A Fast Continuation Method for the Ornstein-Zernike Equations

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Joint work with

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Outline

- The Ornstein-Zernike (OZ) Equations
- Fast solvers for compact fixed point problems Application to OZ + uniqueness problems
- Path following: introduction Nonlinear solvers Pseudo-arclength continuation
- Multilevel method.
- Results

OZ Equations: O-Z, 1914

Used to calculate probability distributions of atoms in fluid states. Unknowns are $h, c \in C[0, L]$.

- *h*: radial pair correlation function, observable
- c: direct correlation function, defined by IE

Integral Equation:

$$\boldsymbol{h}(r) - \boldsymbol{c}(r) - \boldsymbol{\rho}(\boldsymbol{h} \ast \boldsymbol{c})(r)$$

where

$$(\mathbf{h} * \mathbf{c})(\mathbf{r}) = \int_{\mathbb{R}^3} \mathbf{c}(\|\mathbf{r} - \mathbf{r}'\|) \mathbf{h}(\|\mathbf{r}'\|) d\mathbf{r}'.$$

Algebraic Closure Constraint

$$\exp(-\beta U(r) + \mathbf{h}(r) - \mathbf{c}(r)) - \mathbf{h}(r) - 1 = 0.$$

where *u* is the Lennard-Jones potential.

$$U(r) = 4\varepsilon \left(\left(\frac{\sigma}{r}\right)^{12} - \left(\frac{\sigma}{r}\right)^6 \right).$$

Parameters

Data are parameters

- ρ : number density, sometimes unknown
- $\beta = 1/(absolute temperature \times Boltzmann's constant)$
- ε : well depth of the potential
- σ : determines size of the particles

Discretization

- Uniform grid on [0, L]
- Trapezoid rule for integration
- Discrete Hankel transform for evaluation of integrals

$$\mathscr{H}(h)(k) = 4\pi \int_0^\infty \frac{\sin(kr)}{kr} h(r) r^2 dr$$

and

$$h * c = \mathscr{H}^{-1}(\hat{h}\hat{c}).$$

• Fast evaluation via FFT

Solution: $\rho = .2, \sigma = 2; \varepsilon = .1; \beta = 10; L = 9$



Reduction to single equation

Let g = h - c, then the closure constraint expresses c as a function of g.

$$\boldsymbol{c}(r) = \boldsymbol{c}(\boldsymbol{g}(r)) = \exp(-\boldsymbol{\beta}U(r) + \boldsymbol{g}(r)) - \boldsymbol{g}(r) - 1.$$

The integral equation is

$$h - \rho c * h = c.$$

Take Hankel transforms

$$\hat{h} - \rho \hat{h} \hat{c} = \hat{c},$$

and obtain $\hat{h} = \hat{c}/(1 - \rho \hat{c})$.

$g \rightarrow c \rightarrow h$ leads to . . .

$$h = h(c(g)) = c(g) + \mathscr{K}(g).$$

Subtract c and obtain a fixed point problem for g.

$$\underline{g} = \underline{h}(\underline{c}(\underline{g})) - \underline{c}(\underline{g}) = \mathscr{K}(\underline{g}).$$

 \mathscr{K} is a nonlinear integral operator with compact Fréchet derivative.

Alternative: reduce to single equation in *c*

• $c \rightarrow h(c)$ via solution of integral equation

•
$$h(c) - c = \mathscr{G}(c)$$
, \mathscr{G} compact

•
$$\mathscr{K}(c) = \exp(-\beta U - \mathscr{G}(c)) - \mathscr{G}(c) - 1$$

Compact fixed point problem:

$$c = \mathscr{K}(c)$$

More General OZ Equations

Unknowns $h, c, \rho, \in C[0, L]$

$$h(r) = \exp(-\beta U(r) + h(r) - c(r)) - 1$$

$$h(r) = c(r) + \int_{0}^{r} c(r - r')\rho(r')h(r')dr'$$

$$\rho(r) = A_{1}\exp\left(-\beta U(r) + \int_{0}^{r} \rho(r - r')c(r')dr'\right)$$

Also matrix-valued unknowns.

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Compact Fixed Point Problems

We're worried about problems like

 $F(u) = u - \mathscr{K}(u) = 0$, on a Banach space X,

where

- $\mathscr{K} \in C^1_{LIP}(X)$.
- $\mathscr{K}' \in Com(X)$.
- Compactness will lead to fast solvers.

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- Fast evaluation ($O(N \log(N))$) is common.
- Newton-Krylov, Newton-MG nonlinear solvers work with no surprises (most of the time).

World's Easiest Example

Linear Fredholm equation:

$$(I - K)u(x) = u(x) - \int_0^1 k(x, y)u(y) \, dy = f(x),$$

 $f \in X = C[0,1], k \in C([0,1] \times [0,1])$ Approximating space: $V_h =$ span $\{\phi_i\}$ P_h is a projection onto V_h , and we seek $u^h \in V_h$.

$$u^{h}(x) - K_{h}u^{h}(x) = u^{h}(x) - \int_{0}^{1} k_{h}(x, y)u^{h}(y) \, dy = P_{h}f(x)$$

where, $k_h(x, y) = \sum_{i,j=1}^{N_h} k(x_i, x_j) \phi_i(x) \phi_j(y)$

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Solve finite dimensional system for nodal values.

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Solve finite dimensional system for nodal values.

• Other choices of *K_h* are possible Standard quadrature rule + fine-to-coarse by averaging

Nystrom interpolation

- Solve $\tilde{u}^h K_h \tilde{u}^h = f$ rather than $u^h K_h u^h = P_h f$.
- Multiply by P_h and use $K_h = K_h P_h = P_h K_h$ to get

$$(P_h\tilde{u}) - P_hK_h(P_h\tilde{u}) = P_hf.$$

Finite dimensional system. Solve for $u^h = P_h \tilde{u}^h$.

•
$$\tilde{u}^h = f + K_h u^h$$

Performance of GMRES

Avoid the $O(N_h^3)$ cost of a direct solver, and compute

$$u^{h} = (I - K_{h})^{-1} P_{h} f = \sum_{i=1}^{N_{h}} u_{i}^{h} \phi_{i} \in V_{h}.$$

with GMRES.

- Continuous problem: superlinear convergence
- Discrete problem: mesh independent performance
- Cost: One $K_h v$ evaluation/linear iteration Think $N_h \log N_h$ work if done slickly.

Nested iteration (aka grid sequencing) is a good idea.

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 - One iteration/level suffices.

Nonlinear Problems

Generalization to the nonlinear case is easy,

$$u \leftarrow u - (I - \mathscr{K}'_H(u^H))^{-1}F_h(u)$$

if you're careful about the fine-to-coarse transfer. If coarse mesh suff fine,

- Krylovs/Newton independent of *H*
- one Newton/level suffices.

Nested Iteration: Bottom up; K 95

$$h = H, i = 0$$

Solve $F_H(u^H) = 0$ to high accuracy.
 $u \leftarrow u^H$
for $i = 1, \dots m$ do
 $h \leftarrow h/2$
 $u \leftarrow u - (I - \mathscr{K}'_H(u^H))^{-1}F_h(u)$
end for

- All the linear solver work is on the coarse mesh.
- Only two grids *H* and *h* active at any time.
- Cost of solve to truncation error: < 3 fine mesh evals, depending on cost of \mathscr{K}_h

Works great for OZ! K., Pettit 2004

Iteration statistics for three nested iterations

- Multilevel, Newton-GMRES, Picard
- Formulation in c: $c \rightarrow h(c)$ via integral equation $c = \mathscr{K}(c)$ via constraint
- Tabulate:

 i_G^f = fine mesh GMRES/Newton (average) i_G^c = coarse GMRES/Newton (average) incoming nonlinear residual R_h ($R_{2h} \approx 4R_h$)

Iteration Statistics: h = 1/(N-1)

	Picard		Newton-GMRES		Multilevel	
N	R_{δ}	i_G^f	R_{δ}	i_G^f	R_{δ}	i_G^c
65	3.5900e+00	650	3.5900e+00	85	3.5900e+00	85
129	1.3696e-01	11	1.3696e-01	4	1.3696e-01	8
257	2.0031e-02	3	2.9413e-02	5	4.1900e-02	7
513	4.8144e-03	9	6.9937e-03	5	9.4120e-03	7
1025	2.3568e-03	14	1.5400e-03	5	2.0205e-03	7
2049	3.6543e-04	15	3.5596e-04	7	4.6015e-04	8
4097	8.2396e-05	22	8.4570e-05	5	1.0831e-04	8
8193	2.2253e-05	38	2.0784e-05	7	2.6411e-05	8
16385	4.0075e-06	48	5.2729e-06	8	6.5042e-06	8
32769	9.7738e-07	32	1.2263e-06	5	1.6132e-06	8
65537	2.3869e-07	44	3.0647e-07	7	4.0169e-07	8

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- We found two solutions; one was wrong.
- Monte knew which one was correct. Tim did not.
- One can get one or the other by
 - varying the initial iterate,
 - varying the initial grid, or
 - varying the details of the algorithm,
- which motivates a parametric ($\sigma, \varepsilon, \rho \dots$) study of the OZ equations.

Path Following

F : *X* × [*a*,*b*], *F* smooth, *X* a Banach space. Objective: Solve $F(u, \lambda) = 0$ for $\lambda \in [a, b]$ Obvious approach:

Set $\lambda = a$, solve $F(u, \lambda) = 0$ with Newton-(MG, GMRES, ...) to obtain $u_0 = u(\lambda)$. while $\lambda < b$ do Set $\lambda = \lambda + d\lambda$. Solve $F(u, \lambda) = 0$ with u_0 as the initial iterate. $u_0 \leftarrow u(\lambda)$ end while

The implicit function theorem says: You will not find two solutions with identical parameter values this way.

What's the problem?

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A fix: Pseudo-arclength continuation. Set $x = (u, \lambda)$ and solve G(x, s) = 0, where, for example

$$G(x,s) = \begin{pmatrix} F \\ N \end{pmatrix} = \begin{pmatrix} F(u(s),\lambda(s)) \\ \dot{u}^T(u-u_0) + \dot{\lambda}^T(\lambda-\lambda_0) - (s-s_0) \end{pmatrix}$$

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s is an artificial "arclength" parameter. u_0 and λ_0 are from the previous step. $\dot{u} \approx du/ds$ and $\dot{\lambda} \approx d\lambda/ds$,

(say by differences using s_0 and s_{-1}).

Simple Folds

We follow solution paths $\{x(s)\}$. Assume that *F* is smooth and

• *G_x* is nonsingular (not always true) So implicit function theorem holds in *s*.

We are assuming that there is no true bifurcation and that the singularity in λ is at worst simple fold.

dim(Null(
$$F_u$$
)) = 1, $F_\lambda \neq \text{Ran}(F_u)$

Arclength Continuation Algorithm

Set $\lambda = a, s = 0$ solve $F(u, \lambda) = 0$ with Newton-(MG, GMRES, ...) to obtain u_0 . Estimate $ds, \dot{u}, \dot{\lambda}$. while $s < s_{max}$ do $s \leftarrow s + ds$. Solve G(x,s) = 0 with u_0 as the initial iterate. $x_0 \leftarrow x$ Update $ds, \dot{u}, \dot{\lambda}$. end while

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 - Appropriate coarse grid data depend on *s*.

Multilevel Approach

Pathfollowing on coarse mesh + nested iteration fails.

- $F(u,\lambda) = u \mathscr{K}(u,\lambda)$
- $\lambda(s)$ is sensitive to the mesh.
- Track path on fine mesh.
- Use coarse mesh problem to approximate \mathscr{K}^u Apply GMRES to new problem.

Coarse mesh problem construction

For continuation in λ

• $x^h = x^h + dx$, Euler predictor on fine mesh.

•
$$u^H = I_h^H(u^h)$$
, $\lambda = \lambda^H = \lambda^h$.

• Build
$$K_H = I_H^h \mathscr{K}_u^H(u^H, \lambda) I_h^H$$

- Norm convergent (K, 1995) if I_h^H is done right degenerate kernel approximation
- Approximate Newton step by solving $s K_H s = -F_h(u^H, \lambda)$. Fine mesh residual and coarse mesh solve.

Continuation in *s*

Approximate G_x by

$$G_{u,\lambda}^{H,h}(u,\lambda) \equiv \begin{pmatrix} I - \partial \mathscr{K}^{H}(I_{h}^{H}u,\lambda) / \partial u & -\partial \mathscr{K}^{H}(I_{h}^{H}u,\lambda) / \partial \lambda \\ & \\ (I_{h}^{H}\dot{u})^{T} & \dot{\lambda} \end{pmatrix}$$

and apply GMRES.

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and apply GMRES.

- Operator-function product is now on coarse mesh.
- Works for "black-box" functions. Flexible choice of \mathscr{K}^H .
- Theory follows from older work, if you coarsen only in \mathcal{K} , not in G.

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- occasional testing for bifurcation

Numerical Results: Three Solution Paths

For each solution we continue in ρ , and plot three scalars:

• Excess number

$$\int r^2 h(r) \, dr$$

• Pressure

$$\int r^3 U'(r)(h(r)+1)\,dr$$

• Compressibility

$$\int r^2 c(r) \, dr$$

as functions of ρ .

Path through physical solution



Path through non-physical solution



Path through new solution



Conclusions

- OZ integro-algebraic equations Elimination leads to compact fixed point problem
- Multilevel method for integral equations
- Solves OZ, but finds too many solutions
- Bottom-up nesting goes the wrong way for continuation
- Top down works; currently 30% faster than GMRES