# Solving quantum eigenvalue problems by discrete singular convolution 

G W Wei<br>Department of Computational Science, National University of Singapore, Singapore 117543, Singapore

Received 4 August 1999, in final form 19 October 1999


#### Abstract

This paper explores the utility of a discrete singular convolution (DSC) algorithm for solving the Schrödinger equation. DSC kernels of Shannon, Dirichlet, modified Dirichlet and de la Vallée Poussin are selected to illustrate the present algorithm for obtaining eigenfunctions and eigenvalues. Four benchmark physical problems are employed to test numerical accuracy and speed of convergence of the present approach. Numerical results indicate that the present approach is efficient and reliable for solving the Schrödinger equation.


## 1. Introduction

There is an ongoing interest in computational methodology [1-20]. Most efforts are centred on developing either global or local methods for solving a variety of time-dependent and time-independent problems. The well known local methods involve finite differences, finite elements, finite volumes and boundary elements. Local methods are flexible for handling complex boundary and geometry, but are not as accurate as global methods. Global approximations to a function and its derivatives are typically realized by a set of truncated basis expansions which result in a finite approximation. Global methods are highly localized at their spectral representations and thus they provide high computational accuracy. However, they are not convenient for complex boundary and geometry such as occur in waveguide problems. It is desirable to have methods which combine global methods' accuracy with local methods' flexibility for practical applications.

Discrete singular convolution (DSC) [21] was proposed as a potential numerical approach for solving many computational problems, including linear and nonlinear dynamics [22], Hilbert transform, processing of analytic signals, and computational tomography. Based on the DSC formalism, a unification was achieved [23] for computational methods of the global, local, finite difference, finite element, finite volume, Galerkin, collocation, subdomain and Ritz variational types. The underlying mathematical structure of the DSC approach is the theory of distributions. Heaviside and Dirac had exploited the use of the delta distribution before Sobolev, Schwartz [24], Korevaar [25] and others put the distribution theory into a rigorous mathematical form. More general orthogonal series analyses of the delta distribution were studied by Walter [27] and others [28-30]. The numerical use of many delta sequences as probability density estimators was discussed by Walter and Blum [30] and others [29, 32, 33].

The purpose of this paper is to explore the utility of the DSC algorithm for the numerical solution of the Schrödinger equation. This is illustrated by numerically resolving eigenfunctions and eigenvalues. This paper is organized as follows. Section 2 gives a brief
review of the DSC formalism. The reader is referred to the original work [21] for more details. Numerical eigenvalue results are presented in section 3. Four important problems, an $I_{2}$ Morse potential, a two-dimensional (2D) harmonic oscillator, a three-dimensional (3D) harmonic oscillator, and a non-polynomial oscillator (NPO) are selected for illustration. The paper ends with a conclusion.

## 2. Discrete singular convolution

Singular convolutions appear in many problems, such as Hilbert transform, Abel transform and Radon transforms. DSC is a general approach for numerically solving singular convolution problems. By appropriate realizations of a singular convolution kernel, the DSC can be an extremely efficient, accurate and reliable algorithm for scientific computations.

Let $T$ be a distribution and $\eta(t)$ be an element of the space of test functions. A singular convolution can be defined as

$$
\begin{equation*}
F(t)=(T * \eta)(t)=\int_{-\infty}^{\infty} T(t-x) \eta(x) \mathrm{d} x \tag{1}
\end{equation*}
$$

Here $T(t-x)$ is a singular kernel. An interesting example is the singular kernels of the delta type

$$
\begin{equation*}
T(x)=\delta^{(n)}(x), \quad(n=0,1,2, \ldots) \tag{2}
\end{equation*}
$$

where kernel $T(x)=\delta(x)$ is important for interpolation of surfaces and curves (including atomic, molecular and biological potential energy surfaces) and $T(x)=\delta^{(n)}(x)(n=1,2, \ldots)$ are essential for numerically solving partial differential equations. However, since these kernels are singular, they cannot be directly digitized in computers. Hence, the singular convolution, equation (1), is of little numerical merit. To avoid the difficulty of using singular expressions directly in computers, sequences of approximations ( $T_{\alpha}$ ) of the distribution $T$ can be constructed

$$
\begin{equation*}
\lim _{\alpha \rightarrow \alpha_{0}} T_{\alpha}(x) \longrightarrow T(x) \tag{3}
\end{equation*}
$$

where $\alpha_{0}$ is a generalized limit. Obviously, in the case of $T(x)=\delta(x)$, the sequence, $T_{\alpha}(x)$, is a delta sequence. Furthermore, with a sufficiently smooth approximation, it makes sense to consider a DSC

$$
\begin{equation*}
F_{\alpha}(t)=\sum_{k} T_{\alpha}\left(t-x_{k}\right) f\left(x_{k}\right), \tag{4}
\end{equation*}
$$

where $F_{\alpha}(t)$ is an approximation to $F(t)$ and $\left\{x_{k}\right\}$ is an appropriate set of discrete points on which the DSC (4) is well defined. Note that the original test function $\eta(x)$ has been replaced by $f(x)$. The mathematical property or requirement of $f(x)$ is determined by an approximate kernel $T_{\alpha}$.

Shannon's kernel

$$
\frac{\sin \alpha\left(x-x^{\prime}\right)}{\pi\left(x-x^{\prime}\right)}
$$

is a special example for the delta sequence. Other important examples include the Dirichlet kernel

$$
\frac{\sin \left[\left(l+\frac{1}{2}\right)\left(x-x^{\prime}\right)\right]}{2 \pi \sin \left[\frac{1}{2}\left(x-x^{\prime}\right)\right]}
$$

the modified Dirichlet (MD) kernel

$$
\frac{\sin \left[\left(l+\frac{1}{2}\right)\left(x-x^{\prime}\right)\right]}{2 \pi \tan \left[\frac{1}{2}\left(x-x^{\prime}\right)\right]}
$$

and the de la Vallée Poussin (DLVP) kernel

$$
\frac{1}{\pi \alpha} \frac{\cos \left[\alpha\left(x-x^{\prime}\right)\right]-\cos \left[2 \alpha\left(x-x^{\prime}\right)\right]}{\left(x-x^{\prime}\right)^{2}} .
$$

For sequences of delta type, an interpolating (or quasi-interpolating) algorithm sampling at Nyquist frequency $\left(\alpha=\frac{\pi}{\Delta}\right)$ has advantage over a non-interpolating discretization

$$
\begin{equation*}
\frac{\sin \left[\alpha\left(x-x^{\prime}\right)\right]}{\pi\left(x-x^{\prime}\right)} \rightarrow \frac{\sin \frac{\pi}{\Delta}\left(x-x_{k}\right)}{\frac{\pi}{\Delta}\left(x-x_{k}\right)} \tag{5}
\end{equation*}
$$

The uniform, Nyquist rate, interpolating discretization is also used for the Dirichlet kernel:

$$
\begin{equation*}
\frac{\sin \left[\left(l+\frac{1}{2}\right)\left(x-x^{\prime}\right)\right]}{2 \pi \sin \left[\frac{1}{2}\left(x-x^{\prime}\right)\right]} \rightarrow \frac{\sin \left(\frac{\pi}{\Delta}\left(x-x_{k}\right)\right)}{(2 M+1) \sin \left(\frac{\pi}{\Delta} \frac{x-x_{k}}{2 M+1}\right)} . \tag{6}
\end{equation*}
$$

In comparison with Shannon's kernel, the Dirichlet kernel has one more parameter $M$ which can be optimized to achieve better results in computations. Usually, we set a sufficiently large $M$ for various numerical applications. Obviously, the Dirichlet kernel converts to Shannon's kernel at the limit of $M \rightarrow \infty$. This uniform interpolating discretization will also be used for discretizing the MD kernel

$$
\begin{equation*}
\frac{\sin \left[\left(l+\frac{1}{2}\right)\left(x-x^{\prime}\right)\right]}{2 \pi \tan \left[\frac{1}{2}\left(x-x^{\prime}\right)\right]} \rightarrow \frac{\sin \left(\frac{\pi}{\Delta}\left(x-x_{k}\right)\right)}{(2 M+1) \tan \left(\frac{\pi}{\Delta} \frac{x-x_{k}}{2 M+1}\right)}, \tag{7}
\end{equation*}
$$

and for the de la Vallée Poussin kernel

$$
\begin{equation*}
\frac{1}{\pi \alpha} \frac{\cos \left[\alpha\left(x-x^{\prime}\right)\right]-\cos \left[2 \alpha\left(x-x^{\prime}\right)\right]}{\left(x-x^{\prime}\right)^{2}} \rightarrow \frac{2}{3} \frac{\cos \frac{\pi}{\Delta}\left(x-x_{k}\right)-\cos \frac{2 \pi}{\bar{\Delta}}\left(x-x_{k}\right)}{\left[\frac{\pi}{\Delta}\left(x-x_{k}\right)\right]^{2}} \tag{8}
\end{equation*}
$$

where $\bar{\Delta}=\frac{3}{2} \Delta$. Since $\pi / \Delta$ is proportional to the highest frequency which can be reached in the Fourier representation, the $\Delta$ should be very small for a given problem involving very oscillatory functions or very high frequency components.

In the DSC approach we choose a grid representation for the coordinate so that the potential part, $V(x)$, of the Hamiltonian is diagonal. The full DSC matrix representation for the Hamiltonian operator, $H$, is given by

$$
\begin{equation*}
H\left(x_{j}, x_{k}\right)=-\frac{\hbar^{2}}{2 m} \delta_{\alpha}^{(2)}\left(x_{j}-x_{k}\right)+V\left(x_{j}\right) \delta_{j, k}, \tag{9}
\end{equation*}
$$

where $m$ is the mass of the Hamiltonian system and $\delta_{\alpha}^{(2)}\left(x_{j}-x_{k}\right)$ is analytically given by

$$
\begin{equation*}
\delta_{\alpha}^{(2)}\left(x_{j}-x_{k}\right)=\left[\left(\frac{\mathrm{d}}{\mathrm{~d} x}\right)^{2} \delta_{\alpha}\left(x-x_{k}\right)\right]_{x=x_{j}} . \tag{10}
\end{equation*}
$$

Here $\delta_{\alpha}\left(x-x_{k}\right)$ is a collective symbol for any of the right-hand sides of equations (5)-(8). Extending to higher dimensions is obvious. Equation (9) or its multidimensional extension is referred to as a DSC-Hamiltonian matrix.

## 3. Results

In this paper, we limit our attention to DSC kernels of the Shannon, DLVP, Dirichlet and MD type. Nevertheless, various other DSC kernels can be similarly employed. Note that DSC kernels of Shannon and DLVP are parameter free, which is convenient for applications. The $2 M+1$ parameter used for other two kernels is chosen as 71 for all calculations. We note that as long as the $2 M+1$ value is chosen sufficiently large $(2 M+1>W$, where $2 W+1$ is the matrix bandwidth), the numerical results are not sensitive to specific values used. When a potential is given, eigenvalues are obtained by a direct diagonalization of the DSC-Hamiltonian matrix, equation (9) or its multidimensional generalization.

To illustrate the use of the DSC algorithm and test its accuracy for calculating eigenfunctions and eigenvalues, we consider four benchmark problems: the Morse potential for an $\mathrm{I}_{2}$ molecule, a 2D harmonic oscillator, a 3D harmonic oscillator and an NPO. A general form for the Schrödinger equation in the coordinate representation is given by
$\left[-\frac{\hbar^{2}}{2 m} \sum_{i=1}^{n} \frac{\partial^{2}}{\partial x_{i}^{2}}+V\left(x_{1}, \ldots, x_{n}\right)\right] \Phi_{k}\left(x_{1}, \ldots, x_{n}\right)=E_{k} \Phi_{k}\left(x_{1}, \ldots, x_{n}\right)$,
where $\Phi_{k}$ and $E_{k}$ are the $k$ th eigenfunction and eigenvalue respectively.

### 3.1. The $I_{2}$ molecule

The Morse potential for the $\mathrm{I}_{2}$ molecule is given by

$$
\begin{equation*}
V(x)=D\left[\mathrm{e}^{-2 \alpha x}-2 \mathrm{e}^{-\alpha x}+1\right] \tag{12}
\end{equation*}
$$

where $D=0.0224$ and $\alpha=0.9374$. Here, the reduced mass for the Schrödinger equation is $m=119$ 406. The anharmonic character of the Morse potential allows dissociation, hence it is one of the most popular potentials for modelling the spectroscopy and dynamics of the $\mathrm{I}_{2}$ molecule. The Schrödinger equation of the $\mathrm{I}_{2}$ Morse system is actually solvable. Exact eigenfunctions are well known generalized Laguerre polynomials [34]

$$
\begin{equation*}
\Phi_{k}=N_{k} z^{\frac{p}{2}} \mathrm{e}^{-\frac{z}{2}} L_{k}^{p}(z) \tag{13}
\end{equation*}
$$

where $z=\beta \mathrm{e}^{-\alpha x}, p=\beta-2 k-1$ and $\beta=156.047612535$. Here, $N_{k}$ is a normalization constant and is given by [34]

$$
\begin{equation*}
N_{k}=\left[\frac{\Gamma(p)}{\alpha} \sum_{\gamma=0}^{k}(-1)^{\gamma}\binom{-p}{\gamma}\right]^{-1 / 2} . \tag{14}
\end{equation*}
$$

Exact eigenvalues of the $\mathrm{I}_{2}$ molecule are [34]

$$
\begin{equation*}
E_{k}=\kappa\left[k+\frac{1}{2}-\frac{1}{\beta}\left(k+\frac{1}{2}\right)^{2}\right] \tag{15}
\end{equation*}
$$

where $\kappa=5.741837286 \times 10^{-4}$ is calculated according to the physical property of $\mathrm{I}_{2}$. Since $\kappa$ is very small, the density of state of this system is obviously very high. Thus it often serves as a standard problem for testing new numerical algorithms.

In a recent study, Braun et al [18] have used this system to test their efficient ChebyshevLanczos method. They achieve a remarkably high accuracy which ranges from 7 to 9 digits using 128 grid points. For DSC kernels of Shannon, Dirichlet and MD, we choose 64 grid points $(N=64)$ which corresponds to the grid spacing of $0.043077(\Delta=0.043077)$. All grid points $x_{k}$ are equally distributed in the interval $\left[-\frac{\Delta(N+1)}{2}, \frac{\Delta(N+1)}{2}\right]$. For a comparison, we list our calculation and those of Braun et al [18] in table 1. Our 64 grid point results are 200

Table 1. Comparison of errors for $I_{2}$ Morse oscillator.

|  |  |  | Braun et al <br> $(N=128)$ | Shannon <br> $(N=64)$ | Dirichlet <br> $(N=64)$ | MD <br> $(N=64)$ |
| :---: | :--- | :--- | :--- | :--- | :--- | :--- |
| 0 | Analytical | DLVP <br> $(N=96)$ |  |  |  |  |
| 1 | $0.8529966236266942(-03)$ | $-0.10(-10)$ | $-0.14(-13)$ | $-0.14(-13)$ | $-0.14(-13)$ | $-0.14(-13)$ |
| 2 | $0.1964568661834224(-02)$ | $-0.50(-10)$ | $-0.70(-13)$ | $-0.70(-13)$ | $-0.70(-13)$ | $-0.70(-13)$ |
| 3 | $0.2509316055240247(-02)$ | $-0.70(-10)$ | $-0.97(-13)$ | $-0.97(-13)$ | $-0.97(-13)$ | $-0.97(-13)$ |
| 4 | $0.3046704364847777(-02)$ | $-0.89(-10)$ | $-0.12(-12)$ | $-0.12(-12)$ | $-0.12(-12)$ | $-0.12(-12)$ |
| 5 | $0.3576733590656813(-02)$ | $-0.11(-09)$ | $-0.15(-12)$ | $-0.15(-12)$ | $-0.15(-12)$ | $-0.15(-12)$ |
| 6 | $0.4099403732667354(-02)$ | $-0.13(-09)$ | $-0.18(-12)$ | $-0.18(-12)$ | $-0.18(-12)$ | $-0.18(-12)$ |
| 7 | $0.4614714790879402(-02)$ | $-0.15(-09)$ | $-0.20(-12)$ | $-0.20(-12)$ | $-0.20(-12)$ | $-0.20(-12)$ |
| 8 | $0.5122666765292955(-02)$ | $-0.16(-09)$ | $-0.23(-12)$ | $-0.23(-12)$ | $-0.23(-12)$ | $-0.23(-12)$ |
| 9 | $0.5623259655908014(-02)$ | $-0.18(-09)$ | $-0.25(-12)$ | $-0.28(-12)$ | $-0.25(-12)$ | $-0.25(-12)$ |
| 10 | $0.6116493462724579(-02)$ | $-0.20(-09)$ | $-0.28(-12)$ | $-0.28(-12)$ | $-0.28(-12)$ | $-0.28(-12)$ |
| 11 | $0.6602368185742650(-02)$ | $-0.22(-09)$ | $-0.30(-12)$ | $-0.30(-12)$ | $-0.30(-12)$ | $-0.30(-12)$ |
| 12 | $0.7080883824962227(-02)$ | $-0.23(-09)$ | $-0.33(-12)$ | $-0.33(-12)$ | $-0.33(-12)$ | $-0.33(-12)$ |
| 13 | $0.7552040380383310(-02)$ | $-0.25(-09)$ | $-0.35(-12)$ | $-0.35(-12)$ | $-0.35(-12)$ | $-0.35(-12)$ |
| 14 | $0.8015837852005899(-02)$ | $-0.27(-09)$ | $-0.37(-12)$ | $-0.37(-12)$ | $-0.37(-12)$ | $-0.37(-12)$ |
| 15 | $0.8472276239829993(-02)$ | $-0.28(-09)$ | $-0.39(-12)$ | $-0.39(-12)$ | $-0.39(-12)$ | $-0.40(-12)$ |
| 16 | $0.8921355543855595(-02)$ | $-0.30(-09)$ | $-0.41(-12)$ | $-0.41(-12)$ | $-0.41(-12)$ | $-0.41(-12)$ |
| 17 | $0.9363075764082702(-02)$ | $-0.32(-09)$ | $-0.42(-12)$ | $-0.42(-12)$ | $-0.42(-12)$ | $-0.43(-12)$ |
| 18 | $0.9797436900511314(-02)$ | $-0.33(-09)$ | $-0.42(-12)$ | $-0.42(-12)$ | $-0.42(-12)$ | $-0.43(-12)$ |
| 19 | $0.1022443895314143(-01)$ | $-0.35(-09)$ | $-0.39(-12)$ | $-0.39(-12)$ | $-0.39(-12)$ | $-0.39(-12)$ |
| 20 | $0.1064408192197306(-01)$ | $-0.36(-09)$ | $-0.29(-12)$ | $-0.30(-12)$ | $-0.29(-12)$ | $-0.28(-12)$ |
| 21 | $0.1105636580700619(-01)$ | $-0.38(-09)$ | $0.13(-12)$ | $0.13(-12)$ | $0.13(-12)$ | $-0.10(-13)$ |
| 22 | $0.146129060824082(-01)$ | $-0.39(-09)$ | $0.14(-11)$ | $0.14(-11)$ | $0.14(-11)$ | $0.61(-12)$ |
| 23 | $0.1185885632567697(-01)$ | $-0.41(-09)$ | $0.29(-11)$ | $0.29(-11)$ | $0.29(-11)$ | $0.19(-11)$ |
| 24 | $0.1224906295931461(-01)$ | $-0.42(-09)$ | $0.17(-11)$ | $0.17(-11)$ | $0.18(-11)$ | $0.46(-11)$ |
|  |  |  |  |  |  |  |

to 1000 times more accurate than those of Braun et al, obtained by using 128 grid points. It requires about 1.5 times as many grid points $(N=96)$ for the DLVP delta sequence kernel to achieve the same level of accuracy as those obtained by using other kernels.

### 3.2. A 2 D harmonic oscillator

To illustrate further the accuracy and robustness of the DSC algorithm, we consider the 2D Schrödinger equation with a harmonic oscillator potential

$$
\begin{equation*}
V(x, y)=\frac{1}{2}\left(x^{2}+y^{2}\right) \tag{16}
\end{equation*}
$$

One of most important reasons for this choice is the analytical solvability of the model. By setting $\hbar=m=1$ in the Schrödinger equation, analytical eigenvalues are given by

$$
\begin{equation*}
E_{n_{x}, n_{y}}=1+n_{x}+n_{y}=1+n, \tag{17}
\end{equation*}
$$

with the degree of degeneracy of $d_{n}=n+1$ in the $n$th energy level.
For DSC kernels of Shannon, Dirichlet and MD, the number of grid points used in each dimension is $26\left(N_{x}=N_{y}=26, \Delta_{x}=\Delta_{y}=0.4814815\right)$. As listed in table 1 , the first 21 eigenvalues are all accurate to at least ten significant figures. This calculation demonstrates that the DSC algorithm is extremely accurate for handling degenerate eigenvalue problems. Calculations obtained by using the DLVP delta sequence kernel are slightly less accurate. It requires 39 grid points in each dimension to reach the same accuracy as those obtained by using other kernels ( 26 grid points in each dimension). These results have also been presented in table 2 for a comparison of different kernels.

Table 2. Errors for the eigenvalues of the 2D harmonic oscillator.

| $n$ | $d_{n}$ | Exact | Shannon $\left(N_{x}=N_{y}=26\right)$ | Dirichlet $\left(N_{x}=N_{y}=26\right)$ | MD $\left(N_{x}=N_{y}=26\right)$ | DLVP $\left(N_{x}=N_{y}=39\right)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 1 | 1 | 0.71(-14) | 0.30(-12) | 0.24(-12) | 0.92(-12) |
| 1 | 2 | 2 | 0.25(-12) | 0.21(-12) | $0.27(-12)$ | 0.64(-12) |
|  |  |  | 0.21(-12) | 0.64(-13) | 0.29(-12) | 0.38(-12) |
| 2 | 3 | 3 | 0.33(-12) | 0.37(-12) | 0.31(-12) | 0.57(-12) |
|  |  |  | 0.26(-12) | 0.23(-12) | 0.50(-13) | 0.19(-12) |
|  |  |  | 0.51(-13) | -0.89(-15) | -0.14(-12) | -0.41(-12) |
| 3 | 4 | 4 | 0.18(-12) | 0.36(-12) | 0.38(-12) | 0.15(-11) |
|  |  |  | 0.70(-13) | $0.20(-12)$ | $0.34(-13)$ | 0.36(-12) |
|  |  |  | 0.19(-12) | $-0.17(-12)$ | $0.10(-12)$ | 0.10(-12) |
|  |  |  | -0.25(-12) | $-0.25(-12)$ | $-0.27(-13)$ | $-0.31(-12)$ |
| 4 | 5 | 5 | $0.46(-13)$ | 0.31(-12) | $0.33(-12)$ | $0.13(-11)$ |
|  |  |  | -0.22(-12) | -0.27(-12) | $-0.40(-12)$ | 0.51(-12) |
|  |  |  | $-0.40(-12)$ | $-0.37(-12)$ | -0.40(-12) | 0.20(-13) |
|  |  |  | $-0.14(-10)$ | $-0.14(-10)$ | $-0.14(-10)$ | $-0.76(-11)$ |
|  |  |  | -0.14(-10) | -0.14(-10) | -0.14(-10) | -0.85(-11) |
| 5 | 6 | 6 | $-0.17(-12)$ | 0.13(-12) | $-0.90(-13)$ | 0.58(-13) |
|  |  |  | $-0.33(-12)$ | $-0.19(-12)$ | -0.22(-12) | -0.14(-12) |
|  |  |  | -0.14(-10) | -0.14(-10) | -0.14(-10) | -0.76(-11) |
|  |  |  | -0.14(-10) | -0.14(-10) | -0.14(-10) | -0.86(-11) |
|  |  |  | -0.84(-10) | $-0.83(-10)$ | $-0.85(-10)$ | -0.13(-09) |
|  |  |  | -0.84(-10) | -0.84(-10) | -0.85(-10) | -0.13(-09) |

### 3.3. A 3D harmonic oscillator

As an example for solving highly degenerate eigenvalue problems, we consider an isotropic 3D harmonic oscillator with a potential

$$
\begin{equation*}
V(x, y, z)=\frac{1}{2}\left(x^{2}+y^{2}+z^{2}\right) . \tag{18}
\end{equation*}
$$

Eigenvalues of this case are given by

$$
\begin{equation*}
E_{n_{x}, n_{y}, n_{z}}=\frac{3}{2}+n_{x}+n_{y}+n_{z}=\frac{3}{2}+n, \tag{19}
\end{equation*}
$$

with the degree of degeneracy of $d_{n}=\frac{(n+1)(n+2)}{2}$ for $n$th energy level. The present computations use a grid of $22 \times 22 \times 22$ compared to $32 \times 32 \times 32$ used by Braun et al [18]. Both results are listed in table 3. Obviously two sets of results reach the same level of accuracy, while the present ones require less than a third of the grid points used by Braun et al [18].

Since DSC kernels of Shannon, Dirichlet and MD have very similar behaviour, only the result obtained by the Dirichlet kernel is listed in table 3. The grid points required for the DLVP kernel is still $50 \%$ more in each dimension.

### 3.4. A non-polynomial oscillator

Finally, we consider an NPO model

$$
\begin{equation*}
\left[-\frac{\mathrm{d}^{2}}{\mathrm{~d} x^{2}}+x^{2}+\frac{\lambda x^{2}}{1+g x^{2}}\right] \Phi_{k}=E_{k} \Phi_{k} \tag{20}
\end{equation*}
$$

where $\lambda$ and $g$ are two parameters. This model has received much attention in the last 20 years for its connection to nonlinear optics, elementary particle physics, and nonlinear Lagrangian field theory. Mitra calculated the ground state and the first excited state using

Table 3. Errors for the eigenvalues of the 3D harmonic oscillator.

| $n$ | $d_{n}$ | Exact | Braun et al $\left(N_{x}=N_{y}=N_{z}=32\right)$ | Present $\left(N_{x}=N_{y}=N_{z}=22\right)$ |
| :---: | :---: | :---: | :---: | :---: |
| 0 | 1 | 1.5 | 0.59(-13) | -0.27(-11) |
| 1 | 3 | 2.5 | 0.71(-13) | -0.27(-11) |
|  |  |  | 0.87(-13) | -0.25(-11) |
|  |  |  | 0.94(-13) | -0.23(-11) |
| 2 | 6 | 3.5 | 0.20(-12) | -0.27(-11) |
|  |  |  | 0.23(-12) | -0.20(-11) |
|  |  |  | $0.36(-11)$ | -0.19(-11) |
|  |  |  | 0.36(-11) | 0.74(-11) |
|  |  |  | 0.49(-11) | 0.79(-11) |
|  |  |  | 0.56(-11) | 0.79(-11) |
| 3 | 10 | 4.5 | 0.15(-11) | -0.21(-11) |
|  |  |  | 0.37(-11) | 0.57(-11) |
|  |  |  | 0.37(-11) | 0.64(-11) |
|  |  |  | 0.10(-10) | 0.67(-11) |
|  |  |  | 0.12(-10) | 0.72(-11) |
|  |  |  | 0.27(-10) | $0.75(-11)$ |
|  |  |  | 0.45(-10) | 0.80(-11) |
|  |  |  | 0.60(-10) | 0.83(-10) |
|  |  |  | 0.68(-10) | 0.83(-10) |
|  |  |  | 0.76(-10) | 0.84(-10) |

the Ritz variational method in combination with the Givens-Householder matrix eigenvalue algorithm [35]. Finite difference methods are applied to obtain numerical eigenvalues [36,37]. Kaushal studied asymptotic expansions in terms of $g x^{2}$ [38]. Two-parameter scaling transform was employed by Bessis and Bessis [39]. Lai and Lin applied the Hellmann-Feynman and hypervirial theory [40] to calculate eigenvalues from a perturbation series. Flessas showed that exact solutions exist for some special parameters [41]. Varshni [42] and Witwit [43] extended this 1D model to three dimensions. Scherrer et al obtained very accurate ground states by using a matrix-continued-fraction algorithm [44] and compared their results with those of other authors.

In general, this model does not have an exact solution. High-accuracy numerical solution to this problem is nontrivial. This can be noted from the potential plot in figure 1. The ground state is extremely sensitive to the bottom shape of the potential. In particular, convergent eigenvalues of large $\lambda$ and $g$ parameters are difficult to attain. In the present work we employ the DSC algorithm to calculate various ground states associated with a variety of parameters ( $\lambda, g=1,10,100$, and 500). The DSC results are attained by using the MD kernel on a uniform grid. Other kernels perform similarly. Table 4 provides a comparison of the DSC results and results reported in the literature. There are a number of discrepancies among the results of different authors. Our results are in excellent agreement with those of Scherrer et al [44]. The DSC results converge to at least 11 significant figures for all parameters calculated. A potential adapted DSC algorithm is under consideration to achieve better convergence.

## 4. Conclusion

This paper explores the utility of a DSC algorithm for solving the Schrödinger equation. DSC kernels of Shannon, Dirichlet, MD and DLVP are employed for this application. Four


Figure 1. The NPO potential. Values of parameters $\lambda$ and $g$ are: (a) 10, 10; (b) 500, 500; (c) 10, 500. The dotted curve is the harmonic potential $V(x)=x^{2}+\lambda / g$.
benchmark problems are utilized to illustrate the robustness and accuracy of the present approach.

In the first example, a Morse oscillator for the $\mathrm{I}_{2}$ molecule is examined. The corresponding Schrödinger equation is analytically solvable. The DSC algorithm performs extremely well for this model. The first 25 eigenvalues are accurate to 12 significant figures obtained by using 64 grid points, which is 200 to 1000 times better than those of an efficient Chebyshev-Lanczos method [18], obtained by using 128 grid points. These results are the best to date as far as the author is aware (as produced by using a local approach). The DLVP kernel requires 1.5 times grid points ( 96 points) to achieve the same level of accuracy as that of other DSC kernels. This result, however, is still about 100 to 1000 times more accurate than those of Braun et al [18] obtained using 128 grid points.

The next example is a 2 D harmonic oscillator potential. This example is very valuable because it is also analytically solvable. The performances of DSC kernels of Shannon, Dirichlet and MD are excellent: only 26 grid points in each dimension are required to achieve the

Table 4. Ground state eigenvalues of the NPO: (a) Scherrer et al [44], (b) Hautot [46], (c) Mitra [35], (d) Bessis et al [39], (e) Chaudhuri and Mukherjee [45], (f) Lai and Lin [40], (g) Kaushal [38], (h) Galacia and Killingbeck [36].

|  |  |  | $\lambda$ |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
| $g$ |  | 1 | 10 | 100 | 500 |
| 1 | DSC | 1.23235072332 | 2.78233051589 | 9.35941802628 | 21.6587477000 |
| 1 | (a) | 1.23235072 | 2.78233052 | 9.35941803 |  |
| 1 | (b) | 1.23235 | 2.78233 | 9.3542 |  |
| 1 | (c) | 1.23235 | 2.78233 | 9.354 |  |
| 1 | (d) | 1.23237205 | 2.782330 | 9.35941803 | 21.6587477 |
| 1 | (e) | 1.2413 |  |  |  |
| 1 | (f) | 1.23235353 | 2.78233054 | 9.35941803 |  |
| 1 | (g) | 1.227 | 2.754 | 9.3567 |  |
|  |  |  |  |  |  |
| 10 | DSC | 1.05929688081 | 1.58002232743 | 5.79394230020 | 16.7327473820 |
| 10 | (a) | 1.05929688 | 1.58002233 | 5.79394230 |  |
| 10 | (b) | 1.05930 | 1.58002 | 5.79394 |  |
| 10 | (c) | 1.05929 | 1.58002 | 5.794 |  |
| 10 | (d) | 1.05929700 | 1.5800249 | 5.793947 |  |
|  |  |  |  |  |  |
| 100 | DSC | 1.00841059789 | 1.08406333555 | 1.83633583344 | 5.08368391346 |
| 100 | (a) | 1.00841060 | 1.08406334 | 1.83633583 |  |
| 100 | (b) | 1.00841 | 1.08406 | 1.83634 |  |
| 100 | (c) | 1.00841 | 1.08406 | 1.8364 |  |
| 100 | (d) | 1.0084106 | 1.0840643 | 1.8363850 | 5.0840857 |
| 100 | (e) |  | 1.08411 | 1.8411 |  |
| 100 | (h) |  |  | 1.8363373 |  |
| 500 | DSC | 1.0018491547 | 1.01849104511 | 1.1848602397 | 1.9231762554 |
| 500 | (d) | 1.0018491 | 1.0184910 | 1.1848632 | 1.9232260 |
| 500 | (e) |  |  | 1.18451 | 1.92255 |
|  |  |  |  |  |  |

accuracy of 11 significant figures for the first 21 eigenvalues. The same level of accuracy is attained by the DLVP kernel using 39 grid points in each dimension.

The third example considered is a 3D harmonic oscillator potential. This is a problem for objectively testing the ability of handling highly degenerate eigenvalues. As in the first example, the present algorithm performs much better than the efficient Chebyshev-Lanczos method [18]. We choose only a grid of $22 \times 22 \times 22$ to achieve the same accuracy as those of Braun et al obtained by using a grid of $32 \times 32 \times 32$ (the ratio of the two grid points is 1:3.08).

The last example considered is an NPO. In general, this problem does not have an analytical solution. For a certain parameter region, the low-lying eigenvalues are very sensitive to the sharp variation of the bottom curve in the potential and difficult to converge. There are a lot of discrepancies among the results of different authors in the literature. The present calculation helps to clarify the matter. In particular, our results are in excellent agreement with results of Scherrer et al obtained by using a matrix-continued-fraction algorithm [44]. We calculate a number of ground states with at least 11 significant figures. These studies indicate that the DSC algorithm is efficient and reliable for numerically solving the Schrödinger equation.

## Acknowledgments

This work was supported in part by the National University of Singapore. The author is grateful to the referees for valuable comments and suggestions.

## References

[1] Lanczos C 1938 J. Math. Phys. 17123
[2] Harris D O, Engerholm G G and Gwinn W D 1965 J. Chem. Phys. 431515
[3] Cooley J W and Tukey J W 1965 Math. Comput. 19297
[4] Finlayson B A and Scriven L E 1966 Appl. Mech. Rev. 19735
[5] Orszag S A 1972 Stud. Appl. Math. 51253
[6] Kreiss H O and Oliger J 1972 Tellus 24199
[7] Finlayson B A 1972 The Method of Weighted Residuals and Variational Principles (New York: Academic)
[8] Fornberg B 1973 Math. Comput. 2745
[9] Lill J V, Parker G A and Light J C 1982 Chem. Phys. Lett. 89483
[10] Kosloff D and Baysal E 1982 Geophysics 471402
[11] Hutson J M and Le Roy R J 1985 J. Phys. B: At. Mol. Phys. 831197
[12] Friesner R 1985 Chem. Phys. Lett. 11639
[13] Yang W and Peet A C 1988 Chem. Phys. Lett. 15398
[14] Schwenke D W and Truhlar D G 1990 Computing Methods in Applied Sciences and Engineering ed R Glowinski and A Lichnewsky (Philadelphia, PA: SIAM)
[15] Hoffman D K, Nayar N, Sharafeddin O A and Kouri D J 1991 J. Phys. Chem. 958299
[16] Colbert D T and Miller W H 1992 J. Phys. Chem. 961982
[17] Fornberg B 1996 A Practical Guide to Pseudospectral Methods (Cambridge: Cambridge University Press)
[18] Braun M, Sofianos S A, Papageorgiou D G and Lagaris I E 1996 J. Comput. Phys. 126315
[19] Wei G W 1998 Chem. Phys. Lett. 296215
[20] Hu X G, Ho T S and Rabitz H 1998 Comput. Phys. Commun. 113168
[21] Wei G W 1999 J. Chem. Phys. 1108930
[22] Wei G W Physica D at press
[23] Wei G W 1999 Advanced Signal Processing Algorithms, Architectures, and Implementations vol 9, ed F T Luk (Bellingham: SPIE Optical Engineering Press) pp 112-22 Wei G W J. Chem. Phys. submitted
[24] Schwartz L 1951 Théore des Distributions (Paris: Hermann)
[25] Korevaar J 1955 Ned. Akad. Westensh. Proc. Ser. A 58368
Korevaar J 1968 Mathematical Methods vol 1 (New York: Academic)
[26] Korevaar J 1959 Trans. Am. Math. Soc. 9153
[27] Walter G G 1965 Trans. Am. Math. Soc. 116492
[28] Walson G W and Leadbetter M R 1965 Sankhya 26101
[29] Winter B B 1975 Ann. Statist. 3759
[30] Walter G G and Blum J 1977 Ann. Statist. 7328
[31] Walter G G 1992 Wavelets, A Tutorial in Theory and Applications ed C K Chui (San Diego, CA: Academic)
[32] Wahba G 1975 Ann. Statist. 315
[33] Kronmal R and Tarter M 1968 J. Am. Statist. Assoc. 63925
[34] Flügge S 1974 Practical Quantum Mechanics (New York: Springer)
[35] Mitra A K 1978 J. Math. Phys. 192018
[36] Galicia S and Killingbeck J P 1979 Phys. Lett. A 7117
[37] Fack V and Vanden Berghe G 1985 J. Phys. A: Math. Gen. 273355
[38] Kaushal R S 1979 J. Phys. A: Math. Gen. 12 L253
[39] Bessis N and Bessis G 1980 J. Math. Phys. 212780
[40] Lai C L and Lin H E 1982 J. Phys. A: Math. Gen. 151495
[41] Flessas G P 1981 Phys. Lett. A 83121
[42] Varshni Y P 1987 Phys. Rev. A 363009
[43] Witwit M R M 1996 J. Comput. Phys. 129220
[44] Scherrer H, Risken H and Leiber T 1988 Phys. Rev. A 383949
[45] Chaudhuri R N and Mukherjee B 1983 J. Phys. A: Math. Gen. 164031
[46] Hautot A 1981 J. Comput. Phys. 3972

