

# **DIIS SCF Methods and BFGS Optimization**

**Accelerating Convergence to Finding Fixed Points**

**Trevor Oldham**

# Three SCF Algorithms

- `void DIIS_FP(molecule & mol, double tolerance, int history, bool verbose);`
  - A mixture of DIIS and FP methods. Start with FP iterations and collect past Fock matrices until max\_history is reached, then switch to DIIS
- `void DIIS(molecule & mol, double tolerance, int max_history, bool verbose);`
  - A pure DIIS implementation. Start immediately using the DIIS algorithm to build the Fock matrices
- `void fixed_point_iteration(molecule & mol, double tolerance, bool verbose);`
  - The method we used in the problems sets this semester.

# DIIS: Direct Inversion of the Iterative Subspace

## Motivations

- Extrapolate the solution to a set of linear equations by minimizing the error residual
- The newest residual vector is a linear combination of the previous error vectors on the condition that the coefficients must sum to one
- Using Lagrange multipliers construct the DIIS matrix and solve for coefficients
- Construct new Fock matrix as a linear combination of m most recent Fock matrices

$$B_{ij} = e_i \cdot e_j \quad F^\star = \sum_{i=0}^m c_i F_i$$

$$\begin{bmatrix} B_{11} & B_{12} & B_{13} & \dots & B_{1m} & 1 \\ B_{21} & B_{22} & B_{23} & \dots & B_{2m} & 1 \\ B_{31} & B_{32} & B_{33} & \dots & B_{3m} & 1 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ B_{m1} & B_{m2} & B_{m3} & \dots & B_{mm} & 1 \\ 1 & 1 & 1 & \dots & 1 & 0 \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_m \\ -\lambda \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$$

# DIIS: Direct Inversion of the Iterative Subspace

## The Algorithm

1. Perform FP iterations until  $m$  past Fock matrices are saved. Save  $\mathbf{e}_i = F_\alpha P_\alpha - P_\alpha F_\alpha$  at each iteration
2. Save  $P_\alpha$  and  $P_\beta$
3. Build DIIS matrix  $\mathbf{A}$  using  $B_{ij}$  values computed from past  $\mathbf{e}_i$
4. Solve  $\mathbf{y} = \mathbf{A}\mathbf{x}$  for  $\mathbf{x} = [c_0, c_1, c_2, \dots, c_m, -\lambda]$
5. Compute  $F^\star = \sum_{i=0}^m c_i F_i$
6. Solve symmetric eigenvalue problem  $F^\star C^{i+1} = SC^i E$  for new coefficient matrix  $C^{(i+1)}$
7. Compute  $P_\alpha, P_\beta$  and save  $F^\star, e_i, P_\alpha, P_\beta$
8. Continue 3 - 7 until  $P_\alpha^i - P_\alpha^{i+1} < tol$

# DIIS: Direct Inversion of the Iterative Subspace

## Results

- The DIIS/FP method does accelerate convergence
- The DIIS method alone converges too quickly
- Neither method returns the same value found from FP iteration
- The FP method gets very close to the solution, and DIIS makes smaller adjustments toward the fixed point
- The DIIS method is very dependent on the number  $M$ .

# BFGS: Broyden–Fletcher–Goldfarb–Shanno

## Motivations

- Minimize  $f(x)$  with initial guess  $x_0 \in \mathbb{R}^n$
- Choose descent direction using the negative gradient
- Perform line search in direction of the negative gradient
- Approximate the Hessian  $B_k$  using gradient and curvature information
- Complexity  $O(n^2)$

# BFGS: Broyden–Fletcher–Goldfarb–Shanno Algorithm

1. Start with  $B_k = I$
2. Compute search direction  $\mathbf{p}_k = B_k^{-1} \cdot (-\nabla f(\mathbf{x}))$
3. Perform line search for scalar  $\alpha_k$  such that  $\alpha_k = \operatorname{argmin}(f(\mathbf{x}_k) + \alpha_k \mathbf{p}_k)$  using Wolfe Conditions
4. Compute  $\mathbf{s}_k = \alpha_k \mathbf{p}_k$  and  $\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k$
5. Compute  $\mathbf{y}_k = \nabla f(\mathbf{x}_{k+1}) - \nabla f(\mathbf{x}_k)$
6. Approximate  $B_{k+1} = B_k + \frac{\mathbf{y}_k \mathbf{y}_k^T}{\mathbf{y}_k^T \mathbf{s}_k} - \frac{B_k \mathbf{s}_k \mathbf{s}_k^T B_k^T}{\mathbf{s}_k^T B_k \mathbf{s}_k}$
7. Continue 2 - 6 until  $\|\nabla f(\mathbf{x}_k)\| < \epsilon$

•

# BFGS: Broyden–Fletcher–Goldfarb–Shanno

## Results

- Still in the debugging stage - but some interesting results!
- Slow: from performing SCF iterations after each  $\mathbf{x}_k$  update
- Unstable:  $B_k$  can be singular meaning `arma::solve()` will not work. Must use `arma::pinv()`
- Results dependent on line search parameters
- Energy does decrease despite the gradient increasing
- Does not converge before maximum number of iterations is reached
- Atoms stay in similar geometry but get very far apart
- Final Energy approaches the exact value of the electron energy term as nuclear repulsion approaches 0



# References

- [https://en.wikipedia.org/wiki/Broyden-Fletcher-Goldfarb-Shanno\\_algorithm](https://en.wikipedia.org/wiki/Broyden-Fletcher-Goldfarb-Shanno_algorithm)
- [https://en.wikipedia.org/wiki/Wolfe\\_conditions](https://en.wikipedia.org/wiki/Wolfe_conditions)
- <https://medium.com/@tru11631/l-bfgs-algorithm-ecfb832a4176>
- <https://en.wikipedia.org/wiki/DIIS>
- [https://manual.q-chem.com/5.3/sect\\_diis.html](https://manual.q-chem.com/5.3/sect_diis.html)