

Outline  
Sloshing  
Mathematical models  
Why exponentially convergent algorithms?  
Exact difference schemes  
FD-method  
The operator cosine family  
Multidimensional computations



## Epigraph

Theory without practice cannot survive and dies as quickly as it lives

*Leonardo da Vinci 1452-1519, cited from M.Kline, Math. Thought 1972, p. 224*

Theory and practice in the DFG team with A. Timokha (Trondheim, Norway), M.Barnyak, I. Lukovsky, A.Solodun, V.Vasylyk, V., V.Trotsenko and Yu. Trotsenko (Kyiv, Ukraine), M.Kutniv (Lviv, Ukraine)

# Some mathematical problems of hydrodynamics

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## Outline

Sloshing

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(a) Boynton Beach, Florida (8 Megaliter) (b) Sydney (3.2 Megaliter)



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# Open-top fire in a naphtha tank caused by earthquake-induced sloshing





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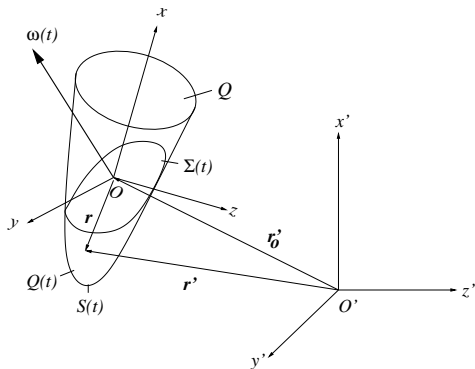
The operator cosine family

Multidimensional computations

Oiltanker - USA, Texas, Galveston 1990: Norway oiltanker  
“Mega Borg” in Golf of Mexiko, 90 km from the coast.  
14.000 t crude oil build ca. 75 km long oil film



# Sloshing in a tank



## Sloshing in a tank

$\zeta(x, y, z, t) = 0$  - equation of free surface

$\phi(x, t)$  - the velocity potential (a harmonic function of

$x = (x_1, x_2, x_3) \in \tilde{\Omega}$

$$\Delta\phi = 0 \quad \text{in } Q,$$

$$\frac{\partial\phi}{\partial n} = 0 \quad \text{on } S, \quad \frac{\partial\phi}{\partial n} = -\frac{\zeta_t}{\sqrt{(\nabla\zeta)^2}} \quad \text{on } \Sigma \quad (\text{kinematic b. c.}),$$

$$\frac{\partial\phi}{\partial t} + \frac{1}{2}(\nabla\phi)^2 + gx = 0 \quad \text{on } \Sigma \quad (\text{dynamic b.c.})$$

## Sloshing in a tank

$\zeta(x, y, z, t) = x - f(y, z, t) \Rightarrow \frac{\partial \phi}{\partial x} = \frac{\partial f}{\partial t}$  - simplified kinematic b.c.  
Differentiated (in  $t$ ) dynamic b.c.+simplified kinematic b.c.  $\Rightarrow$

$$\frac{\partial^2 \phi}{\partial t^2} + g \frac{\partial \phi}{\partial x} = 0$$

## Sloshing in a tank

A new unknown function  $u$ : the velocity potential  $\phi$  on the unperturbed free surface  $\Sigma_0$

These functions are connected by the equations

$$\begin{aligned}\Delta\phi &= 0 \text{ in } Q, \\ \phi|_{\Sigma_0} &= u, \quad \phi_n|_S = 0\end{aligned}$$

The function  $\phi$  depends on  $u$  uniquely and linearly so that in a space  $H$  of functions depending on  $x, y$  a linear operator  $\mathcal{A}$  can be defined (the Dirichlet-to-Neumann operator)

$$\mathcal{A}u = \left. \frac{\partial\phi}{\partial x} \right|_{\Sigma_0}$$

## Linear sloshing in a tank: problem in the time domain

Now the boundary condition on  $\Sigma_0$  yields the equation

$$\frac{d^2 u}{dt^2} + \mathcal{A}u = 0 \text{ on } \Sigma_0,$$
$$u(0) = u_0, \quad u'(0) = 0,$$

where  $u : \mathbb{R}_+ \rightarrow H$  is a vector-valued function

The solution operator is the operator cosine function

$$C(t) = \cos\left(\sqrt{\mathcal{A}}t\right):$$

$$u(t) = C(t)u_0$$

# Linear sloshing in a chute: problem in the frequency domain

Eigenoscillations:  $u = e^{i\lambda t} v, \quad v \neq v(t)$

$$-\lambda^2 v + \mathcal{A}v = 0$$

Equivalent formulation provided that

$$\phi(x, y, z, t) = \cos(\sigma t + \epsilon) \tilde{\phi}(x, y, z, t), \quad \kappa = \frac{\sigma^2}{g}:$$

$$\Delta \tilde{\phi} = 0 \text{ in } Q,$$

$$\frac{\partial \tilde{\phi}}{\partial x} = \kappa \tilde{\phi} \quad \text{on } \Sigma_0, \quad \frac{\partial \tilde{\phi}}{\partial n} = 0 \quad \text{on } S$$

## Nonlinear sloshing in a tank: modal models

Variational problem:

$$W = -\rho \int_{t_1}^{t_2} \int_Q \left[ \frac{\partial \phi}{\partial t} + \frac{1}{2} (\nabla \phi)^2 + gx \right] dQ$$

Ansatz:

$$x = f(y, z, t) = \sum_{i=1}^{\infty} \beta_i(t) f_i(y, z), \quad \phi(x, y, z, t) = \sum_{n=1}^{\infty} R_n(t) \phi_n(x, y, z)$$

Result: an initial or boundary value problem for a system of nonlinear ODE w.r.t.  $\beta_i(t)$ ,  $R_n(t)$



## $n$ -width: a measure of accuracy

$$X \in C(\overline{D}); \phi : X \rightarrow \mathbf{R}^n, f \rightarrow \xi = (f(t_1), \dots, f(t_n))$$

$$d[\phi^{-1}(\xi)] = \sup_{g, h \in \phi^{-1}(\xi)} |g - h|_{\infty}$$

- a measure which shows the goodness of the approximation of an element  $f | \phi(f) = \xi$  by  $\xi$

$$\mathcal{E}(X, \mathbf{R}^n; \phi) = \sup_{f \in X} d[\phi^{-1} \circ \phi(f)]$$

- the accuracy of the approximation in worst case

## $n$ -width: a measure of accuracy

$$\Delta_n(X, C(\overline{D})) = \inf_{\phi} \mathcal{E}(X, \mathbf{R}^n; \phi)$$

- the grid  $n$ -width: the measure of goodness of the best possible approximation of an arbitrary element of  $X$  by its values on the grid

## Curse of dimensionality

Let  $X = W_\rho^r(M; I)$  with  $M = (M_1, \dots, M_d)$  and  $r = (r_1, \dots, r_d)$  be the class of anisotropic Sobolev spaces defined on the  $d$ -dimensional interval  $I = \prod_{j=1}^d [a_j, b_j]$ .

$\rho = 1/(\sum_{j=1}^d r_j^{-1})$  – the effective *class smoothness*

$\mu = \prod_{j=1}^d M_j^{\rho/r_j}$  – the *class constant*.

It is known that for this class we need

$$N_\varepsilon^{(opt)} \asymp \text{const}(\mu) \cdot \varepsilon^{-1/(\rho - 1/p)}$$

parameters (optimal complexity) in order to approximate an arbitrary function of this class with a given tolerance  $\varepsilon$ . Note that  $N_\varepsilon^{(opt)}$  grows exponentially as  $d \rightarrow \infty$  (“curse of dimensionality”).

$|\log \varepsilon| = \log \frac{1}{\varepsilon}$  is the measure unity for the best possible

## Curse of dimensionality for analytical functions

$$N_\varepsilon = \mathcal{O}\left((\log|\log\varepsilon|)^d |\log\varepsilon|^d\right)$$

numbers are needed to approximate an analytical function of  $d$  variables, i.e.  $|\log\varepsilon| = \log\frac{1}{\varepsilon}$  remains the measure unity for the best possible approximation

$\Rightarrow$  an exponential approximation accuracy required!

## Sol. for Curse of $d$ . and exp. conv. alg.

$$u'(t) + Au = 0, \quad u(0) = u_0$$

$$u(t) = e^{-At} u_0 = \int_{\Gamma} e^{-zt} (z - A)^{-1} dz u_0$$

*Sinc – quadrature*  $\Rightarrow$  exp. conv.+ linear in  $d$  algorithms!

## EDS for BVPs for systems of nonlinear ODEs

$$\mathbf{u}'(x) + A(x)\mathbf{u} = \mathbf{f}(x, \mathbf{u}), \quad x \in (0, 1), \quad B_0\mathbf{u}(0) + B_1\mathbf{u}(1) = \mathbf{d}, \quad (1)$$

$$A(x), B_0, B_1, \in \mathbb{R}^{d \times d}, \quad \text{rank}[B_0, B_1] = d, \quad \mathbf{f}(x, \mathbf{u}), \mathbf{d}, \mathbf{u}(x) \in \mathbb{R}^d$$

$\mathbf{u}$  is an unknown  $d$ -dimensional vector-function

$$\hat{\omega}_h = \{x_j : 0 = x_0 < x_1 < x_2 < \cdots < x_N = 1\}$$

## EDS for BVPs for systems of nonlinear ODEs

IVPs (each of the dimension  $d$ )

$$\frac{d\mathbf{Y}^j(x, \mathbf{v}_{j-1})}{dx} + A(x)\mathbf{Y}^j(x, \mathbf{v}_{j-1}) = \mathbf{f}(x, \mathbf{Y}^j(x, \mathbf{v}_{j-1})), \quad x \in (x_{j-1}, x_j],$$

$$\mathbf{Y}^j(x_{j-1}, \mathbf{v}_{j-1}) = \mathbf{v}_{j-1}, \quad j = 1, 2, \dots, N. \tag{2}$$

- multishooting method

## EDS for BVPs for systems of nonlinear ODEs

$$\mathbf{u}_j = \mathbf{Y}^j(x_j, \mathbf{u}_{j-1}), \quad j = 1, 2, \dots, N, \quad (3)$$

$$B_0 \mathbf{u}_0 + B_1 \mathbf{u}_N = \mathbf{d}. \quad (4)$$



## Truncated difference scheme

$m$ -TDS:

$$\mathbf{y}_j^{(m)} = Y^{(m)j}(x_j, \mathbf{y}_{j-1}^{(m)}), \quad j = 1, 2, \dots, N, \quad (5)$$

$$B_0 \mathbf{y}_0^{(m)} + B_1 \mathbf{y}_N^{(m)} = \mathbf{d} \quad (6)$$

$Y^{(m)j}(x_j, \mathbf{y}_{j-1}^{(m)})$  - the num. sol. of IVP (2) on  $[x_{j-1}, x_j]$  which has been obtained by some one-step method of the order  $m$

$$\left\| \mathbf{y}^{(m,n)} - \mathbf{u} \right\|_{0, \infty, \hat{\omega}_h} \leq M (q_2^n + |h|^m), \quad (7)$$

where  $q_2 \equiv q + M|h| < 1$ ,  $n$  is the number of the fixed point iteration step

A posteriori error estimation and automatic grid generation is based on the embedded IVP-solver of the orders  $m$  and  $m + 1$

## Truncated difference scheme: Troesch test

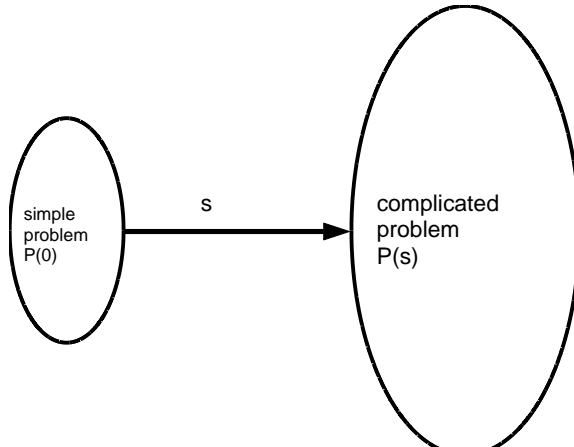
$$u'' = \lambda \sinh(\lambda u), \quad x \in (0, 1), \quad \lambda > 0, \quad u(0) = 0, \quad u(1) = 1. \quad (8)$$

$\lambda = 10$  ( $\lambda = 61, 62$  is possible)

$\varepsilon$	$N$	$NFUN$	<i>Error</i>
$10^{-4}$	72	11323	$0.143 \cdot 10^{-5}$
$10^{-6}$	124	19435	$0.538 \cdot 10^{-7}$

**Table:** Numerical results for the TDS with  $m = 8(7)$

## The homotopy idea



## FD-method: eigenvalue problem

Problem  $P(t)$ :

$$(A + W(t))u(t) - \lambda(t)u(t) = \theta, \quad t \in [0, 1]$$

Problem  $P(1)$ :

$$(A + B)u - \lambda u = \theta \quad \text{in } H$$

Problem  $P(0)$ :

$$(A + \bar{B})u^{(0)} - \lambda^{(0)}u^{(0)} = \theta$$

## FD-method: eigenvalue problem

Representation:

$$\lambda(t) = \sum_{j=0}^{\infty} \lambda^{(j)} t^j, u(t) = \sum_{j=0}^{\infty} u^{(j)} t^j$$

Recurrence equations:

$$(A + \bar{B})u^{(j+1)} - \lambda^{(0)}u^{(j+1)} = F^{(j+1)}, j = 0, 1, \dots$$

with  $\lambda^{(0)}, u^{(0)}$  - solution of  $P(0)$  and

$$\begin{aligned} F^{(j+1)} &= F^{(j+1)}(\lambda^{(0)}, \dots, \lambda^{(j+1)}; u^{(0)}, \dots, u^{(j)}) = \\ &= \lambda^{(j+1)}u^{(0)} - [B - \bar{B}]u^{(j)} + \sum_{p=1}^j \lambda^{(j+1-p)}u^{(p)}, j = 0, 1, \dots \end{aligned}$$

## FD-method: eigenvalue problem

Approximation for  $P(1)$ :

$$\lambda^N = \sum_{j=0}^N \lambda^{(j)}, \quad u^N = \sum_{j=0}^N u^{(j)}$$

Convergence result:

$$|\lambda - \lambda^N| \leq \|B - \bar{B}\| \frac{C}{(1+N)^{1+\varepsilon}} q^N,$$

$$\|u - u^N\| \leq \frac{C}{(1+N)^{1+\varepsilon}} q^{N+1}$$

provided that  $q = C \|B - \bar{B}\| < 1$

## FD-method: eigenvalue problem

Example:

$$u^{(4)}(x) + \left[ \left( x - \frac{1}{2} \right)^2 - \lambda \right] u(x), \quad x \in (0, 1)$$
$$u^{(k)}(0) = u^{(k)}(1) = 0, \quad k = 2, 3.$$

Here the operators  $A, B$  are defined by

$$D(A) = \{v \in H^4(0, 1) : v^{(k)}(0) = v^{(k)}(1) = 0, k = 2, 3\}, \quad Av = v^{(4)}(x) \quad \forall v \in D(A);$$
$$D(B) = L_2(0, 1), \quad Bv = \left( x - \frac{1}{2} \right)^2 v(x).$$

## FD-method: Example

$$u^{(4)}(x) + \left[ \left( x - \frac{1}{2} \right)^2 - \lambda \right] u(x), \quad x \in (0, 1)$$
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## FD-method: Example

The pair of smallest eigenvalues is

$$\lambda_{0,-}^{\text{ex}} = 0.0833223112249938\dots, \quad \lambda_{0,+}^{\text{ex}} = 0.14999891773580\dots$$

The base problem  $P(0)$  with  $\bar{B} = 0$  possesses the double eigenvalue  $\lambda^{(0)} = 0$  corresponding to the orthonormal eigenfunctions

$$u_{01}(x) = 1, \quad u_{02}(x) = 12x - 6.$$

Rank $N$	$\lambda_{0,-}^N(\bar{B})$	$\lambda_{0,+}^N(\bar{B})$
0	0	0
1	0.08(3)	0.15
2	0.0833223104056437	0.14999891774891
3	0.0833223112249098	0.14999891773580

## FD-method: Example

The error:

Rank $N$	$ \lambda_{0,-}^{\text{ex}} - \lambda_{0,-}^N(\bar{B}) $	$ \lambda_{0,+}^{\text{ex}} - \lambda_{0,+}^N(\bar{B}) $
0	$0.84 \cdot 10^{-1}$	0.15
1	$0.12 \cdot 10^{-4}$	$0.11 \cdot 10^{-5}$
2	$0.83 \cdot 10^{-9}$	$0.14 \cdot 10^{-10}$
3	$0.84 \cdot 10^{-13}$	$0.39 \cdot 10^{-15}$

## The IVP

$$\frac{d^2 u(t)}{dt^2} + Au(t) = f(t), \quad u(0) = u^{(0)}, \quad u'(0) = u^{(1)}$$

## The operator cosine and sine families

$$B \equiv 0, \quad u^{(1)} \equiv 0 \Rightarrow u(t) = C(t)u^{(0)}$$

$$\frac{d^2 C(t)}{dt^2} + AC(t) = 0, \quad C(0) = I, \quad C'(0) = 0$$

$$S(t) = S(t; \sqrt{A}) = \int_0^t C(t) dt$$

## Representation of solution

$$\begin{aligned}u(t) &= u_h(t) + u_p(t) \\u_h(t) &= C(t)u^{(0)} + A^{-1/2}S(t)u^{(1)} \\&= \cos(\sqrt{A}t)u^{(0)} + A^{-1/2}\sin(\sqrt{A}t)u^{(1)} \\u_p(t) &= \int_0^t S(t-s)f(s)ds\end{aligned}$$

## The Cayley transform method for cos

$$\begin{aligned}
 x(t) &\equiv x(t; A) = (\cos \sqrt{A}t)x_0 \\
 &= \frac{1}{2}e^{-\delta t} \sum_{n=0}^{\infty} \left( L_n^{(0)}(t) - L_{n-1}^{(0)}(t) \right) \times (W_+^n + W_-^n)x_0 \\
 &= e^{-\delta t} \sum_{n=0}^{\infty} \left( L_n^{(0)}(t) - L_{n-1}^{(0)}(t) \right) u_n,
 \end{aligned} \tag{9}$$

$$\begin{aligned}
 C(t) &\equiv \cos \sqrt{A}t = \frac{1}{2}e^{-\delta t} \sum_{n=0}^{\infty} \left( L_n^{(0)}(t) - L_{n-1}^{(0)}(t) \right) (W_+^n + W_-^n) \\
 &= e^{-\delta t} \sum_{n=0}^{\infty} \left( L_n^{(0)}(t) - L_{n-1}^{(0)}(t) \right) \mathcal{U}_n,
 \end{aligned}$$

## The Cayley transform method for cos

The sequences of vectors  $\{u_n\}$  and of operators  $\{\mathcal{U}_n\} \equiv \{\mathcal{U}_n(A)\}$  are defined by

$$u_{n+1} = 2(A + \delta(\delta - 1)I)(A + (\delta - 1)^2I)^{-1}u_n - (A + \delta^2I)(A + (\delta - 1)^2I)^{-1}u_{n-1}, \quad n \geq 1, \quad (10)$$

$$u_0 = x_0, \quad u_1 = (A + \delta(\delta - 1)I)(A + (\delta - 1)^2I)^{-1}x_0$$

and

$$\mathcal{U}_{n+1} = 2(A + \delta(\delta - 1)I)(A + (\delta - 1)^2I)^{-1}\mathcal{U}_n - (A + \delta^2I)(A + (\delta - 1)^2I)^{-1}\mathcal{U}_{n-1}, \quad n \geq 1, \quad (11)$$

$$\mathcal{U}_0 = I, \quad \mathcal{U}_1 = (A + \delta(\delta - 1)I)(A + (\delta - 1)^2I)^{-1}$$

without using  $\sqrt{A}$ !

## The Cayley transform method for cos

One can observe that In order to find  $\{u_n\}$  one has to solve the following sequence of operator equations

$$(A + (\delta - 1)^2 I)u_{n+1} = \bar{u}_{n+1} \quad , \quad n \geq 1; \quad (A + (\delta - 1)I)u_1 = \bar{u}_1 \quad (12)$$

with the same operator  $A + (\delta - 1)^2 I$  and with various right-hand sides, where

$$\begin{aligned} \bar{u}_{n+1} &= 2(A + \delta(\delta - 1)I)u_n - (A + \delta^2 I)u_{n-1} \quad , \quad n \geq 1, \\ u_0 &= x_0 \quad , \quad \bar{u}_1 = (A + \delta(\delta - 1)I)u_0. \end{aligned} \quad (13)$$



## The Cayley transform method for cos

**Algorithm:** the truncated sum with  $N$  terms

**Estimate:** Let  $A$  be a densely defined, strongly  $P$ -positive operator and  $x_0 \in \mathcal{D}(A^\sigma)$ . Then

$$\sup_{t \in [0, T]} \|x^N(t) - x(t)\| \leq cN^{-(\sigma - \frac{3}{4} - \varepsilon)} \|A^\sigma x_0\| \quad (14)$$

No accuracy saturation, but an exponential accuracy for analytical vectors only!

## The Danford-Cauchy representation

For a strongly P-positive operator:

$$C(t) = \frac{1}{2\pi i} \int_{\Gamma} \cos \sqrt{z}t (z - A)^{-1} dz$$

Parametrization+Laguerre quadrature  $\Leftrightarrow$  Alg. without saturation  
Other Approximations???

## Tensor product representations: with MPI for Mathematics in the Sciences Leipzig

$$N_{\varepsilon}^{(opt)} = \mathcal{O}\left((\log|\log\varepsilon|)^d |\log\varepsilon|^d\right)$$

numbers are needed to represent an analytical function of  $d$  variables with a tolerance  $\varepsilon$

$$\mathcal{L}u = f$$

in a  $d$ -dimensional rectangle one uses a discretization

$$\mathcal{L}_h u_h = f_h$$

with  $N = n^d$  nodes and a matrix  $\mathcal{L}_h \in \mathbb{R}^{n^d \times n^d}$

## Tensor product representations

The complexity of computation of  $u_h = \mathcal{L}_h^{-1} f_h$  is in general  $\mathcal{O}(n^{2d})$   
(again the curse of dimensionality)

## Tensor product representations

Supposing the tensor-product representations

$$\mathcal{L}_h^{-1} = \mathcal{L}_1 \otimes \mathcal{L}_2 \otimes \cdots \otimes \mathcal{L}_d, \quad f_h = f_1 \otimes f_2 \otimes \cdots \otimes f_d$$

we have due to

$$\begin{aligned} \mathcal{L}_h^{-1} f_h &= (\mathcal{L}_1 \otimes \mathcal{L}_2 \otimes \cdots \otimes \mathcal{L}_d) \cdot (f_1 \otimes f_2 \otimes \cdots \otimes f_d) \\ &= (\mathcal{L}_1 \cdot f_1) \otimes (\mathcal{L}_2 \cdot f_2) \otimes \cdots \otimes (\mathcal{L}_d \cdot f_d) \end{aligned}$$

the polynomial in  $d$  complexity  $\mathcal{O}(dn^2)$ .

## Epilogue

Also geht alles zu Ende allhier:  
Feder, Tinte, Tobak und auch wir,  
Zum letztenmal wird eingetunkt,  
Dann kommt der große schwarze ●  
(*W. Busch, Bilder zur Jobsiade 1872*)