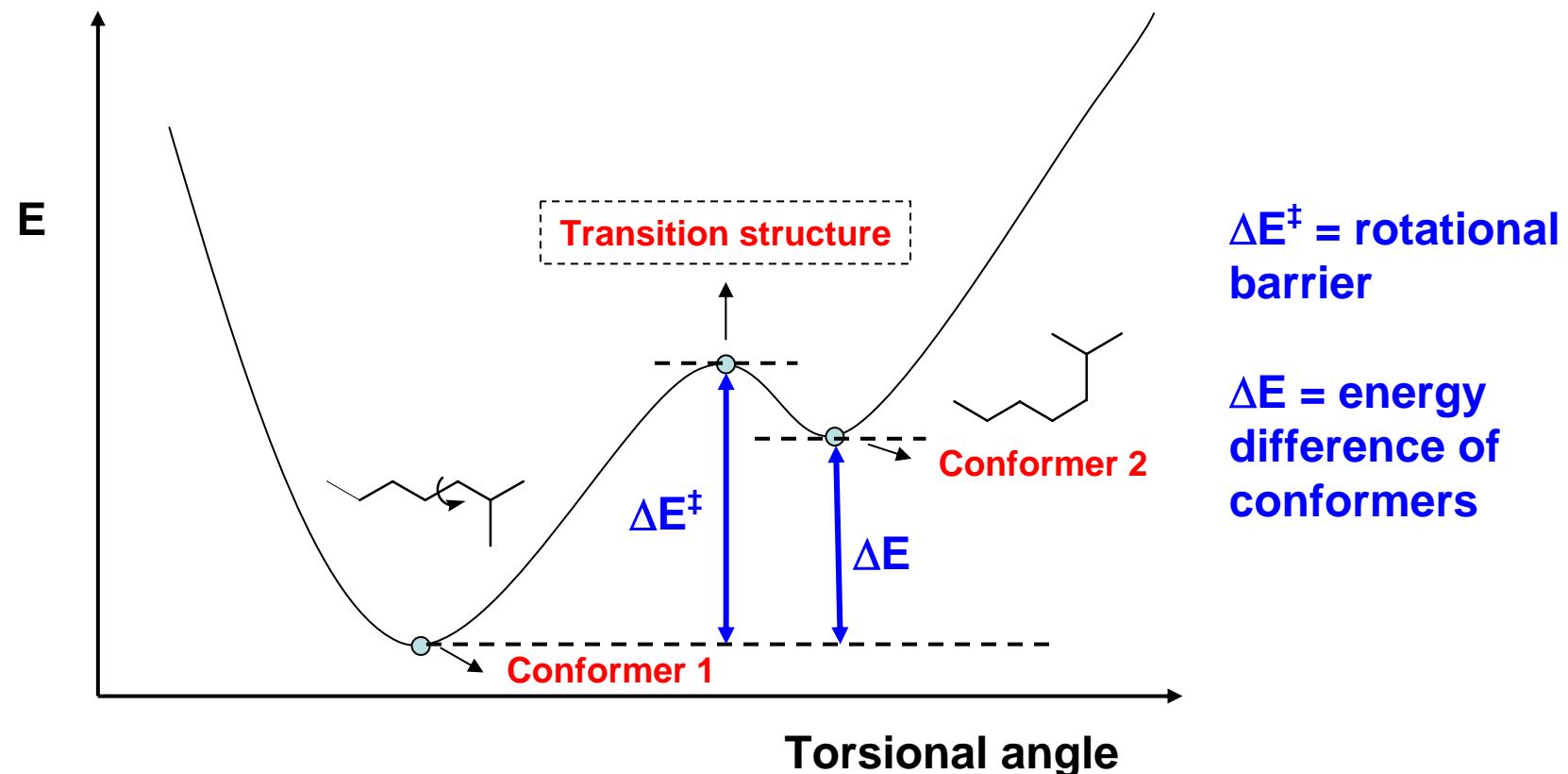
One negative eigenvalue:  
1st order saddle point  
(correspond to the transition state  
along a minimum energy path)

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# Significance of Stationary Points



# Significance of Stationary Points



# Energy Minimization

- Coordinates are gradually changed to produce configurations with lower and lower energies until the minimum is reached
- Algorithms are of two types: *with* the use of derivatives of the energy and *without*
- Why are derivatives important? – Reveal the shape of the energy surface, can significantly enhance the efficiency in searching the local minimum
- Why derivatives are not always used? – Could be time consuming if derived numerically

# Energy Minimization

- Where you start the minimization decides what you get!

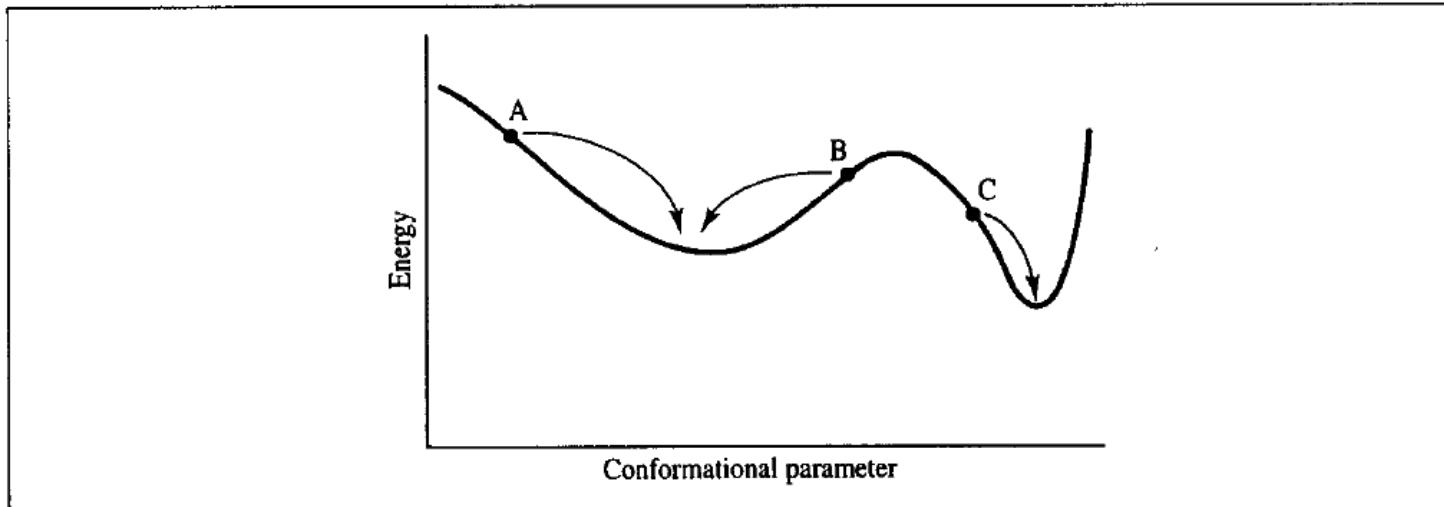


Fig. 5.3: A schematic one-dimensional energy surface. Minimisation methods move downhill to the nearest minimum. The statistical weight of the narrow, deep minimum may be less than a broad minimum which is higher in energy.

If you start at a local maximum, you may be trapped there since  $\text{gradient} = 0$

⇒ Must do frequency analysis to confirm the nature of the stationary point!

⇒ Ex: corannulene \*\*\*

- No algorithm has yet proved capable of locating the global energy minimum from an arbitrary starting position

# Minimization Methods

- Non-derivative minimization methods
  - The simplex method
  - The sequential univariate method
- First-order minimization methods
  - The steepest descents method
    - Line search
    - Arbitrary step approach
  - Conjugate gradients minimization
- Second derivative methods
  - The Newton-Raphson Method
  - Variants on the Newton-Raphson Method
  - Quasi-Newton methods (Variable metric methods)

# The simplex method

- A simplex is a geometrical figure with  $M + 1$  vertices;  $M$  is the dimensionality of the energy function (for  $E(x,y,z)$ ,  $M = 3$ )
- In the simplex method, the figure moves on the potential energy surface (imagine an amoeba)

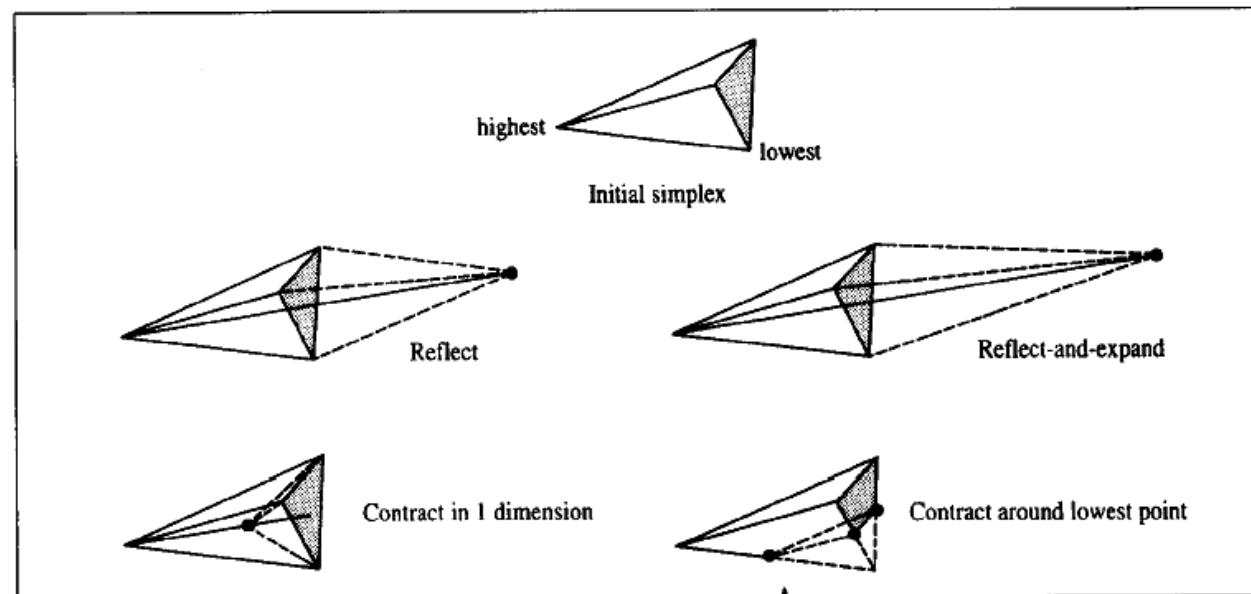


Fig. 5.4: The three basic moves permitted to the simplex algorithm (reflection, and its close relation reflect-and-expand; contract in one dimension and contract around the lowest point). (Figure adapted from Press W H, B P Flannery, S A Teukolsky and W T Vetterling 1992. Numerical Recipes in Fortran. Cambridge, Cambridge University Press.)

# The simplex method

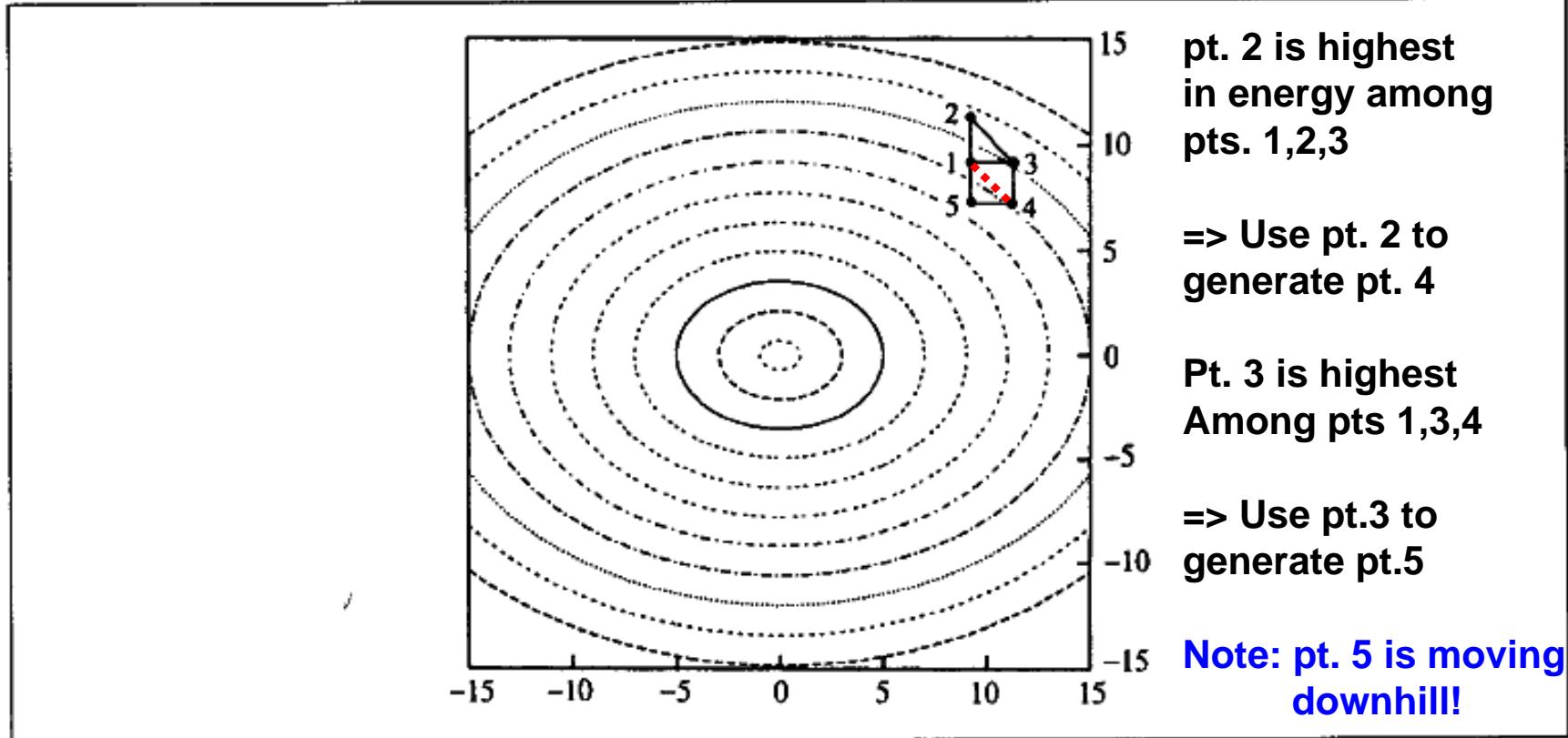
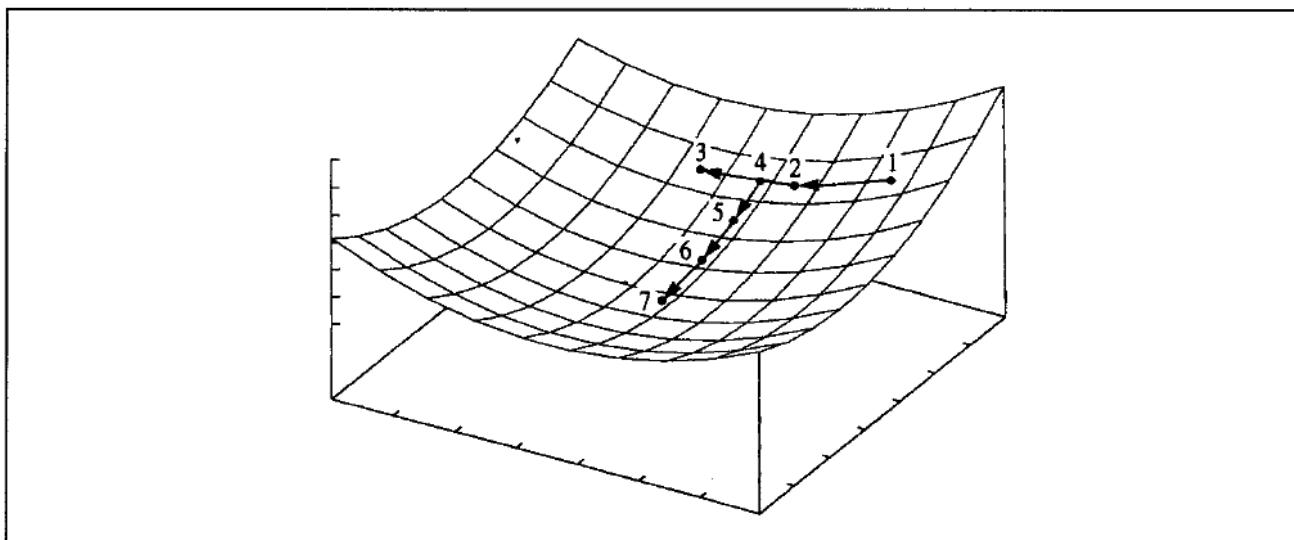


Fig. 5.5: The first few steps of the simplex algorithm with the function  $x^2 + 2y^2$ . The initial simplex corresponds to the triangle 123. Point 2 has the largest value of the function and the next simplex is the triangle 134. The simplex for the third step is 145.

- 3N +1 vertices, lots of energy evaluations! (N: number of atoms)
- Rarely considered for quantum mechanical calculations

# The Sequential Univariate Method

- In each cycle, only one coordinate is varied. ( $x_i + \delta x_i$  and  $x_i + 2\delta x_i$  : pts. 1,2,3)
- A parabola fitted through the three points
- The minimum of the quadratic function determined and the new starting point is changed to the position of the minimum (pt. 4)
- A new cycle start for the next coordinate (y : pts. 5, 6, 7)



- Fewer energy evaluation than simplex
- Could be problematic if strong coupling between coordinates

Fig. 5.6: The sequential univariate method. Starting at the point labelled 1 two steps are made along one of the coordinates to give points 2 and 3. A parabola is fitted to these three points and the minimum located (point 4). The same procedure is then repeated along the next coordinate (points 5, 6 and 7). (Figure adapted from Schlegel H B 1987. Optimization of Equilibrium Geometries and Transition Structures. In Lawley K P (Editor). *Ab Initio Methods in Quantum Chemistry - I*. New York, John Wiley, pp. 249-286.)

# The Steepest Descents Method

- Move along the gradient (force) direction
- Useful when gradient is large and far from minimum

## With Line Search in One Dimension

- Multiple points to locate the minimum in the direction of the gradient

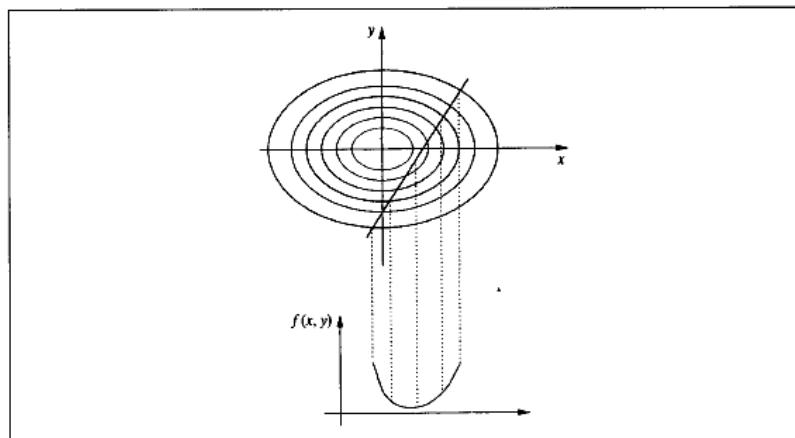


Fig. 5.7: A line search is used to locate the minimum in the function in the direction of the gradient.

## Arbitrary Step Approach

- Step size decrease when energy does not decrease (assuming the valley has been leapt across)

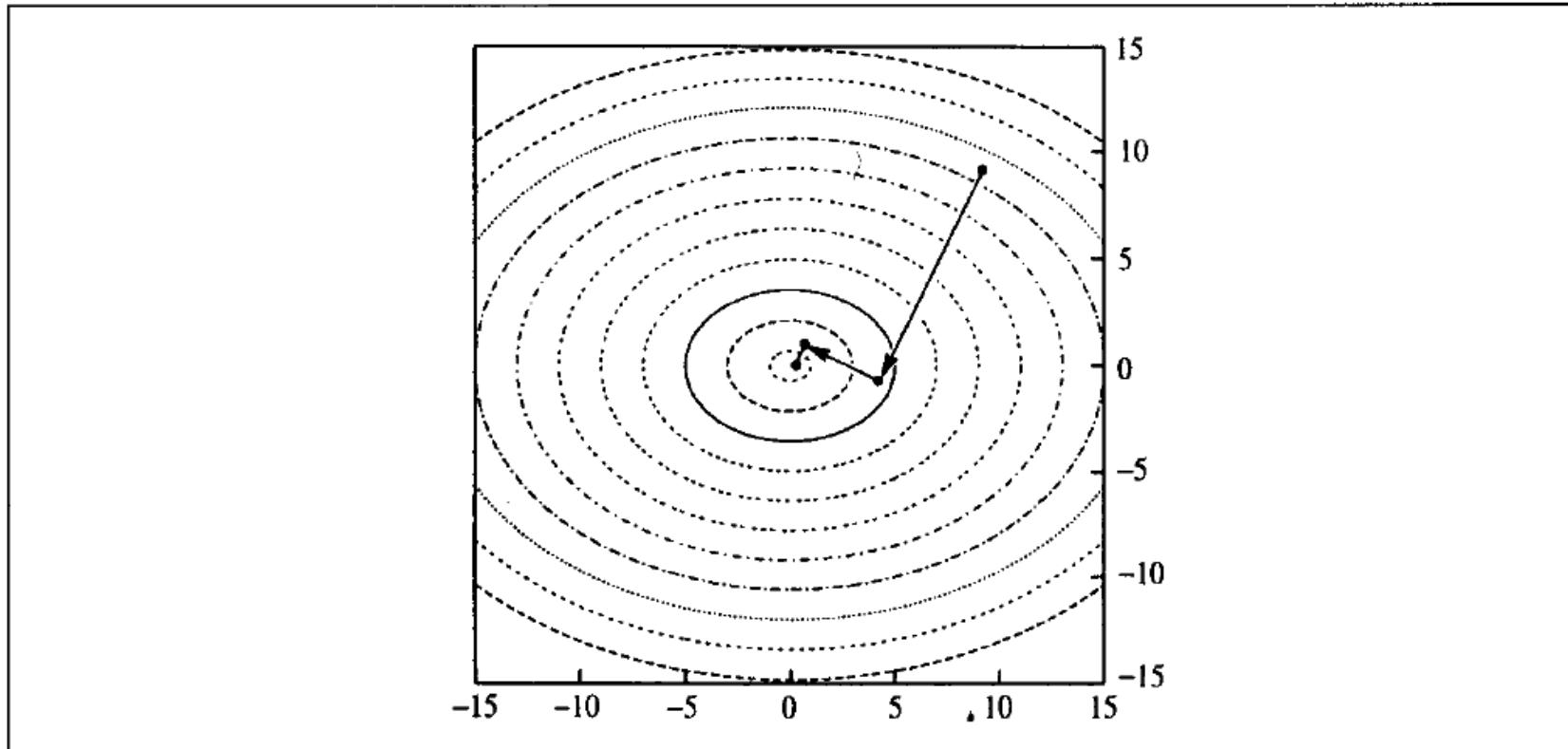


Fig. 5.9: Application of steepest descents to the function  $x^2 + 2y^2$ .

# Conjugate Gradients Minimization

- Less oscillatory behavior in narrow valleys compared to steepest descents

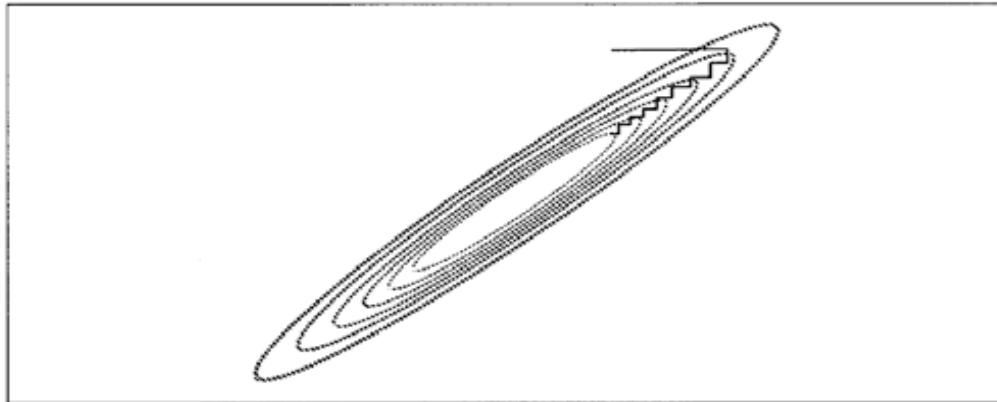


Fig. 5.10: The steepest descents method can give undesirable behaviour in a long narrow valley.

- Conjugate direction : new direction is computed from the gradient and the previous direction

$$\mathbf{v}_k = -\mathbf{g}_k + \gamma_k \mathbf{v}_{k-1} \quad (5.6)$$

$$\gamma_k = \frac{\mathbf{g}_k \cdot \mathbf{g}_k}{\mathbf{g}_{k-1} \cdot \mathbf{g}_{k-1}} \quad \text{Fletcher-Reeves algorithm} \quad (5.7)$$

# Conjugate Gradients Minimization

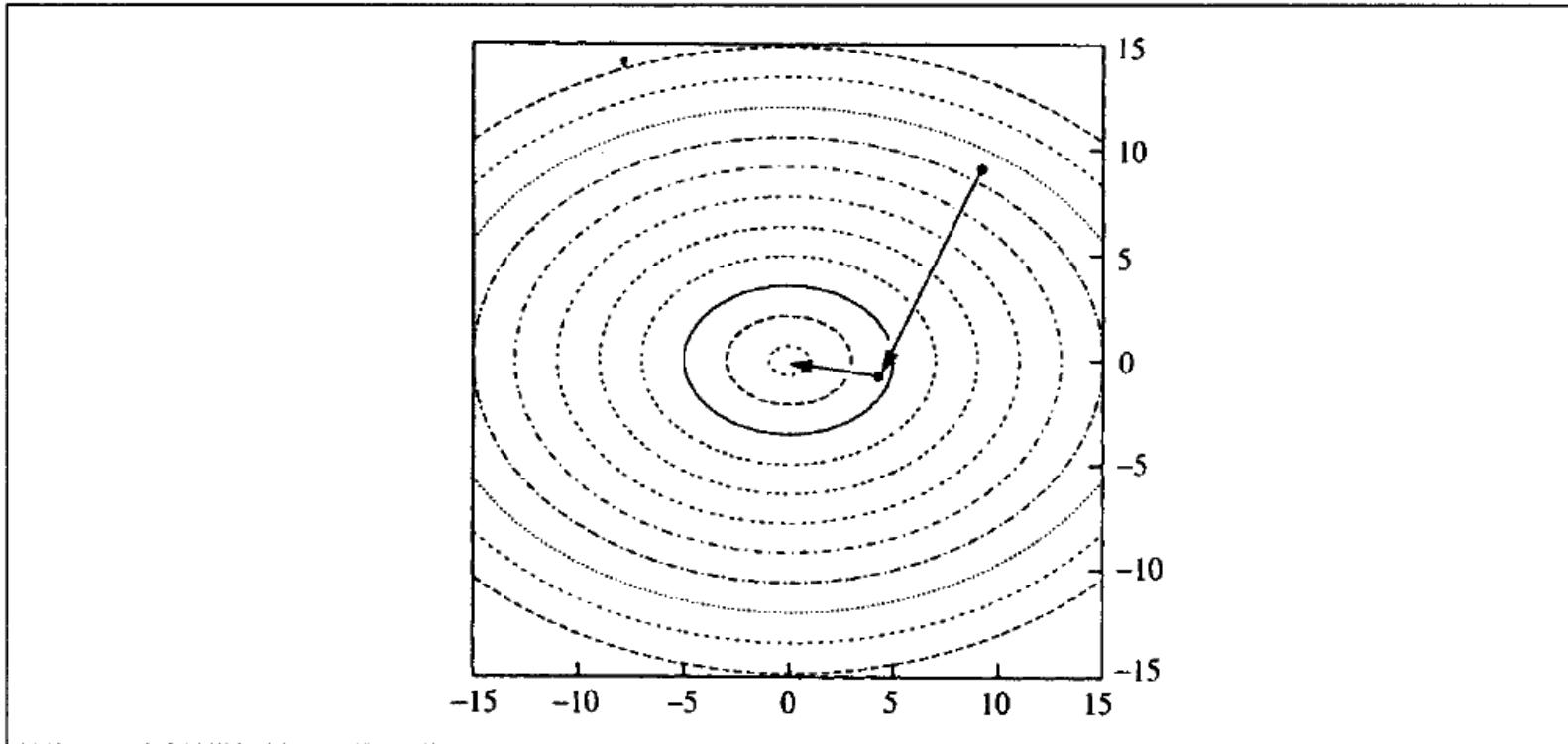


Fig. 5.11: Application of conjugate gradients method to the function  $x^2 + 2y^2$ .

- Different algorithms have different definitions of the scalar constant

**Polak-Ribiere algorithm**

$$\gamma_k = \frac{(\mathbf{g}_k - \mathbf{g}_{k-1}) \cdot \mathbf{g}_k}{\mathbf{g}_{k-1} \cdot \mathbf{g}_{k-1}}$$

# The Newton-Raphson Method

Taylor series expansion about the point  $x_k$

$$\mathcal{V}(x) = \mathcal{V}(x_k) + (x - x_k)\mathcal{V}'(x_k) + (x - x_k)^2\mathcal{V}''(x_k)/2 + \dots \quad (5.13)$$

$$\mathcal{V}'(x) = \mathcal{V}'(x_k) + (x - x_k)\mathcal{V}''(x_k) \quad (5.14)$$

At local minimum,  $\mathcal{V}'(x)$  is 0  $\Rightarrow x^* = x_k - \mathcal{V}'(x_k)/\mathcal{V}''(x_k)$

- For multidimensional function,  $\mathcal{V}''(x_k)$  correspond to the inverse Hessian Matrix of second derivatives (3N x 3N in dimension) : large storage needed if # of atoms exceed 100!
- Real surface is not quadratic, so multiple steps needed
- Quadratic approximation is more realistic near minimum, so N-R performs better around minimum

## Variants on the Newton-Raphson Method

- Update Hessian occasionally, but gradients recalculated at each iteration
- Block-diagonal Newton-Raphson method : only one atom is moved at each iteration (not efficient when motions of some atoms are closely coupled, e.g. a phenyl ring.)

## Quasi-Newton Methods

- The new position ( $x_{k+1}$ ) are obtained from  $x_k$ , the gradient  $g_k$  and the **approximated Hessian ( $H_k$ )**  
Each algorithm has a unique definition of approximated Hessian. Commonly seen algorithm: DFP, BFGS, MS  
Davidon-Fletcher-Powell, Broyden-Fletcher-Goldfarb-Shanno, Murtaugh-Sargent

# Convergence Criteria

- Changes in **energy** between successive steps  
< threshold value
- Changes in **coordinate** between successive  
steps < threshold
- Root-mean-square of **gradient (force)** <  
threshold (should also monitor the *maximum* value of  
the gradient)

# Performance of Minimization Methods

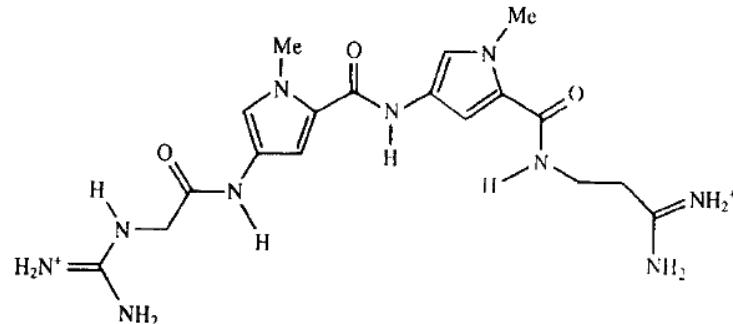


Fig. 5.12: The DNA inhibitor netropsin.

<b>Method</b>	<b>Initial refinement</b> (Av. gradient <1 kcal Å <sup>-2</sup> )		<b>Stringent minimisation</b> (Av. gradient <0.1 kcal Å <sup>-2</sup> )	
	<b>CPU time (s)</b>	<b>Number of iterations</b>	<b>CPU time (s)</b>	<b>Number of iterations</b>
Steepest descents	67	98	1405	1893
Conjugate gradients	149	213	257	367

Table 5.1 A comparison of the steepest descents and conjugate gradients methods for an initial refinement and a stringent minimisation.

# Choosing Minimization Methods

- Size of the system?

Newton-Raphson may not be good when too many atoms are present, due to the storage problem of Hessian matrix)

- Availability of analytical derivatives?

- Shape of the potential energy surface?

Far from the minimum: Steepest descents could be good  
Close to the minimum: Newton-Raphson or conjugate gradients may be superior

# Normal Mode Analysis and Thermodynamic properties

- Frequency analysis (diagonalisation of Hessian matrix based on mass-weighted coordinates) at the stationary point can get vibration normal modes (eigenvectors) and the corresponding vibration frequencies (eigenvalues)

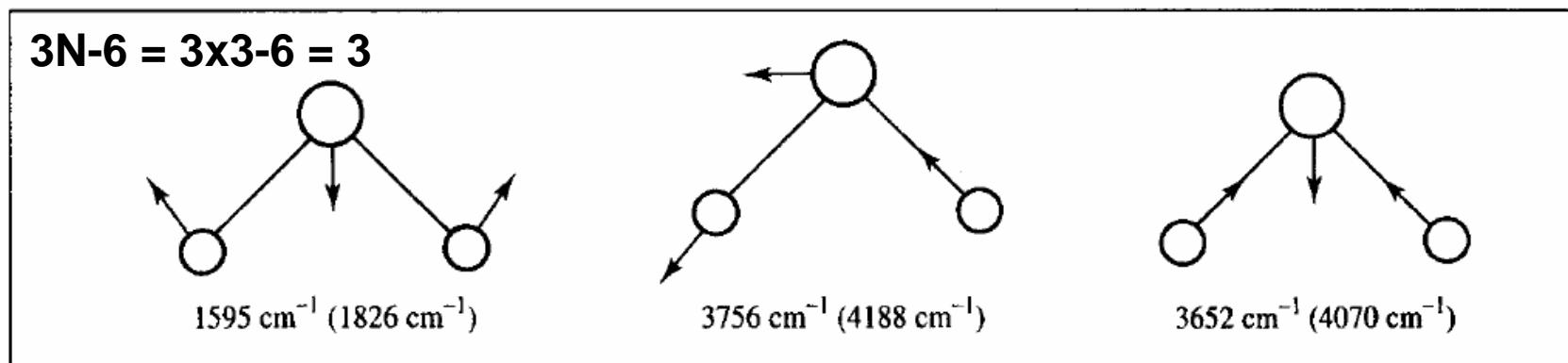


Fig. 5.15: Normal modes of water. Experimental and (calculated) frequencies are shown. Theoretical frequencies calculated using a 6-31G\* basis set.

# Normal Mode Analysis and Thermodynamic properties

- Energy from energy minimization corresponds to a hypothetical and motionless energy minimum at 0K
- Each normal mode is at the ground state at 0K  
=> zero-point vibration energy \*\*\*
- To compare with experimental : need corrections!

$$U(T) = U_{\text{trans}}(T) + U_{\text{rot}}(T) + U_{\text{vib}}(T)$$

$$H = U + RT$$

$$G = H - TS ***$$