# 1 The Poisson problem in $\mathbb{R}^2$

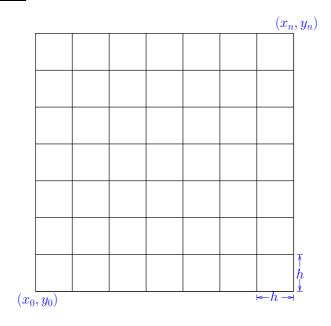
The 2D-Poisson problem is given by

$$-\nabla^2 u = f \qquad \text{in } \Omega = (0,1) \times (0,1),$$
  

$$u = 0 \qquad \text{on } \partial\Omega,$$
(1)

where  $\nabla^2 u = \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}$ .

# Finite difference grid:



## Discrete equations:

By using the notation

$$u_{i,j} \simeq u(x_i, y_j) = u(ih, jh),$$

and discretizing (1) using the 5-point stencil, the discrete equations read:

$$-\frac{(u_{i+1,j}-2u_{i,j}+u_{i-1,j})}{h^2}-\frac{(u_{i,j+1}-2u_{i,j}+u_{i,j-1})}{h^2}=f_{i,j} \qquad 1 \le i, j \le n-1.$$

### 1.1 Diagonalization

Let

$$\underline{\mathbf{U}} = \begin{bmatrix} u_{1,1} & \dots & \dots & u_{1,n-1} \\ \vdots & & & \vdots \\ \vdots & & & \vdots \\ u_{n-1,1} & \dots & \dots & u_{n-1,n-1} \end{bmatrix}$$

and

$$\underline{\mathbf{T}} = \begin{bmatrix} 2 & -1 & & & 0 \\ -1 & 2 & -1 & & \\ & & \ddots & & \\ & & -1 & 2 & -1 \\ 0 & & & -1 & 2 \end{bmatrix}$$

Then,

$$\begin{split} &(\underline{\mathbf{T}}\,\underline{\mathbf{U}})_{ij} = 2u_{i,j} - u_{i+1,j}, & i = 1, \\ &(\underline{\mathbf{T}}\,\underline{\mathbf{U}})_{ij} = -u_{i-1,j} + 2u_{i,j} - u_{i+1,j}, & 2 \leq i \leq n-2, \\ &(\underline{\mathbf{T}}\,\underline{\mathbf{U}})_{ij} = -u_{i-1,j} + 2u_{i,j}, & i = n-1. \end{split}$$

and thus,

$$\frac{1}{h^2} (\mathbf{\underline{T}} \underline{\mathbf{U}})_{ij} \simeq -\left(\frac{\partial^2 u}{\partial x^2}\right)_{i,j}.$$

Similarly,

$$\frac{1}{h^2} (\underline{\mathbf{U}} \, \underline{\mathbf{T}})_{ij} \simeq - \left( \frac{\partial^2 u}{\partial y^2} \right)_{i,j}.$$

**Exercise**: Show this!

Our finite difference system can then be expressed as

$$\frac{1}{h^2} (\mathbf{\underline{T}} \mathbf{\underline{U}} + \mathbf{\underline{U}} \mathbf{\underline{T}})_{i,j} = f_{i,j} \quad \text{for} \quad \begin{array}{c} 1 \le i \le n-1, \\ 1 \le j \le n-1, \end{array}$$

or

$$\underline{\mathbf{T}}\underline{\mathbf{U}} + \underline{\mathbf{U}}\underline{\mathbf{T}} = \underline{\mathbf{G}} \tag{2}$$

where

$$\underline{\mathbf{G}} = h^2 \begin{bmatrix} f_{1,1} & \dots & \dots & f_{1,n-1} \\ \vdots & & & \vdots \\ \vdots & & & \vdots \\ f_{n-1,1} & \dots & \dots & f_{n-1,n-1} \end{bmatrix}$$

The matrix,  $\underline{\mathbf{T}}$ , may be diagonalized by

$$\underline{\mathbf{T}} = \mathbf{Q}\underline{\boldsymbol{\Lambda}}\mathbf{Q}^T,$$

where  $\underline{\Lambda}$  is a diagonal matrix and  $\underline{\mathbf{Q}}^T\underline{\mathbf{Q}} = \underline{\mathbf{I}}$ , the identity matrix. Inserted into (2), we get

$$\underline{\mathbf{Q}}\underline{\mathbf{\Lambda}}\underline{\mathbf{Q}}^{T}\underline{\mathbf{U}} + \underline{\mathbf{U}}\underline{\mathbf{Q}}\underline{\mathbf{\Lambda}}\underline{\mathbf{Q}}^{T} = \underline{\mathbf{G}}.$$

Multiplying from the right with  $\underline{\mathbf{Q}}$  and multiplying from the left with  $\underline{\mathbf{Q}}^T$  gives:

$$\underline{\underline{\Lambda}}\underline{\underline{Q}^{T}}\underline{\underline{U}}\underline{\underline{Q}} + \underline{\underline{Q}^{T}}\underline{\underline{U}}\underline{\underline{Q}}\underline{\underline{\Lambda}} = \underline{\underline{Q}^{T}}\underline{\underline{G}}\underline{\underline{Q}}.$$

Hence, (2) may be solved in three steps:

# Step 1)

$$\boxed{\widetilde{\underline{\mathbf{G}}} = \underline{\mathbf{Q}}^T \underline{\mathbf{G}} \underline{\mathbf{Q}}} \quad - \quad \begin{array}{c} \text{matrix-matrix} \\ \text{products.} \end{array}$$

# Step 2)

$$\mathbf{\Lambda} \, \widetilde{\mathbf{U}} + \widetilde{\mathbf{U}} \, \mathbf{\Lambda} = \widetilde{\mathbf{G}}$$

or

$$\lambda_{i}\widetilde{u}_{i,j} + \widetilde{u}_{i,j}\lambda_{j} = \widetilde{g}_{i,j}, \qquad 1 \leq i, j \leq n - 1$$
$$(\lambda_{i} + \lambda_{j})\widetilde{u}_{i,j} = \widetilde{g}_{i,j}, \qquad 1 \leq i, j \leq n - 1$$
$$\widetilde{u}_{i,j} = \frac{\widetilde{g}_{i,j}}{\lambda_{i} + \lambda_{j}} \qquad 1 \leq i, j \leq n - 1.$$

## Step 3)

$$\boxed{\underline{\mathbf{U}} = \underline{\mathbf{Q}} \widetilde{\underline{\mathbf{U}}} \underline{\mathbf{Q}}^T } \quad - \quad \begin{array}{c} \text{matrix-matrix} \\ \text{products.} \end{array}$$

Note:

$$\underline{\mathbf{U}}, \underline{\widetilde{\mathbf{U}}}, \underline{\widetilde{\mathbf{G}}}, \underline{\mathbf{Q}}, \underline{\mathbf{Q}}^T \in \mathbb{R}^{(n-1)\times(n-1)}.$$

## 1.1.1 Computational cost

$$N = N_{d.o.f.} = (n-1)^2 \sim \mathcal{O}(n^2)$$
  $(n \gg 1).$ 

# Step 1)

$$\underline{\widetilde{\mathbf{G}}} = \underline{\underline{\mathbf{Q}}^T \underline{\mathbf{G}} \underline{\mathbf{Q}}}_{\mathcal{O}(n^3)} \longrightarrow \mathcal{O}(n^3) \text{ operations.}$$

## Step 2)

$$\widetilde{u}_{i,j} = \frac{\widetilde{g}_{i,j}}{\lambda_i + \lambda_j} \longrightarrow \mathcal{O}(n^2) \text{ operations.}$$

# Step 3)

$$\underline{\mathbf{U}} = \underbrace{\widetilde{\mathbf{Q}}\widetilde{\mathbf{U}}\mathbf{Q}^T}_{\mathcal{O}(n^3)} \longrightarrow \mathcal{O}(n^3) \text{ operations.}$$

In summary, we can compute the discrete solution,  $\underline{\mathbf{U}}$ , in  $\underline{\mathcal{O}(n^3)} = \mathcal{O}(N^{3/2})$  operations.

### Note:

This method is an example of a <u>direct method</u>.

#### 1.1.2 Comparison with other direct methods

Computational cost				
Method	Operations	Memory requirement		
Diagonalization	$\mathcal{O}(N^{3/2}) = \mathcal{O}(n^3)$	$\mathcal{O}(N) = \mathcal{O}(n^2)$		
Full LU	$\mathcal{O}(N^3) = \mathcal{O}(n^6)$	$\mathcal{O}(N^2) = \mathcal{O}(n^4)$		
Banded LU	$\mathcal{O}(Nb^2) = \mathcal{O}(n^4)$	$\mathcal{O}(Nb) = \mathcal{O}(n^3)$		

**Table 1:** Computational cost and memory requirement for direct methods. For the bandwidth, we have  $b \sim \mathcal{O}(n)$ .

The diagonalization method is much more attractive in  $\mathbb{R}^2$  than in  $\mathbb{R}^1$ !

# 1.1.3 The matrices, $\underline{\mathbf{Q}}$ and $\underline{\boldsymbol{\Lambda}}$ .

Consider the eigenvalue problem

$$-u_{xx} = \lambda u \qquad \text{in } \Omega = (0, 1),$$
  
$$u(0) = u(1) = 0,$$

which has solutions

$$\bar{u}_j(x) = \sin(j\pi x),$$
  
 $\bar{\lambda}_j = j^2 \pi^2,$   $j = 1, 2, \dots, \infty.$ 

Consider now the discrete eigenvalue problem:

$$\underline{\mathbf{T}}\underline{\widetilde{q}}_{j} = \lambda_{j}\underline{\widetilde{q}}_{j}.$$

Try

$$(\underline{\widetilde{q}}_{j})_{i} = \overline{u}_{j}(x_{i})$$

$$= \sin(j\pi x_{i})$$

$$= \sin(j\pi(ih)), \qquad \left(h = \frac{1}{n}\right)$$

$$= \sin\left(\frac{ij\pi}{n}\right)$$

Operating on  $\underline{\widetilde{q}}_j$  with  $\underline{\mathbf{T}}$  gives

$$(\underline{\mathbf{T}}\underline{\widetilde{q}}_{j})_{i} = \underbrace{2\left(1 - \cos\left(\frac{j\pi}{n}\right)\right)}_{\lambda_{j}} \underbrace{\sin\left(\frac{ij\pi}{n}\right)}_{(\widetilde{q}_{i})_{i}}.$$

Set  $\underline{q}_j = \alpha \underline{\widetilde{q}}_j,$  and choose  $\alpha$  such that  $\underline{q}_j$  is normalized:

For  $j \ll n$ , we observe that

$$\lambda_j \simeq 2 \left( 1 - \left( 1 - \frac{1}{2} \frac{j^2 \pi^2}{n^2} + \dots \right) \right) \simeq \frac{j^2 \pi^2}{n^2}.$$

Since  $h = \frac{1}{n}$ , we have

$$\lambda_j \simeq h^2 j^2 \pi^2 = h^2 \bar{\lambda}_j, \quad \text{for } j \ll n.$$

This is the same as saying that the first (lowest) eigenvalues for the continuous case are well approximated by our finite difference formulation.

Note that in this case

$$Q_{ij} = (\underline{q}_j)_i = \sqrt{\frac{2}{n}} \sin\left(\frac{ij\pi}{n}\right), \qquad 1 \le i, j \le n - 1,$$

and that indeed

$$\underline{\mathbf{Q}}^T = \underline{\mathbf{Q}}.$$

From the comparison of computational cost shown earlier, the diagonalization approach to solving the discrete Poisson problem appears promising.

## Question 1:

Can the matrix-matrix multiplications be done fast?

### Question 2:

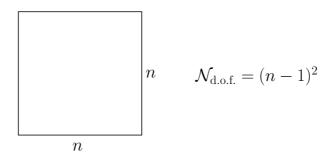
Can the matrix-matrix multiplications be parallelized?

### Question 3:

Can we do better?

## 1.1.4 Numerical results

- Diagonalization
- $\bullet$  "Standard"  $m\times m$
- PC, Pentium III, 512 MB RAM



$$\tau^n=$$
 total simulation time (in seconds)  
 $\tau^n_1=\frac{\tau}{n^2}$   
 $r_n=\frac{\tau^n_1}{\tau^{\frac{n}{2}}}$ 

n	$\tau^n$	$ au_1^n$	$r^n$
32	$1.80 \cdot 10^{-2}$	$1.76 \cdot 10^{-5}$	
64	$1.50 \cdot 10^{-1}$	$3.66 \cdot 10^{-5}$	2.1
128	1.20	$7.34 \cdot 10^{-5}$	2.0
256	9.84	$1.50 \cdot 10^{-4}$	2.0
512	103.9	$3.96 \cdot 10^{-4}$	2.6
1024	873.2	$8.33 \cdot 10^{-4}$	2.1
	$\tau^n \sim \mathcal{O}(n^3)$	$\tau_1^n \sim \mathcal{O}(n)$	

**Table 2:** Simulation results for the numerical approximation of the two-dimensional Poisson equation by the use of diagonalization techniques.

### 1.2 Fast diagonalization methods

The most expensive operation in the diagonalization method introduced in the previous section is of the type,

$$\underline{v}^* = \underline{\mathbf{Q}}\underline{v} = \underline{\mathbf{Q}}^T\underline{v},$$

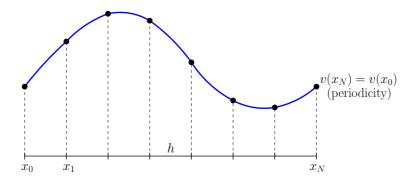
where

$$Q_{ij} = \sqrt{\frac{2}{n}} \sin\left(\frac{ij\pi}{n}\right)$$
  $1 \le i, j \le n - 1.$ 

We will now consider ways to obtain  $\underline{v}^*$  in  $\mathcal{O}(n \log n)$  operations instead of  $\mathcal{O}(n^2)$ .

### 1.2.1 Discrete Fourier Transform (DFT)

Consider a periodic function v(x) with period  $2\pi$ . Consider sampling this function at the equidistant points  $x_j$ ,  $j=0,1,\ldots,N$ , with  $x_j=jh$ ,  $h=\frac{2\pi}{N}$ . Let  $v_j=v(x_j)=v(jh)$ ,  $j=0,1,\ldots,N$ .



Consider the vectors  $\underline{\varphi}_k$ , where

$$(\underline{\varphi}_k)_j = e^{ikx_j}, \qquad j, k = 0, 1, \dots, N - 1.$$

Note that the vector elements in  $\underline{\varphi}_k$  represent the values of the function  $\varphi_k(x) = e^{ikx}$  sampled at the discrete points  $x_j$ ,  $j = 0, 1, \dots, N-1$ . Note also that the function  $\varphi_k(x) = e^{ikx}$  is an eigenfunction of the Laplace operator with periodic boundary conditions.

The vectors  $\{\underline{\varphi}_k\}_{k=0}^{N-1}$  form a basis for the N-dimensional vector space  $\mathbb{C}^N$ . In particular, we have that

$$\underline{\varphi}_k^H \underline{\varphi}_k = \begin{cases} N, & k = l, \\ 0, & k \neq l, \end{cases} \qquad k, l = 0, 1, \dots, N - 1.$$

The vector

$$\underline{v} = \begin{bmatrix} v_0 \\ \vdots \\ v_{N-1} \end{bmatrix} \in \mathbb{R}^N$$

can be expressed in this basis as

$$\underline{v} = \sum_{k=0}^{N-1} \hat{v}_k \underline{\varphi}_k$$

or

$$v_j = \sum_{k=0}^{N-1} \hat{v}_k (\underline{\varphi}_k)_j = \sum_{k=0}^{N-1} \hat{v}_k e^{ikx_j},$$

where  $\hat{v}_k$ , are the discrete Fourier coefficients given by

$$\hat{v}_k = \frac{1}{N} \sum_{j=0}^{N-1} v_j e^{-ikx_j},$$
  $x_j = jh$   
 $h = \frac{2\pi}{N}$   $k = 0, 1, \dots, N-1$ 

# Summary (DFT):

$$v_j = \sum_{k=0}^{N-1} \hat{v}_k e^{ijkh},$$
  $j = 0, 1, \dots, N-1,$ 

where

$$\hat{v}_k = \frac{1}{N} \sum_{j=0}^{N-1} v_j e^{-ijkh}, \qquad k = 0, 1, \dots, N-1,$$

and

$$h = \frac{2\pi}{N}.$$

#### 1.2.2 Discrete Sine Transform (DST)

The Discrete Sine Transform is applicable to a function v(x) which is <u>periodic</u> with period  $2\pi$  and <u>odd</u>. Discretize the function on an equidistant grid on  $[0,\pi]$  with  $h=\frac{\pi}{n}$ . Set

$$v_j = v(x_j) = v(jh) = v\left(\frac{j\pi}{n}\right),$$
  $j = 0, 1, \dots, n.$ 

Since v is odd,

$$v(x_0) = v(x_n) = 0.$$

The discretized function is therefore represented by the (n-1) real values  $v_1, \ldots, v_{n-1}$ , i.e., by the vector

$$\underline{v} = \begin{bmatrix} v_1 \\ \vdots \\ v_{n-1} \end{bmatrix} \in \mathbb{R}^{n-1}.$$

An orthogonal basis for  $\mathbb{R}^{n-1}$  is given by the vectors  $\underline{\psi}_k$ ,  $k=1,\ldots,n-1$ , where

$$(\underline{\psi}_k)_j = \sin\left(\frac{kj\pi}{n}\right), \qquad j = 1, \dots, n-1,$$

and with

$$\underline{\psi}_{k}^{T}\underline{\psi}_{l} = \begin{cases} \frac{n}{2}, & k = l, \\ 0, & k \neq 0. \end{cases}$$

In terms of this basis, we can write  $\underline{v}$  as

$$v_j = \sum_{k=1}^{n-1} \widetilde{v}_k \sin\left(\frac{kj\pi}{n}\right), \qquad j = 1, \dots, n-1,$$

where

$$\widetilde{v}_k = \frac{2}{n} \sum_{j=1}^{n-1} v_j \sin\left(\frac{jk\pi}{n}\right), \quad k = 1, \dots, n-1.$$

We can also write this as

$$\widetilde{\underline{v}} = \underline{\mathbf{S}}(\underline{v}) \qquad (DST).$$

and

$$\underline{v} = \underline{\mathbf{S}}^{-1}(\underline{\widetilde{v}})$$
 (inverse DST).

Note that  $\underline{\mathbf{S}}(\cdot)$  and  $\underline{\mathbf{S}}^{-1}(\cdot)$  are related as

$$\underline{\mathbf{S}} = \frac{2}{n}\underline{\mathbf{S}}^{-1}$$

Also note that

$$\underline{\mathbf{Q}} = \sqrt{\frac{2}{n}}\underline{\mathbf{S}}^{-1},$$

and

$$\underline{\mathbf{Q}} = \sqrt{\frac{2}{n}}\underline{\mathbf{S}}.$$

Now, consider the matrix  $\underline{\mathbf{F}}^{(N)}$  where

$$\begin{split} F_{k,j}^{(N)} &= e^{-ijkh} \\ &= \cos \left(\frac{jk2\pi}{N}\right) - i \sin \left(\frac{jk2\pi}{N}\right), \qquad 0 \leq j, k \leq N-1. \end{split}$$

Note that

$$F_{k,j}^{(2n)} = \cos\left(\frac{jk\pi}{n}\right) - i\sin\left(\frac{jk\pi}{n}\right), \qquad 0 \le j, k \le 2n - 1.$$

Now, consider

$$\underline{v} = \begin{bmatrix} v_1 \\ \vdots \\ v_{n-1} \end{bmatrix} \in \mathbb{R}^{n-1}.$$

Construct the extended vector as an "odd" extension

$$w = \begin{bmatrix} 0 \\ v_1 \\ \vdots \\ v_{n-1} \\ 0 \\ -v_{n-1} \\ \vdots \\ -v_1 \end{bmatrix} \in \mathbb{R}^{2n}.$$

First, note that

$$(\underline{\mathbf{F}}^{(2n)}\underline{w})_k = \sum_{j=0}^{2n-1} e^{\frac{-ijk\pi}{n}} w_j = 2n\hat{w}_k,$$

where  $\hat{w}$ ,  $k = 0, 1, \dots, 2n - 1$ , are the discrete Fourier coefficients. Second,

$$(\underline{\mathbf{F}}^{(2n)}\underline{w})_k = \sum_{j=0}^{2n-1} \left[ \cos\left(\frac{jk\pi}{n}\right) - i\sin\left(\frac{jk\pi}{n}\right) \right] w_j$$

$$= \sum_{j=0}^{2n-1} w_j \cos\left(\frac{jk\pi}{n}\right) - i\sum_{j=0}^{2n-1} w_j \sin\left(\frac{jk\pi}{n}\right)$$

$$= -2i\sum_{j=0}^{n-1} w_j \sin\left(\frac{jk\pi}{n}\right)$$

$$= -2i\sum_{j=1}^{n-1} w_j \sin\left(\frac{jk\pi}{n}\right) \qquad \text{(since } w_0 = 0\text{)}.$$

Hence

$$\frac{i}{2}(\underline{\mathbf{F}}^{(2n)}\underline{w})_k = \sum_{j=1}^{n-1} w_j \sin\left(\frac{jk\pi}{n}\right) = \frac{n}{2}\widetilde{w}_k.$$

Since

$$w_j = v_j, \qquad j = 1, \dots, n-1,$$

it follows that

$$\widetilde{w}_k = \widetilde{v}_k, \qquad k = 1, \dots, n - 1.$$

In summary, for  $k = 1, \ldots, n - 1$ ,

$$\widetilde{v}_k = \widetilde{w}_k = \frac{2}{n} \frac{i}{2} (\underline{\mathbf{F}}^{(2n)} \underline{w})_k$$

$$= \frac{i}{n} (\underline{\mathbf{F}}^{(2n)} \underline{w})_k$$

$$= \frac{i}{n} 2n \hat{w}_k$$

$$= 2i \hat{w}_k.$$

By computing the discrete Fourier coefficients  $\hat{w}_k$ , we can find the discrete sine coefficients  $\tilde{v}_k$ ,  $k = 1, \ldots, n-1$ , where

$$\widetilde{\underline{v}} = \underline{\mathbf{S}}(\underline{v}) = \sqrt{\frac{2}{n}}\underline{\mathbf{Q}}\underline{v}.$$

The operator  $(\underline{\mathbf{F}}^{(2n)}\underline{w})$  can be computed efficiently by a FFT in  $\mathcal{O}(2n\log 2n) \sim \mathcal{O}(n\log n)$  operations.

This leads to the modified algorithm (Poisson solver):

$$\begin{split} & \underline{\widetilde{\mathbf{G}}} = \underline{\mathbf{Q}}^T \underline{\mathbf{G}} \underline{\mathbf{Q}} \\ \Rightarrow & \underline{\widetilde{\mathbf{G}}}^T = \underline{\mathbf{Q}}^T \underline{\mathbf{G}}^T \underline{\mathbf{Q}} \\ &= \underline{\mathbf{Q}} \underline{\mathbf{G}}^T \underline{\mathbf{Q}}^T \qquad (\underline{\mathbf{Q}} = \underline{\mathbf{Q}}^T) \\ &= \underline{\mathbf{Q}} (\underline{\mathbf{Q}} \underline{\mathbf{G}})^T \\ &= \sqrt{\frac{2}{n}} \underline{\mathbf{S}}^{-1} \left( \left( \sqrt{\frac{n}{2}} \underline{\mathbf{S}} (\underline{\mathbf{G}}) \right)^T \right) \\ &= \underline{\mathbf{S}}^{-1} ((\underline{\mathbf{S}} (\underline{\mathbf{G}}))^T) & \mathcal{O}(n^2 \log n) \end{split}$$

$$\widetilde{U}_{ji} = \frac{\widetilde{G}_{ji}}{\lambda_j + \lambda_i} \qquad \mathcal{O}(n^2)$$

3)

$$\begin{split} \underline{\mathbf{U}} &= \underline{\mathbf{Q}} \widetilde{\underline{\mathbf{U}}} \underline{\mathbf{Q}}^T \\ &= \underline{\mathbf{Q}} (\underline{\mathbf{Q}} \widetilde{\underline{\mathbf{U}}}^T)^T \\ &= \underline{\mathbf{S}}^{-1} ((\underline{\mathbf{S}} (\widetilde{\underline{\mathbf{U}}}^T))^T) \end{split} \qquad \mathcal{O}(n^2 \log n) \end{split}$$

Again,

$$\underline{\mathbf{S}} = \frac{2}{n}\underline{\mathbf{S}}^{-1}$$

and  $\underline{\widetilde{v}} = \underline{\mathbf{S}} \, \underline{v}$  is obtained as follows

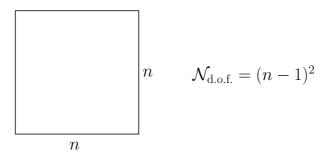
i) 
$$v \in \mathbb{R}^{n-1} \quad \to \quad w \in \mathbb{R}^{2n}$$

ii) Compute  $\underline{\hat{w}}$  via FFT  $(\mathcal{O}(n \log n))$ .

iii) 
$$\widetilde{v}_k = 2i\hat{w}_k, \qquad k = 1, \dots, n-1.$$

### 1.2.3 Numerical results

- Diagonalization
- DST (FFT)
- PC, Pentium III, 512 MB RAM



$$\tau^n=$$
 total simulation time (in seconds) 
$$\tau^n_1=\frac{\tau}{n^2}$$

n	$ au^n$	$ au_1^n$	$\tau_1^n(m \times m)$
32	$2.36 \cdot 10^{-2}$	$2.31 \cdot 10^{-5}$	$1.76 \cdot 10^{-5}$
64	$1.11 \cdot 10^{-1}$	$2.71 \cdot 10^{-5}$	$3.66 \cdot 10^{-5}$
128	$5.19 \cdot 10^{-1}$	$3.17 \cdot 10^{-5}$	$7.34 \cdot 10^{-5}$
256	2.35	$3.58 \cdot 10^{-5}$	$1.50 \cdot 10^{-4}$
512	10.5	$3.99 \cdot 10^{-5}$	$3.96 \cdot 10^{-4}$
1024	46.2	$4.41 \cdot 10^{-5}$	$8.33 \cdot 10^{-4}$
	$\tau^n \sim \mathcal{O}(n^2 \log n)$	$\tau_1^n \sim \mathcal{O}(\log n)$	$\tau_1^n \sim \mathcal{O}(n)$

**Table 3:** Simulation results for the numerical approximation of the two-dimensional Poisson equation by the use of fast diagonalization techniques.