Separated Representations and

## Fast Adaptive Algorithms in Multiple Dimensions

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## Start with an example

We have

$$
\left|\frac{1}{\|r\|}-\sum_{m=1}^{M} w_{m} e^{-p_{m}\|r\|^{2}}\right| \leq \frac{\epsilon}{\|r\|}
$$

for $\delta \leq\|r\| \leq 1$, where $p_{m}, w_{m}>0$ and $M=\mathcal{O}(-\log \delta)$.


Error $\left(\log _{10}\right)$ of approximating the Poisson kernel for $10^{-9} \leq\|r\| \leq 1, M=89$.

## The Poisson kernel

Due to the homogenuity of the Poisson kernel, we have

$$
t_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{n ; 1}=2^{-2 n} t_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{1}
$$

where

$$
t_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{1}=t_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{l_{1}, l_{2}, l_{3}}=\frac{1}{4 \pi} \int_{-1}^{1} \int_{-1}^{1} \int_{-1}^{1} \frac{1}{\|\mathbf{x}+\mathbf{l}\|} \Phi_{i i^{\prime}}\left(x_{1}\right) \Phi_{j j^{\prime}}\left(x_{2}\right) \Phi_{k k^{\prime}}\left(x_{3}\right) d \mathbf{x}
$$

and

$$
\Phi_{i i^{\prime}}(x)=\int_{0}^{1} \phi_{i}(x+y) \phi_{i^{\prime}}(y) d y, \quad i, i^{\prime}=0, \ldots, k-1
$$

are the cross-correlation functions of the scaling functions of the multiwavelet basis.

## Separated representation of the Poisson kernel

Theorem: For any $\epsilon>0$ the coefficients $t_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{1}$ have an approximation with a low separation rank,

$$
r_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{1}=\sum_{m=1}^{M} \frac{w_{m}}{b} F_{i i^{\prime}}^{m, l_{1}} F_{j j^{\prime}}^{m, l_{2}} F_{k k^{\prime}}^{m, l_{3}}
$$

such that

$$
\begin{aligned}
& \qquad \begin{array}{ll}
\left|t_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{1}-r_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{1}\right| & \leq \frac{2 \epsilon}{\pi}
\end{array} \max _{i}\left|l_{i}\right| \geq 2 \\
& \qquad\left|t_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{1}-r_{i i^{\prime}, j j^{\prime}, k k^{\prime}}^{1}\right| \leq C \delta^{2}+\frac{2 \epsilon}{\pi} \quad \max _{i}\left|l_{i}\right| \leq 1 \\
& \qquad F_{i i^{\prime}}^{m, l}=\int_{-1}^{1} e^{-p_{m} / b^{2}(x+l)^{2}} \Phi_{i i^{\prime}}(x) d x \\
& b=\sqrt{3}+\|\mathbf{l}\| \mid \text { and } \delta, M=O(-\log \delta)+O(-\log \epsilon), p_{m}, w_{m}, m=1, \ldots, M \text { are } \\
& \text { from the separated representation of the kernel. }
\end{aligned}
$$

## The projector on the divergence-free functions

For the projector on the divergence-free functions, we have

$$
\left|\frac{1}{\|r\|^{3}}-\sum_{m=1}^{M} w_{m} e^{-p_{m}\|r\|^{2}}\right| \leq \frac{\epsilon}{\|r\|^{2}},
$$

for $\delta \leq\|r\| \leq 1$, where $p_{m}, w_{m}>0$ and $M=\mathcal{O}(-\log \delta)$.


Error of the approximation with 110 terms over the domain $10^{-7} \leq\|r\| \leq 1$.

## Other Examples

```
1. e}\mp@subsup{e}{}{iKr}/r\approx\mp@subsup{\sum}{m}{}\mp@subsup{w}{m}{}\mp@subsup{e}{}{\mp@subsup{\tau}{m}{}\mp@subsup{r}{}{2}}\quad\mathrm{ for the Helmholtz kernel, }K~10
2. }\mp@subsup{J}{0}{}(x)
3. }\operatorname{sin}(x)/
4. }\mp@subsup{D}{N}{}(x
5. }\pi\operatorname{cot}(\pix
```

6. $\log (\sin (\pi x))$
7. $\tanh (x)$
8. ...

## Quantum Chemistry

With R. Harrison, G. Fann and T. Yanai

- Complete elimination of the basis error
- Implementation for one-electron models (HF, DFT)
- Most accurate computations up to now (within these models)
- Correct scaling of cost with system size
- Much smaller computer code than "Gaussians" ( $<$ R. Harrison)

With R. Cramer, V. Cheruvu and F. Pérez

- Adaptive PDE solvers
- Operator calculus in 3D


## Examples: elements, small molecules...



Adaptive subdivision of space for the benzene molecule $\mathrm{C}_{6} \mathrm{H}_{6}$ (from R. Harrison, G. Fann and G. Beylkin)

## Current timing results for 3D adaptive Poisson solver

Platform: Pentium 4-2.8 GHz with 1 GB of RAM for which flops.c gives $\sim$ 950 MFLOPS for add-multiply code.
All timings made for $\epsilon=5 \times 10^{-3}$.

| $N_{\text {nod }}$ | 6 | 8 | 10 | 12 |
| :---: | :---: | :---: | :---: | :---: |
| $N_{\text {blocks }}$ | 512 | 120 | 120 | 64 |
| $t(s)$ | 36 | 12.1 | 19.3 | 10.4 |
| $t /$ block $(s)$ | 0.07 | 0.1 | 0.16 | 0.16 |
| MFLOPS | 171 | 317 | 430 | 505 |

Some comments:

- MADNESS (R. Harrison et. al, ORNL) already implements improvements which make it at least $50 X$ faster than our code (our improvements will be different but should produce a similar speedup)
- Already very competitive with multigrid codes for small $\epsilon$, where multigrid slows down dramatically.
- Need to test against FMM-adaptive results in 2d (Greengard \& Etheridge 2001).
- Python overhead measured at $\sim 1-2 \%$.


## Problem

- Multiresolution representation of operators
- Classes of operators represented by banded matrices acting at different scales
- Curse of dimensionality
- Number of entries in a banded matrix: $\mathcal{O}(b M)$
- Cost of multiplication of two banded matrices: $\mathcal{O}\left(b^{2} M\right)$
- Number of entries in a banded operator in dimension $d: \mathcal{O}\left(b^{d} M^{d}\right)$
- Cost of multiplication of two banded operators in dimension $d$ : $\mathcal{O}\left(b^{2 d} M^{d}\right)$


## The Separated Representation

The standard separation of variables: $f\left(x_{1}, x_{2}, \ldots, x_{d}\right)=\phi_{1}\left(x_{1}\right) \cdot \phi_{2}\left(x_{2}\right) \cdot \ldots \cdot \phi_{d}\left(x_{d}\right)$ Definition: For a given $\epsilon$, we represent a matrix $\mathbb{A}=A\left(j_{1}, j_{1}^{\prime} ; j_{2}, j_{2}^{\prime} ; \ldots ; j_{d}, j_{d}^{\prime}\right)$ in dimension $d$ as

$$
\sum_{l=1}^{r} s_{l} A_{1}^{l}\left(j_{1}, j_{1}^{\prime}\right) A_{2}^{l}\left(j_{2}, j_{2}^{\prime}\right) \cdots A_{d}^{l}\left(j_{d}, j_{d}^{\prime}\right)
$$

where $s_{l}$ is a scalar, $s_{1} \geq \cdots \geq s_{r}>0$, and $\mathbb{A}_{i}^{l}$ are matrices with entries $A_{i}^{l}\left(j_{i}, j_{i}^{\prime}\right)$ and norm one. We require the error to be less than $\epsilon$ :

$$
\left\|\mathbb{A}-\sum_{l=1}^{r} s_{l} \mathbb{A}_{1}^{l} \otimes \mathbb{A}_{2}^{l} \otimes \cdots \otimes \mathbb{A}_{d}^{l}\right\| \leq \epsilon
$$

We call the scalars $s_{l}$ separation values and the rank $r$ the separation rank.
The smallest $r$ that yields such a representation for a given $\epsilon$ is the optimal separation rank.

## Beyond the definition

- How to construct such representations?
- How to use them?
- What is the class of operators that yields a small separation rank for a given $\epsilon$ ?

Trivial examples:

- Identity: $\mathbb{I}=\mathbb{I}_{1} \otimes \mathbb{I}_{2} \otimes \cdots \otimes \mathbb{I}_{d}$
- Laplacian: $\mathcal{T}=\Delta_{1} \otimes \mathbb{I}_{2} \otimes \cdots \otimes \mathbb{I}_{d}+\mathbb{I}_{1} \otimes \Delta_{2} \otimes \cdots \otimes \mathbb{I}_{d}+\ldots+\mathbb{I}_{1} \otimes \mathbb{I}_{2} \otimes \cdots \otimes \Delta_{d}$ Non-trivial examples to follow...


## First example: a new trigonometric identity

Consider the function $\sin \left(x_{1}+x_{2}+\ldots+x_{d}\right)$ and represent it in the separated form. The usual trigonometric formulas produce $2^{d-1}$ terms.
Lemma:

$$
\sin \left(\sum_{j=1}^{d} x_{j}\right)=\sum_{j=1}^{d} \sin \left(x_{j}\right) \prod_{k=1, k \neq j}^{d} \frac{\sin \left(x_{k}+\alpha_{k}-\alpha_{j}\right)}{\sin \left(\alpha_{k}-\alpha_{j}\right)}
$$

for all choices of $\alpha_{1}, \alpha_{2}, \ldots, \alpha_{d}$, such that $\sin \left(\alpha_{k}-\alpha_{j}\right) \neq 0$ for all $j \neq k$. Observations:

- Only $d$ terms
- Separated representation is not unique
- It can be ill-conditioned!


## Condition number of separated representation

## Definition:

We call the ratio

$$
\kappa=\frac{\sum_{l=1}^{r} s_{l}}{\|\mathbb{A}\|}
$$

the condition number of separated representation.

It is a natural definition since $\left\|s_{l} \mathbb{A}_{1}^{l} \otimes \mathbb{A}_{2}^{l} \otimes \cdots \otimes \mathbb{A}_{d}^{l}\right\|=s_{l}$.

We need to maintain $\kappa \mu\|\mathbb{A}\| \leq \epsilon$, where $\mu$ is the machine roundoff.

## Similarities and differences with SVD

If $d=2$ then the separated representation can be obtained via SVD.
(Actually, we use a much simpler algorithm since we do not insist on orthogonality between vectors in a given direction).

If $d \geq 3$ then the analogy with SVD breaks down: by changing $\epsilon$ we change all terms in the representation rather than add/delete terms

Many attempts to treat separated representation as a generalization of SVD but the construction depends on $\epsilon$ !

## The Poisson kernel in higher dimensions

Theorem: For any $\epsilon>0$, the Poisson kernel

$$
\frac{1}{(d-2) \Omega_{d}} \frac{1}{|x|^{d-2}}
$$

when applied to functions with the Fourier transform supported in the annulus $\left(\sum_{i=1}^{d} \xi_{i}^{2}\right)^{1 / 2} \in[\sqrt{\delta}, \sqrt{D}]$, can be approximated to within $\epsilon$ by

$$
\sum_{l=1}^{r} \alpha_{l} \bigotimes_{i=1}^{d} \frac{1}{\sqrt{4 \pi \tau_{l}}} \exp \left(-x_{i}^{2} / 4 \tau_{l}\right)
$$

where the separation rank grows as $r=\mathcal{O}(\log (D /(\delta \epsilon)))$.
For functions with the Fourier transform in the "cubic annulus", the separation rank grows as $r=\mathcal{O}\left(\log \left(d^{2} D /(\delta \epsilon)\right)\right)$.

## Multiparticle Schrödinger operator

The Hamiltonian for the multiparticle Schrödinger operator is the sum of three terms

$$
\mathcal{H}=-\sum_{i=1}^{N} \Delta_{i}-\sum_{i=1}^{N} V_{i}+\sum_{i=1}^{N-1} \sum_{m=i+1}^{N} W_{i m},
$$

where the 3D Laplacian corresponding to electron $i$ is defined as $\frac{\partial^{2}}{\partial x_{i}^{2}}+\frac{\partial^{2}}{\partial y_{i}^{2}}+\frac{\partial^{2}}{\partial z_{i}^{2}}$, the nuclear potential $V_{i}$ is operator of multiplication by $1 / r_{i}$ and the electron-electron potential $W_{i m}$ is multiplication by $1 /\left|r_{i}-r_{m}\right|$.
$\mathcal{T}=-\Delta_{1} \otimes \mathbb{I}_{2} \otimes \cdots \otimes \mathbb{I}_{N}-\mathbb{I}_{1} \otimes \Delta_{2} \otimes \cdots \otimes \mathbb{I}_{N}-\cdots-\mathbb{I}_{1} \otimes \mathbb{I}_{2} \otimes \cdots \otimes \Delta_{N}$
$\mathbb{V}=-V_{1} \otimes \mathbb{I}_{2} \otimes \cdots \otimes \mathbb{I}_{N}-\mathbb{I}_{1} \otimes V_{2} \otimes \cdots \otimes \mathbb{I}_{N}-\ldots-\mathbb{I}_{1} \otimes \mathbb{I}_{2} \otimes \cdots \otimes V_{N}$
$W=\ldots$ has $\mathcal{O}\left(N^{2}\right)$ terms.
Thus, the nominal separation rank grows as $\mathcal{O}\left(N^{2}\right)$.
It turns out that ...

## Separation rank of the Schrödinger operator

## Theorem:

The representation of $\mathcal{T}+\mathbb{V}$ to within $\epsilon$ in the operator norm has separation rank

$$
\mathrm{r}=\mathcal{O}\left(\frac{\log \left(N\left\|-\Delta_{1}-V_{1}\right\| / \epsilon\right)}{\log (1 / \mu)-\log \left(N\left\|-\Delta_{1}-V_{1}\right\| / \epsilon\right)}\right)
$$

Let us symmetrically separate $W_{i m}=\sum_{k=1}^{r_{w}} W_{i}^{k} W_{m}^{k}+\mathcal{O}(\epsilon)$. For each value of $k$ the operator has the form $\mathcal{A}=\sum_{i=1}^{N-1} \sum_{m=i+1}^{N} \mathcal{A}_{i} \mathcal{A}_{m}$.
Theorem:
The representation of $\mathcal{A}$ to within $\epsilon$ in the operator norm has separation rank

$$
\mathrm{r}=\mathcal{O}\left(\frac{\log \left(N^{2}\left\|\mathcal{A}_{1}\right\|^{2} / \epsilon\right)}{\log (1 / \mu)-\log \left(N^{2}\left\|\mathcal{A}_{1}\right\|^{2} / \epsilon\right)}\right)
$$

Thus, the separation rank of the Schrödinger operator grows only as $\log (N)$

## Constructive proof

Consider

$$
\mathbb{G}(t)=\left\|-\Delta_{1}-V_{1}\right\| \bigotimes_{i=1}^{N}\left(\mathbb{I}_{i}+t \frac{-\Delta_{i}-V_{i}}{\left\|-\Delta_{1}-V_{1}\right\|}\right)
$$

and note that $\mathbb{G}^{\prime}(0)=\mathcal{T}+\mathbb{V}$. Using finite difference formula of order $r$, we approximate

$$
\mathbb{G}^{\prime}(0) \approx \sum_{j=1}^{r} \alpha_{j} \mathbb{G}^{\prime}\left(t_{j}\right)
$$

Similarly, we using $\mathcal{A}_{i}$ instead of $-\Delta_{i}-V_{i}$ in the definition of $\mathbb{G}$, we note that $\mathbb{G}^{\prime \prime}(0)=2 \mathcal{A} /\left\|\mathcal{A}_{1}\right\|$ and use the same approach.
(This approximation was first discovered numerically).

## Linear algebra for separated representations

- Addition and multiplication of operators in separated form leads to operators of the same form
- $\mathcal{O}\left(d \cdot r \cdot M^{2}\right)$ or $\mathcal{O}(d \cdot r \cdot M)$ to store
- $\mathcal{O}\left(d \cdot \tilde{r} \hat{r} \cdot M^{3}\right)$ (or better) to multiply operators
- Separation rank grows, e.g. $\tilde{r} \hat{r}$ for multiplication of operators

We need to reduce the separation rank.

## Reduction of separation rank via alternating least squares

Core algorithm:
We start with the initial approximation of separation rank $r^{\prime}<\tilde{r} \hat{r}$,

$$
\sum_{l=1}^{r^{\prime}} s_{l} \mathbb{A}_{1}^{l} \otimes \mathbb{A}_{2}^{l} \otimes \cdots \otimes \mathbb{A}_{d}^{l}
$$

and then iteratively refine it. We refine one direction, $k$, at a time, and then alternate the directions, $k=1,2, \ldots, d$. To refine in direction $k$, we fix the vectors in the other directions and then solve for new $\mathbb{A}_{k}^{l}$ and $s_{l}$ to minimize the residual. It is easy to show that the residual decreases at each step. Each refinement requires solving a linear least squares problem to minimize the residual.
We detect if the residual does not change anymore and, if it is not small enough, increase the separation rank $r^{\prime}$, etc.

## Some details

- Convergence is not guaranteed but the algorithm performs well in practice
- The condition number of separated representation is included into least squares
- The algorithm loses $1 / 2$ of the digits, so that the best accuracy obtainable is $\epsilon=\sqrt{\mu}$, where $\mu$ is the machine roundoff
- One iteration cost roughly $\mathcal{O}\left(d \cdot \tilde{r}^{3} \cdot M\right)$.
- Several preliminary steps to reduce computational cost
- We have discovered a new trigonometric identity and an approximation technique using this algorithm


## Example

Simplified single-atom N -electron model

$$
\mathbb{H}=-\Delta+2 N \sum_{i=1}^{N} \cos \left(x_{i}\right)+\sum_{i=1}^{N} \sum_{k>i}^{N} \cos \left(x_{i}-x_{k}\right)
$$

- The number of "particles" $N=30$
- We use power method for $\mathbb{A}=C_{N} \mathbb{I}-\mathbb{H}$, where $C_{N} \approx\|\mathbb{H}\| / 2$
- Nominal computational cost: $10^{80}$


## Results of computation

$\mathbf{F}_{k}$ is the scalar multiple of the eigenvector corresponding to the smallest eigenvalue.
$\mathbf{F}_{0}$ is chosen with the separation rank one.
Accuracy is increased gradually.

| $\epsilon$ | iterations | $r\left(\mathbf{F}_{k}\right)$ | time $(\mathbf{s e c})$ |
| :---: | :---: | :---: | :---: |
| $1 \mathrm{e}-2$ | 521 | 1 | $2.7 \mathrm{e}+1$ |
| $1 \mathrm{e}-3$ | 2557 | 2 | $1.4 \mathrm{e}+2$ |
| $1 \mathrm{e}-4$ | 4130 | 5 | $1.5 \mathrm{e}+3$ |
| $1 \mathrm{e}-5$ | 5230 | 6 | $6.4 \mathrm{e}+3$ |
| $1 \mathrm{e}-6$ | 6160 | 11 | $2.0 \mathrm{e}+4$ |
| $1 \mathrm{e}-7$ | 6368 | 12 | $2.2 \mathrm{e}+4$ |

## Solving linear systems in separated representation

Linear system $\mathbb{A} \mathbf{F}=\mathbf{G}$, where $\mathbb{A}$ is the Laplacian in dimension 20 , size in each direction $M=30$

| $r(\mathbf{F})$ | $\\|\mathbb{A} \mathbf{F}-\mathbf{G}\\| /\\|\mathbf{G}\\|$ | time |
| :---: | :---: | :---: |
| 1 | $2.5 \cdot 10^{-2}$ | 13 |
| 3 | $3.8 \cdot 10^{-3}$ | 84 |
| 5 | $6.8 \cdot 10^{-4}$ | 213 |
| 9 | $8.0 \cdot 10^{-5}$ | 789 |
| 13 | $8.4 \cdot 10^{-6}$ | 2048 |
| 19 | $9.5 \cdot 10^{-7}$ | 6121 |

G is random, with separation rank one.
Separation rank of the solution cannot exceed that of the inverse Laplacian

## Antisymmetry

Since electrons are fermions, the wave function must be antisymmetric, e.g., $\psi\left(\gamma_{2}, \gamma_{1}, \gamma_{3}, \ldots\right)=-\psi\left(\gamma_{1}, \gamma_{2}, \gamma_{3}, \ldots\right)$, where $\gamma=((x, y, z), \sigma)$ and $\sigma$ is the spin.
Given a function of $N$ variables, its "antisymmetrizer" is defined by

$$
\mathcal{A}=\frac{1}{N!} \sum_{p \in S_{N}}(-1)^{p} \mathcal{P}
$$

where $S_{N}$ is the permutation group on $N$ elements. If $\mathcal{A}$ is applied to a separable function, then the result can be expressed as a Slater determinant,

$$
\mathcal{A} \prod_{j=1}^{N} \phi_{j}\left(\gamma_{j}\right)=\frac{1}{N!}\left|\begin{array}{cccc}
\phi_{1}\left(\gamma_{1}\right) & \phi_{1}\left(\gamma_{2}\right) & \cdots & \phi_{1}\left(\gamma_{N}\right) \\
\phi_{2}\left(\gamma_{1}\right) & \phi_{2}\left(\gamma_{2}\right) & \cdots & \phi_{2}\left(\gamma_{N}\right) \\
\vdots & \vdots & \ddots & \vdots \\
\phi_{N}\left(\gamma_{1}\right) & \phi_{N}\left(\gamma_{2}\right) & \cdots & \phi_{N}\left(\gamma_{N}\right)
\end{array}\right|
$$

## Do we have a problem?

The number of terms in $\mathcal{A} \prod_{j=1}^{N} \phi_{j}\left(\gamma_{j}\right)$ grows exponentially fast and, although this number can algebraically be reduced somewhat, are we in trouble?
If we care only about computing inner products with $\mathcal{A} \prod_{j=1}^{N} \phi_{j}\left(\gamma_{j}\right)$, then the so-called Löwdin rules provide a solution,

$$
\left\langle\mathcal{A} \prod_{j=1}^{N} \phi_{j}\left(\gamma_{j}\right), \mathcal{A} \prod_{j=1}^{N} \tilde{\phi}_{j}\left(\gamma_{j}\right)\right\rangle=\frac{1}{N!}\left|\begin{array}{cccc}
\left\langle\phi_{1}, \tilde{\phi}_{1}\right\rangle & \left\langle\phi_{1}, \tilde{\phi}_{2}\right\rangle & \cdots & \left\langle\phi_{1}, \tilde{\phi}_{N}\right\rangle \\
\left\langle\phi_{2}, \tilde{\phi}_{1}\right\rangle & \left\langle\phi_{2}, \tilde{\phi}_{2}\right\rangle & \cdots & \left\langle\phi_{2}, \tilde{\phi}_{N}\right\rangle \\
\vdots & \vdots & \ddots & \vdots \\
\left\langle\phi_{N}, \tilde{\phi}_{1}\right\rangle & \left\langle\phi_{N}, \tilde{\phi}_{2}\right\rangle & \cdots & \left\langle\phi_{N}, \tilde{\phi}_{N}\right\rangle
\end{array}\right| .
$$

Computing determinant costs at most $\mathcal{O}\left(N^{3}\right)$, but for large $N$ the matrix is banded and the cost is $\mathcal{O}(N)$, so that we are O.K.

## Example of computing the antisymmetric ground state

Separated rank, achieved approximation, and eigenvalue estimates for the separable $\left(\mathbf{F}_{0}\right)$ and main approximations to the wavefunction.

|  | $r$ | $\epsilon$ | $\\| \mathcal{A} \mathbb{H} \mathbf{F}$ | $\langle\mathcal{A} \mathbb{H} \mathbf{F}, \mathcal{A} \mathbf{F}\rangle$ |
| :---: | :---: | :---: | :---: | :---: |
| $\mathbf{F}_{0}$ | 1 | $3.4 \cdot 10^{-3}$ | 322.6727395 | 322.3859013 |
| $\mathbf{F}$ | 2 | $10^{-4}$ | 321.8852595 | 321.8844158 |


| $\phi_{1}$ | $\phi_{2}$ | $\phi_{3}$ | $\phi_{4}$ | $\phi_{5}$ |
| :---: | :---: | :---: | :---: | :---: |



The computed separable approximation $\mathbf{F}_{0}$ to the wave function.

## Structure of the antisymmetric ground state

$$
i=1 \quad i=2 \quad i=3 \quad i=4 \quad i=5
$$

$l=1 ; ~ 0.999350$

$l=2 ; 0.033093$


## Conclusions and future work

- Powerful method for multidimensional problems
- Lattice sums
- Operators in 3D (e.g., oscillatory Green's functions)
- Operators in 6D for multiresolution quantum chemistry (two-electron models)
- We are attempting to solve the multiparticle Schrödinger equation
- Complete MADNESS (Multiresolution ADaptive NumErical Scientific Simulation)

